Financial Constraints and Employment Dynamics following Natural Disasters*

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Abstract

We use confidential loan-level regulatory data to show that financial constraints can weigh on credit access and employment after a natural disaster at both the local and national level. Banks cut back on lending in disaster areas, particularly to the most financially constrained firms, and these reductions in credit supply lead to larger initial declines and slower subsequent recoveries in employment. Bank profitability is a key driver of this result: Borrowers more reliant on less-profitable lenders obtain fewer loans and pay higher interest rates following disasters. These less-profitable lenders also respond by providing fewer loans and charging higher interest rates to financially constrained borrowers in other unaffected areas. We show that these financial spillovers ultimately distort employment growth. Our findings suggest a potential role for policies that improve access to credit in the aftermath of natural disasters.

JEL Classification: **G11, G12, G21**

Keywords: Bank lending; Financial constraints; Natural disasters; Spillovers

*Views and opinions expressed in this paper reflect those of the authors and do not necessarily reflect those of the Federal Reserve System.

1 Introduction

Natural disasters impose tremendous financial burdens on the communities they hit. The National Oceanic and Atmospheric Administration (NOAA) estimates that in 2024 alone the US experienced 27 disasters causing more than one billion dollars in direct property damage[1], and these estimates likely understate the full costs of a disaster to the local economy (Strobl, 2011). To the extent that external finance can help meet these costs, which are often exacerbated by reduced revenues from depressed demand and the destruction of the capital stock, the terms and quantity of financing available to firms can play a key role in determining the scale of recovery and rebuilding efforts in a disaster's aftermath. In this paper, we provide empirical evidence for this channel using confidential loan-level regulatory data. We find that banking networks are a crucial determinant of not only the local effects of natural disasters, but also their national effects: Increased bank lending mitigates the direct employment effects of a natural disaster, but also generate spillovers that affect credit supply and employment in unaffected areas.

We begin by studying the firm-level consequences of exposure to natural disasters. We find that firms exposed to disasters have higher perceived probabilities of default, obtain fewer loans, and pay higher interest rates in the following years. However, these effects are sharply attenuated for the least financially constrained firms. These effects survive aggregation to the county level and have real consequences: Counties exhibiting more symptoms of financial constraint immediately prior to a disaster experience larger initial declines and slower subsequent recoveries in employment, and counties with higher default rates or lower inflows of credit following a disaster tend to experience worse ex-post employment outcomes. Together, these results suggest that firms' financial constraints matter for the real effects of a disaster.

Next, we show that a key driver of these firm-level financial constraints in this context is the financial health of their *lenders*. Among firms exposed to the exact same disaster, we find those matched with less-profitable lenders tend to pay higher interest rates and obtain less credit. Counties with lower average lender profitability also experience slower employment recoveries, suggesting that banks' operational footprints leave some areas more exposed to disasters.

We also find that bank profitability causes the effects of disasters to spill over and affect credit supply in other parts of the country by constructing a measure of firms' indirect disaster exposure

[1] For more details, see `https://www.climate.gov/news-features/blogs/beyond-data/2024-active-year-us-billion-dollar-weather-and-climate-disasters`.

based on their lender's share of loan volume flowing to disaster areas in *all other counties*. For firms who rely more on borrowing from low-profitability banks, increased external disaster exposure leads to less credit and higher interest rates, suggesting that banking networks can affect credit supply throughout the country. We also find that the spillovers of disasters through the lending networks of less-profitable banks are driven by more financially constrained borrowers.

Finally, we show that these spillovers affect employment outcomes: Counties with greater indirect exposure to natural disasters via less-profitable lenders experience brief but economically significant declines in employment. To the extent that this pattern also applies to a broader set of local shocks, these results suggest that the distribution of lender profitability can generate persistent heterogeneity in firms' ability to obtain credit following shocks originating elsewhere, and that these changes in credit supply ultimately affect real activity.

Related Literature. Our paper contributes to past work that analyzes the effects of natural disasters on firms' financial outcomes and studies their spillover effects through the banking system. The paper closest to ours is Ivanov et al. 2022, who show that natural disasters cause directly affected firms to draw down their credit lines—a result echoed in Brown et al. (2021)—and that firms in unaffected areas who rely on less-healthy lenders experience reductions in credit following natural disasters. We build on this work along two dimensions. First, we use a loan-level regulatory data set that contains all large commercial and industrial (C&I) loans from large US banks, including non-syndicated loans that are more likely to flow to small and non-public borrowers.[2] These data contain detailed borrower characteristics, which allow us to analyze how the spillover effects from natural disasters vary across firms as well as banks. Second, we analyze county-level employment outcomes, which allows us to study the real consequences of borrower and lender financial heterogeneity in response to natural disasters in both affected and unaffected areas.

Another closely related paper is Cortes and Strahan 2017, who use mortgage origination data to show that increases in local lending caused by natural disasters reduce banks' credit supply in unaffected areas. While consumer mortgages come from one bank, firms in our sample frequently obtain C&I loans from multiple banks at once, which provides rich within-county variation in

[2]Ivanov et al. (2022) use loan data from the Shared National Credit Program, which include information about all syndicated loans totaling $20 million or more and held by three or more financial institutions supervised by one of the main US banking regulators (the Federal Reserve, Federal Deposit Insurance Commission, and the Office of the Comptroller of the Currency). Our data will also include all commitments part of these facilities as long as they total $1 million or more and are held on the balance sheets of one of the banks subject to the Comprehensive Capital and Analysis Review. We describe our data in detail in Section 2.

lender exposure that we use to trace out shocks through banks' lending networks. We build on the work of Koetter et al. 2020, who also study the effects of natural disasters on business lending in Germany, by showing that changes in credit supply affect employment outcomes. Beyond the study of natural disasters specifically, an extensive literature has sought to use exogenous sources of variation to analyze how shocks to one part of a banking network affect lending in other parts (e.g. see Peek and Rosengren 1997, Peek and Rosengren 2000, and Schnabl 2012). Examples include shocks arising from commodities (Gilje et al. 2016, Wang 2021, Marsh et al. 2024, and Bidder et al. 2021), the 2007 global financial crisis (see Bord et al. 2021, Ceterolli and Goldberg 2012, De Haas and Van Lelyveld 2014, and Acharya and Schnabl 2010), or the COVID-19 pandemic (see Greenwald et al. 2024).

The remainder of the paper is structured as follows. Section 2 describes our data. Section 3 shows that financial constraints limit firms' ability to obtain credit following a disaster, and that these constraints affect the response of county-level employment. Section 4 shows that the financial health of a firm's lenders similarly affects disaster responses. Section 5 shows that disasters propagate through the lending networks of less-profitable banks and distort credit supply and employment in unaffected areas. Section 6 concludes.

2 Data

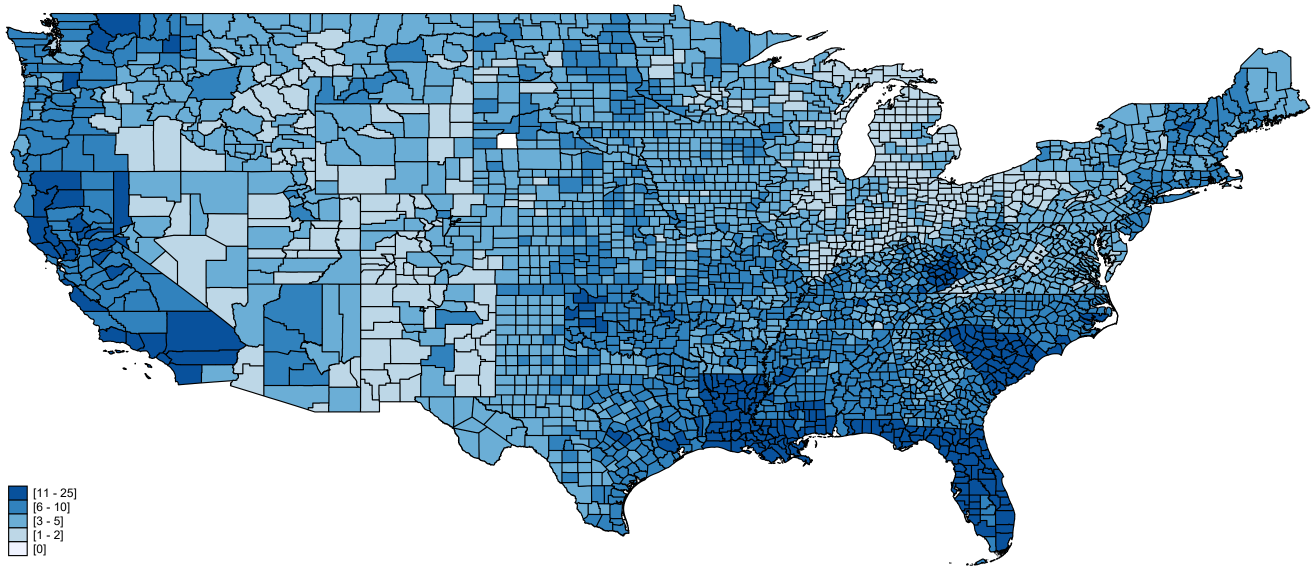
Natural Disasters. We use FEMA disaster declarations to identify the timing and location of natural disasters, choosing a sample period of 2015–2023 to align with available Y-14 data. Our data consists of both disasters associated with an emergency declaration and disasters that were declared a major disaster and hence received more aid than incidents in the former group.[3]

The resulting sample of natural disasters covers the entire country. Figure 1 is a heat map and documents the geographic distribution of disasters during the years 2015-2023. Disasters are mostly concentrated in coastal regions, as well as the Midwestern states, while the mountain region has been less affected. Further, due to the COVID-19 outbreak almost every county has been subject to at least one disaster.

Table 1 provides a summary of the frequency and severity of various types of disasters over the sample period. *Storm* events are the most common disaster type, followed by *Biological* disasters

[3]For more details, see `https://www.fema.gov/disaster/how-declared`.

Figure 1: Number of Disasters by County



***Notes**: The chart shows the number of FEMA disasters for each county between 2015-2023. Disasters include both emergency declarations and major disaster declarations.*

related to the COVID-19 outbreak. The table also illustrates considerable variation in disaster severity. For example, the median storm disaster incurs \$8.3 million in Public Assistance, whereas the 99th percentile incurs \$2.2 billion. The distribution for *Biological* disasters is even more skewed.[4] In our subsequent analysis, we aggregate over all events to maximize the sample size. A further breakdown of disaster types by states and time is available in Table A1 and Figure A1 in the Appendix.

One potential complication when studying the effects of natural disasters on the real economy through bank lending is the presence of disaster relief programs. However, we believe that these programs are unlikely to materially affect our results. FEMA grants are directed towards households, and loans by the Small Business Administration (SBA) are only meant for businesses that cannot receive conventional financing at reasonable terms, limiting their relevance for the firms in our sample. While disaster insurance claims can also help satisfy firms' funding needs, these claims can take several months to pay out and generally will not cover all expenses, making them imperfect substitutes for bank credit.[5] Nonetheless, to the extent that these programs are at least partially

[4]Damage estimates come from FEMA's Public Assistance (PA) program. PA is FEMA's largest grant program, which provides funds to state and local governments to assist communities responding to and recovering from major declared disasters or emergencies.

[5]A full distribution of large insurance claims can take several months (see `https://www.philadelphiafed.org/-/media/frbp/assets/economy/briefs/timing-of-flood-insurance-payments.pdf`). Insurance coverage is also often limited; for example, FEMA's National Flood Insurance Program (NFIP) only insures up to 1 million dollars.

able to satisfy firms' financing needs following a disaster, they suggest that the effects we document are conservative.

Table 1: Disasters: Type and Severity

Incident Type	# Events	Total Aid	25th Percentile	50th Percentile	75th Percentile	99th Percentile
Storm	9,399	29,591	1.2	8.3	27.4	2,217
Biological	6,395	76,990	0.0	0.0	248.8	14,016
Cold	1,407	984	1.7	10.1	35.1	111
Fire	675	6,210	0.0	0.2	2.4	375
Other	67	526	0.0	0.6	31.3	172

Notes*: Column 2 counts the total number of disasters for each disaster category over the years 2015-2023. Column 3 shows the approved public assistance across all disaster events within a particular category (in millions of dollars). The remaining columns display the 25th, 50th, 75th, and 99th percentile in the aid distribution for each disaster category (in millions of dollars).*

Y-14 Banks. Our primary data source for bank lending is the Y-14Q report. Data is collected at a quarterly frequency and the respondent panel consists of U.S. BHCs, U.S. IHCs of foreign banking organizations (FBOs), and covered SLHCs with $100 billion or more in total consolidated assets. Specifically, we use the corporate loan schedule (Schedule H.1) which contains loans with committed balances greater than or equal to $1 million. To obtain bank characteristics, we further link domestic BHCs in the Y-14Q report to their respective Y-9C report.

Table 2 reports descriptive statistics for the Y-14 banks at the bank-quarter level, and over the sample period 2015-2023. The bottom two rows provide a sense of coverage for the Y-14Q report. Reported Y-14 loans, on average, account for nearly 90 percent of the total commercial and industrial (C&I) lending for each bank. Thus, the Y-14 report provides a comprehensive overview of each bank's C&I lending portfolio. The average bank lends across 312 counties, suggesting the typical Y-14 bank has a broad geographic presence.

Table 2: Bank-Quarter Summary Statistics

Object	N	Mean	5p	10p	50p	90p	95p
Return on Equity (%)	960	7.9	-1.0	2.6	8.8	13.7	15.1
Return on Assets (%)	960	0.84	-0.13	0.27	0.92	1.41	1.56
Net Interest Margin (%)	960	2.07	0.43	0.63	2.2	2.97	3.42
# Lending Counties	960	312	15	58	257	665	879
Y-14 Loan % Total C&I	960	88.6	71.5	77.2	89.7	97.7	98.9

Notes*: All objects are annualized and ratios are reported in percent. Sample: 2015 Q1 - 2023 Q4.*

We use the loan-level Y-14Q data to create a firm-level panel. Our final cleaned data set excludes the following loans: All loans to firms in the finance, insurance, or real estate industries; any loan with a reported interest rate, probability of default, or loss given default of less than zero or more than 100 percent; loans missing a PD, origination date, or amount; loans below the minimum reporting threshold of $1 million; and loans for which the utilized amount exceeds the committed amount. After these cleaning procedures, we collapse the data to the firm-level using either a sum or loan-volume weighted average based on each loan's reported obligor TIN/EIN.

Table 3 provides firm-level descriptive statistics for the corporate loans in the Y-14Q report over the sample period 2015-2023. The average total outstanding loan commitment to a firm across all banks in our sample in each quarter is $67 million. Of the firms in our sample, the majority of corporate loans are revolving, meaning that borrowers have discretion over when they draw down their funds. Thus, not only do Y-14Q loans serve as a source of capital financing for firms, but they can also insure firms against negative shocks to their cashflow. The average firm with revolving credit utilizes 34.7 percent of their total committed amount.

The median values of sales and assets for firms in our sample are roughly $30 million and $50 million, respectively. These are both much smaller than the corresponding values from Compustat, largely because more than 90 percent of the firms in our data are not publicly traded. This enhanced coverage of small and privately held firms makes the Y-14Q data uniquely well suited to analyzing how the real effects of natural disasters depend on firms' financial constraints.

In addition to borrower and loan characteristics, we also observe banks' internal risk assessments for each borrower. For example, banks estimate and report a default probability for each loan. Aggregating to the firm level, the average probability of default is 3.2 percent with a median of 0.9 percent. Banks hedge their exposure to these potential losses through the use of loan seniority and/or collateral, which are reflected in their estimated losses given default (LGD). LGD averages 34 percent in our sample but climbs to more than 60 percent in the 95th percentile.

Real Activity. We use data from the Quarterly Census of Employment and Wages (QCEW) for employment in each county. Due to the smaller population size of some counties, we focus on total private nonfarm employment. We use this measure to proxy for the real economy in the specific area, absent other reliable granular data on economic activity at this level of geographic disaggregation.

Table 3: Y-14 Firm-Quarter Summary Statistics

Object	N	Mean	5p	10p	50p	90p	95p
Total Loan Commitments ($mil)	1.1m	67.0	1.0	1.1	4.5	94.7	224.8
Share of Revolving Loans (%)	1.1m	57.2	0	0	98.8	100	100
Revolving Utilization Rate (%)	719k	34.7	0	0	22.4	100	100
Interest Rate (%)	889k	4.5	1.75	2.19	4.08	7.49	8.5
Probability of Default (%)	1.1m	3.23	0.12	0.19	0.94	5.8	12.1
Loss Given Default (%)	1.1m	34	5.0	11.6	34.3	54.3	60.5
Firm Assets ($mil)	948k	40,412	1.83	3.27	29.5	1,604	5,319
Firm Sales ($mil)	947k	8,175	1.83	7.1	52.7	1,318	3,811
Public Firm Indicator	1.1m	0.08	0	0	0	0	1

***Notes**: Committed loan amounts, firm assets and firm sales are reported in millions of dollars. Loss Given Default is reported as a percentage of the bank's exposure. Sample: 2015 Q1 - 2023 Q4.*

3 Direct Disaster Effects

This section examines the direct local effects of natural disasters. In Section 3.1, we show that the average firm exposed to a disaster experiences higher probabilities of default and that they obtain less credit and pay higher interest rates in the following years. We also find that firms' access to revolving credit—which is far more common for large and publicly traded firms—sharply mitigates these effects. In Section 3.2, we then show that these financial responses matter for the real effects of the disaster: Initial employment declines are deeper, and the subsequent recoveries are slower, when firms in affected areas are more financially constrained.

3.1 Firm-Level Disaster Responses

We begin by estimating average firm-level effects of disaster exposure based on the following local projection (Òscar Jordà, 2005):

$$y_{i,t+h} = \delta^h y_{i,t-1} + \gamma^h D_{i,c,t} + \alpha_i^h + \beta_t^h + \epsilon_{i,t+h}^h, \tag{1}$$

where $y_{i,t+h}$ is the h-quarter ahead realization of variable y for firm i. α_i and β_t are firm and time fixed effects, respectively. The firm fixed effect absorbs time invariant firm-characteristics, including the greater disaster risk for firms located in areas prone to more frequent disasters. The time fixed effect accounts for national trends. We only include firms with at least 12 quarterly observations during our sample period (2015Q1 - 2023Q4) to precisely estimate α_i. The primary coefficient of interest is γ^h, which represents the h-quarter ahead effect of a binary indicator $D_{i,c,t}$ equal to one if a disaster occurred in firm i's county c at time t (and zero otherwise).[6] Standard errors are clustered by county.

The results are shown below in Figure 2. The top-left panel shows that banks increase their perceived probability of default (PD) for exposed borrowers by around 10 basis points following a disaster. This is an economically significant effect given that the median PD in our sample is less than 1 percent. Consistent with higher perceived riskiness, the top-right panel shows that borrowers in affected areas experience statistically significant increases of roughly 2 basis points on their average interest rates. While this effect is small relative to firms' average interest rate of 4.5 percent, it would still represent an annual increase in interest expenses of about \$134 thousand for a firm with the average loan volume of \$67 million. This increase in expenses is also accompanied by a reduction in lending: Following the disaster, firms' total committed lending exposure (bottom-left panel) declines by around 0.5 percent, which would imply a contraction in lending of more than \$330 thousand for the average firm in our sample.

Firms can mitigate this reduction by drawing down pre-existing credit lines. The bottom-right panel shows that firms respond by increasing their revolving credit utilization rate by about 25 basis points, which is consistent with the findings of Brown et al. (2021), who show that firms draw down credit lines in response to severe snowfall. However, taking advantage of this opportunity requires having a credit line in the first place, and roughly one in four firms never obtain one during our sample period. As Greenwald et al. (2020) emphasize, the firms that are best positioned to take advantage of unutilized credit capacity during times of stress also tend to exhibit the fewest symptoms of being financially constrained across a range of other dimensions commonly used in the literature.

To test whether these financial frictions generate firm-level heterogeneity in disaster responses, we estimate the following state-dependent regression (see also Auerbach and Gorodnichenko, 2012, or Ramey and Zubairy, 2018):

$$y_{i,t+h} = S_{i,t-1}\left[\delta^h_{s=1} y_{i,t-1} + \gamma^h_{s=1} D_{i,c,t}\right] + (1 - S_{i,t-1})\left[\delta^h_{s=0} y_{i,t-1} + \gamma^h_{s=0} D_{i,c,t}\right] + \alpha^h_i + \beta^h_{c,t} + \epsilon_{c,t+h}. \quad (2)$$

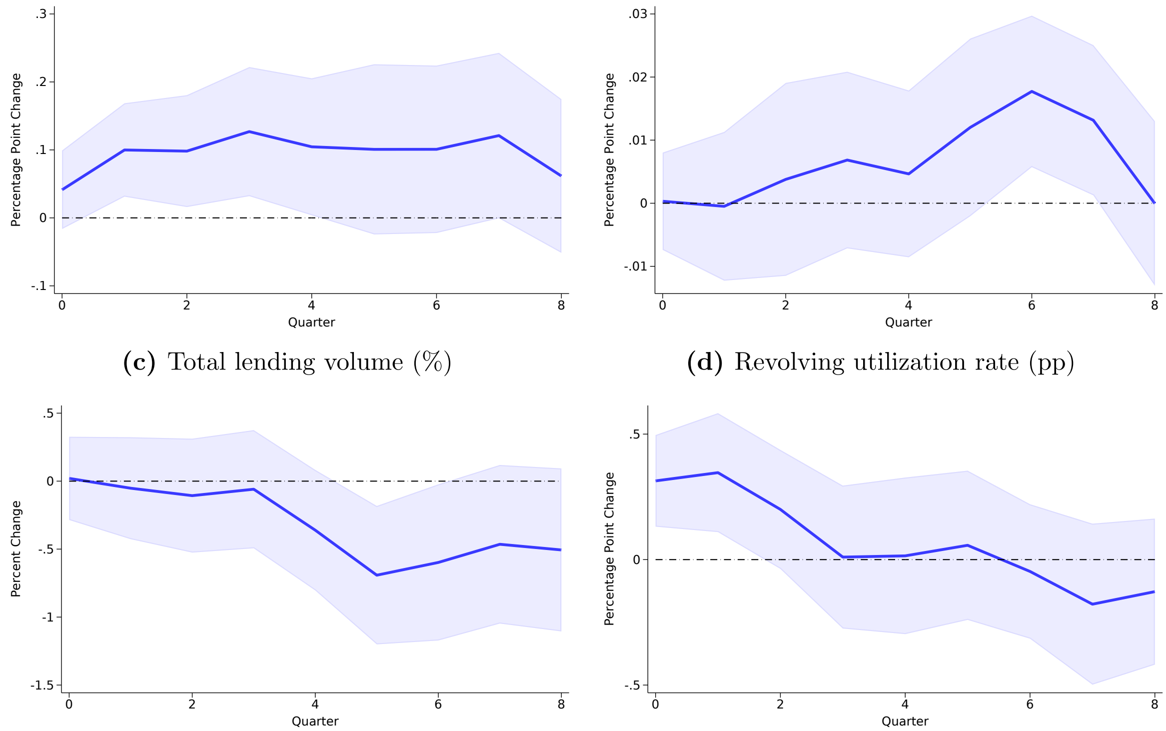
Relative to equation (1), this specification adds two features. The first is the addition of a binary

[6] We assign each firm to the county in which it had the highest total committed loan volume across all loans in our sample. For the small number of firms with loans from multiple counties in a quarter, we calculate $D_{i,c,t}$ as a loan volume-weighted average across all reported counties, though our results are virtually identical if we instead use the disaster indicator for their primary county.

Figure 2: Lending, Interest Rates, and Default Risk

(a) Probability of default (pp) **(b)** Interest rate (pp)

(c) Total lending volume (%) **(d)** Revolving utilization rate (pp)



Notes: *The charts show the impact of a natural disaster in $t = 0$ on various financial variables displayed in the title of each panel measured at the firm-level. The local projection is specified in equation* (1). *Shaded areas indicate 95 percent confidence intervals. Sample: 2015 Q1 - 2023 Q4.*

state variable $S_{i,t-1}$ that allows us to test for heterogeneity in firm-level disaster responses. The second is the inclusion of county-time fixed effects $\beta^h_{c,t}$, which absorb the average effect of a disaster common to all firms in the county and allow us to estimate whether firms with different values of $S_{i,t-1}$ responded differently to the exact same disaster at the exact same time. We test whether disaster responses differ depending on whether a firm is (i) publicly traded or (ii) is above the median firm size in terms of reported assets or (iii) whether the firm is perceived as risky from the perspective of the lending bank, all three of which are generally thought to be correlated with firms' access to credit. As before, we restrict the sample to firms with at least 12 observations during our sample period to precisely estimate the firm fixed effect α_i. We also include only county-quarters with at least 10 firms to narrow down $\beta_{c,t}$. The primary object of interest is difference between $\gamma^h_{s=1}$ and $\gamma^h_{s=0}$, which captures the different effect of a disaster for a firm with $S_{i,t-1} = 1$ relative to $S_{i,t-1} = 0$. As before, we cluster standard errors by county.

In Figure 3 below, we report the responses of total utilized credit and the average interest rate. We focus on utilized credit because it nets out the potentially offsetting effects of credit line drawdowns and decreased lending commitments shown in Figure 2. For example, a firm that does not renew an expiring $1 million loan and instead draws down $1 million of revolving credit will report a decline of $1 million in total committed exposure, but no change in utilized credit. Following a disaster, the left panels show that total utilized credit increases for public firms relative to private firms by about 15 percent on impact before fading over the next few quarters. Similarly, credit utilization increases by about 4 percent for large relative to small firms. Despite this increased utilization, the right panels show that large and public firms experience declines in their interest rates of roughly 5 basis points on average relative to small or private firms. We observe similar results when looking at the probability of default as assessed by the lending bank. Firms with an above median PD contract their credit utilization by 2 percent, while interest rates increase by 5 basis points.

These results, which show that less-constrained firms are able to obtain more and cheaper credit relative to constrained firms following a natural disaster, have two key implications. First, to the extent that this access to financing allows exposed firms to avoid reducing output or employment, it suggests that the real effects of a disaster will be more severe when they hit an area with more financially constrained firms. And second, they also highlight a potentially important source of risk for banks: Because they cannot refuse firms' access to revolving credit once it is committed (see Greenwald et al., 2020), a disaster in one area could have broader consequences if the resulting drawdowns induce exposed banks to adjust the terms or volume of credit they provide in other, unaffected areas. We test the first prediction in Section 3.2, and the second prediction in Section 5.

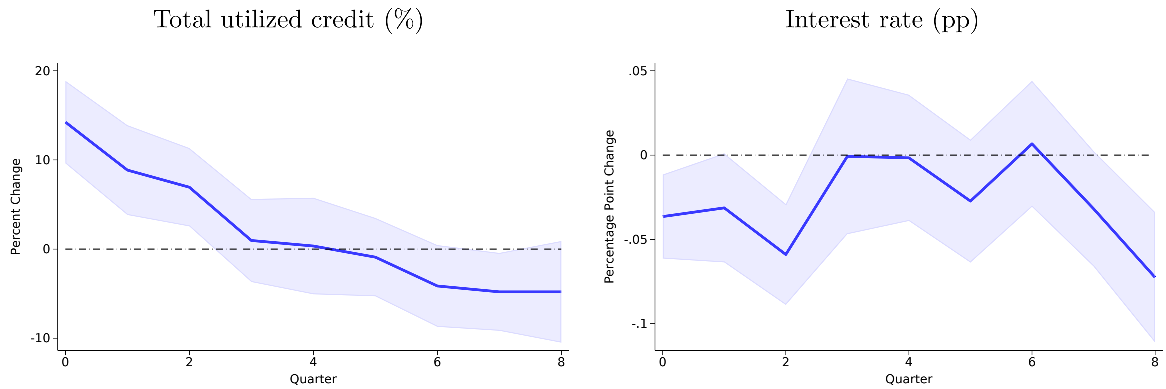
3.2 Financial Conditions Shape the Real Effects of a Disaster

In this section, we first show that employment in counties exposed to natural disasters declines immediately, but then subsequently increases over the following years as the area recovers. We then show that this pattern is exacerbated by financial frictions: Counties in which firms show more signs of being financially constrained display deeper initial downturns and smaller recoveries across a range of metrics commonly cited in the literature, suggesting that financial constraints are an important source of heterogeneity when studying the direct effects of a disaster.

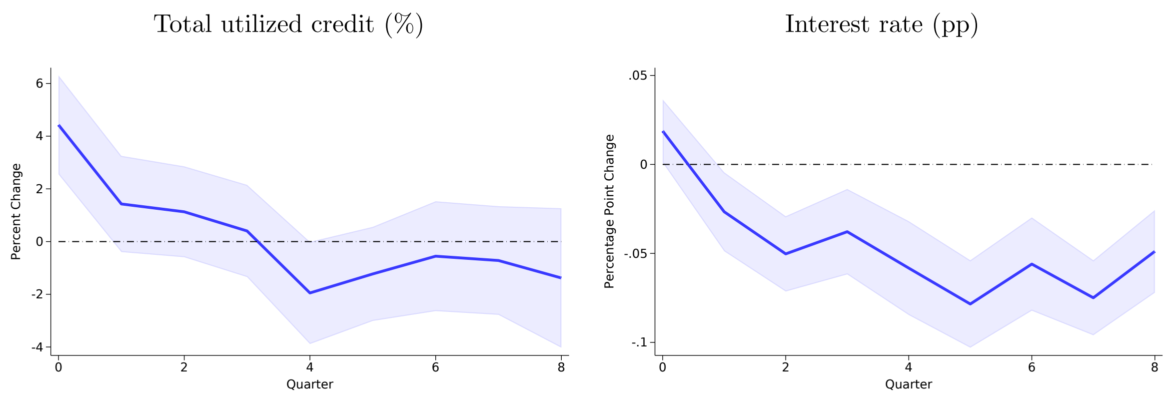
To study the average effect of a disaster on employment, we estimate the following regression:

Figure 3: Lending Terms and Borrower Characteristics

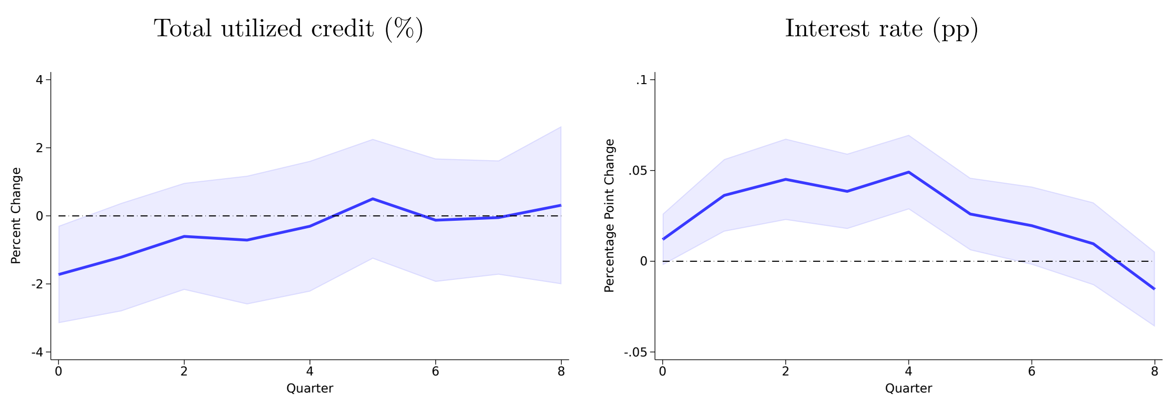
(a) Public versus Private Firms



(b) Large versus Small Firms



(c) High versus Low Risk Firms

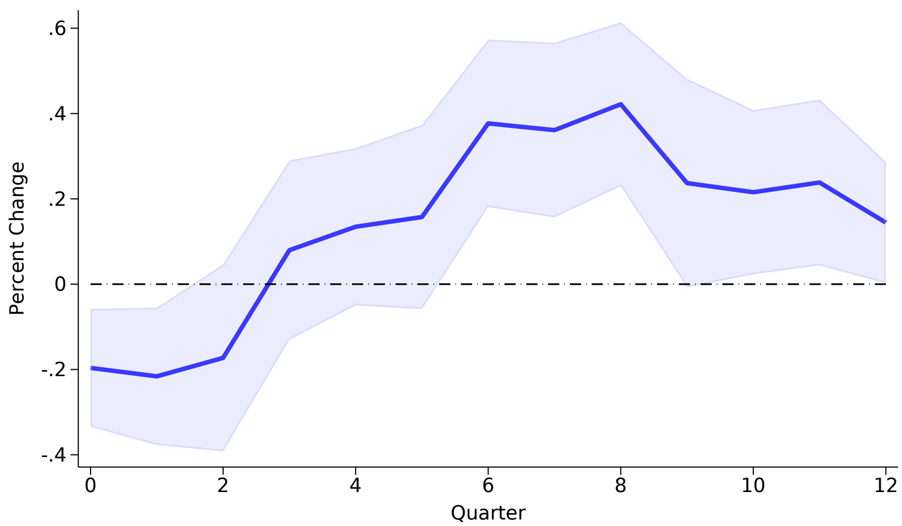


Notes: *The charts show the impact of a natural disaster in* $t = 0$ *on utilized credit (left panels) and interest rates (right panels) measured at the firm-level for different firm-level characteristics. The local projection is specified in equation* (2)*. Shaded areas indicate 95 percent confidence intervals. Sample: 2015 Q1 - 2023 Q4.*

$$y_{c,t+h} = \sum_{j=1}^{4} \delta_j^h y_{c,t-j} + \gamma^h D_{c,t} + \alpha_c^h + \beta_t^h + \epsilon_{c,t+h}. \tag{3}$$

The dependent variable $y_{c,t+h}$ is total nonfarm employment in logs at the county-level c. The independent variable of interest is the disaster indicator $D_{c,t}$. We include a county fixed effect α_c and a time fixed effect β_t, and include four lags of the dependent variable to account for pre-trends. To preserve aggregation, estimates are weighted by employment at $t-1$. As in the previous section, we cluster standard errors by county. The coefficient of interest is γ^h, which shows the effect of a disaster on employment after h periods and is plotted below in Figure 4.

Figure 4: Employment Response to a Disaster



***Notes**: The plot shows the trajectory of employment after a natural disaster in $t = 0$. The local projection is specified in equation (3). Shaded areas indicate 95 percent confidence intervals. Sample: 2015 Q1 - 2023 Q4.*

Following a disaster, employment briefly declines by about 0.2 percent before steadily recovering over the following two years. This pattern is consistent with other recent work studying the economic effects of natural disasters including Tran and Wilson (2020), Deryugina (2017), and Jerch et al. (2023). One natural explanation for this "overshooting" phenomenon is that an increase in employment can help to at least partially rebuild the capital stock destroyed by the disaster, an idea which is supported by the findings of Tran and Wilson (2020) that much of the employment recovery is driven by the construction sector.[7]

However, large-scale construction projects rely heavily on external financing even under normal circumstances; in the aftermath of a disaster that has often destroyed productive capital, dampened sales, and made finding workers difficult, access to external capital is likely to be even more

[7] These results do not imply that disasters are beneficial on net, particularly when they lead to destruction of the capital stock. Nonetheless, Hornbeck and Keniston (2017) provide a historical case study of how a disaster can generate coordination benefits that ultimately leave some aspects of the local economy—in this case, the quality of buildings—persistently better off.

important for generating the recoveries shown in Figure 4. Thus, we would expect that areas in which firms display more signs of being financially constrained would experience some combination of deeper initial declines and slower subsequent recoveries in employment. To test this hypothesis, we estimate the effect of pre-existing financial conditions on employment after a natural disaster:

$$y_{c,t+h} = S_{c,t-1}\left[\gamma^h_{s=1} D_{c,t} + \delta^h_{s=1} Z_{c,t-}\right] + (1 - S_{c,t-1})\left[\gamma^h_{s=0} D_{c,t} + \delta^h_{s=0} Z_{c,t-}\right] + \alpha^h_c + \beta^h_t + \epsilon_{c,t+h}. \quad (4)$$

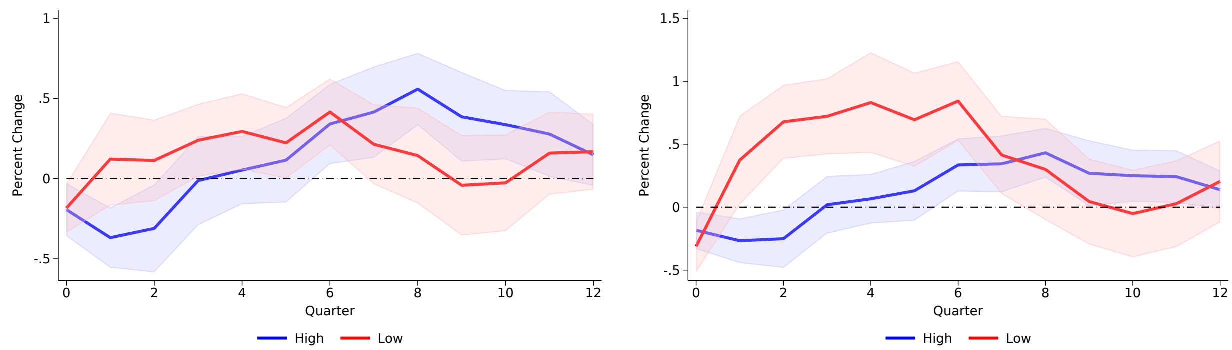
For convenience, we summarized the four lags of the dependent variable into a vector $Z_{c,t-}$. The key difference relative to equation (3) is the inclusion of a binary county-level indicator $S_{c,t-1}$ that reflects whether an underlying indicator of financial constraint is *high* or *low* in a county in the quarter prior to the disaster. The financial variables are aggregated sums or loan-weighted averages from the loan-level Y-14 data. The remaining setup, including controls, fixed effects, and standard errors is identical to the baseline equation (3).

Figure 5 plots the results for two different underlying financial variables that determine the regime of $S_{c,t-1}$: Probability of default (Panel (a)) and revolving credit utilization (Panel (b)). In each case, the high (low) state indicates that the measure in a given county was above (below) the median across all counties in the quarter prior to the disaster. The left panel suggests that counties with riskier firms prior to the disaster experience larger and more persistent declines in employment. Similarly, and consistent with our findings in the previous section, the right panel shows that counties with less utilized revolving credit prior to the disaster experience stronger and more rapid recoveries in employment relative to counties with high utilization. Together, these results show that ex-ante measures of financial constraint play an important role in determining the severity of a disaster's impact on local employment.

Next, we provide some suggestive evidence that the *ex-post* response of these financial variables also matters in shaping a county's disaster response. Our approach seeks to understand whether counties that fare relatively better financially in the wake of a disaster are also, on average, the same counties that fare relatively better in terms of their employment outcomes. Because both employment and financial conditions are likely to respond to a range of unobservable shocks, we emphasize that these effects should not be thought of as causal. Nonetheless, they are useful in understanding the unconditional correlations between real and financial outcomes following a disaster. We estimate the following regression:

Figure 5: State Contingent Employment Response

(a) Probability of Default **(b)** Revolving credit utilization



Notes: *The charts show the impact of a natural disaster in $t = 0$ on employment conditional on different states at $t-1$. The classification of the state variable into a 'high' or 'low' regime is based on the quarterly median of the variable displayed in the title of each panel. The local projection is specified in equation (4). Shaded areas indicate 95 percent confidence intervals. Sample: 2015 Q1 - 2023 Q4.*

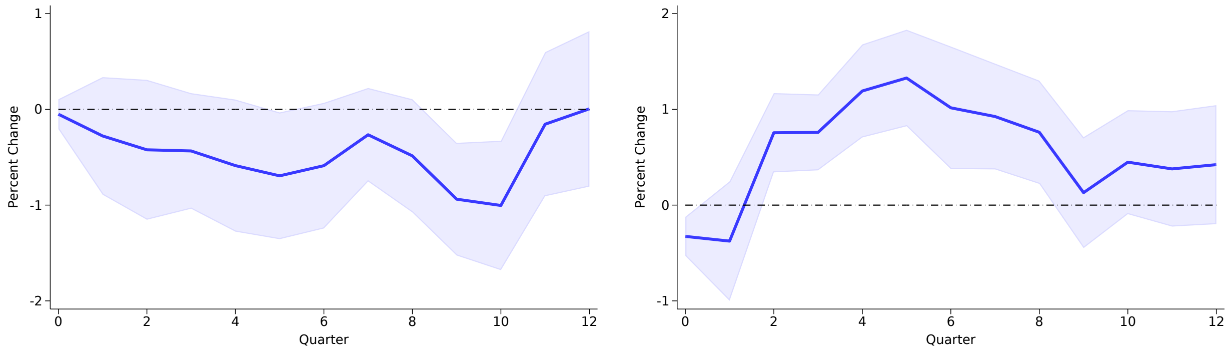
$$\Delta_h y_{t(i)} = \gamma^h \Delta_h x_{t(i)} + \epsilon_{h,t(i)}, \tag{5}$$

where h refers to the horizon (in quarters) after a disaster i at time t. $\Delta_h y_{t(i)}$ is the cumulative change in log employment during the first h quarters after the disaster at $t(i)$. We use the notation $t(i)$ to emphasize that we, for this exercise only, zoom in on data in the immediate aftermath of a diaster. The counterfactual is hence not the absence of a disaster, but a disaster with a different response of some financial variable x. The right hand variable $\Delta_h x_{t(i)}$ is then defined as the cumulative change (or growth rate) of x during the h quarters after a disaster. The growth rate $\Delta_h x_{t(i)}$ is standardized for comparison. Because $x_{t(i)}$ is itself endogenous, we reiterate that γ^h can't be interpreted in a causal sense. We weight estimates by employment in the period prior to a disaster and report heteroskedastic-robust standard errors.

The left panel of Figure 6 shows that disasters which lead to more defaults also unsurprisingly lead to lower employment: a one standard deviation increase in the default rates of loans in a county leads to an additional decline of roughly 1 percent in employment. In contrast, the right panel shows that areas which subsequently increase their utilization of revolving credit tend to have better employment outcomes: A one standard deviation increase in ex-post utilized lending volume is associated with an additional 1 percent increase in employment in the aftermath of a disaster. On their own, these results cannot tell us whether this increase in utilized credit was the cause of the increase in employment, its consequence, or simply the joint result of a shock affecting both

Figure 6: Employment and Financial Outcomes after the Disaster

(a) Default rate **(b)** Revolving credit utilization



Notes: *The charts show the results from a bivariate regression specified in equation* (5) *with cumulative employment growth as the dependent variable and the standardized cumulative change of the variable described in the title of each panel as the dependent variable. Shaded areas indicate 95 percent confidence intervals. Sample: 2015 Q1 - 2023 Q4.*

simultaneously. Nonetheless, they are consistent with our results in the previous section showing that greater *ex-ante* financial flexibility mitigates the negative employment effects of a disaster and emphasize the important link between real and financial consequences for local borrowers. In the next section, we show that the financial health of *lenders* is also crucially important for understanding this mechanism.

4 Lender Profitability and Natural Disasters

The previous section showed that financial constraints limit firms' opportunities to obtain credit in the aftermath of a disaster, and that more severe constraints lead to deeper declines and slower recoveries in employment. In this section, we show that the financial flexibility of the *lenders* operating in a particular county also plays an important role in determining the disaster's real effects. Less-profitable banks will have greater difficulty absorbing loan losses and credit line drawdowns that accompany a local disaster without adjusting the terms or quantity of credit. Hence, we expect that firms matched with less-profitable banks are more likely to experience a tightening in lending terms following a disaster. We provide empirical evidence supporting this prediction in this section. We then show that counties in which firms tend to borrow from less-profitable banks experience worse employment outcomes following a disaster, highlighting an important role for lender profitability in driving the local employment response to a disaster. Finally, in Section 5, we show that disasters generate nationwide spillovers through less-profitable banks by inducing them to change their lending in other *unaffected* areas.

4.1 Measuring Bank Profitability

Our baseline measure of profitability is net interest margin (NIM), which measures the difference between the interest revenues earned on a bank's assets and the interest expenses paid on its liabilities as a share of assets. Banks with a higher NIM are able to earn more interest income relative to their interest expense, and are thus better positioned to absorb losses or make new loans. Because banks are fundamentally reliant on interest-bearing assets and liabilities, this measure is a key metric for bank profitability (e.g. see Drechsler et al. (2021) and Whited et al. (2021)) and is of first-order importance when evaluating a bank's overall condition. Nonetheless, we show in the appendix that our results are robust to alternate measures of profitability, including return on equity or return on assets.

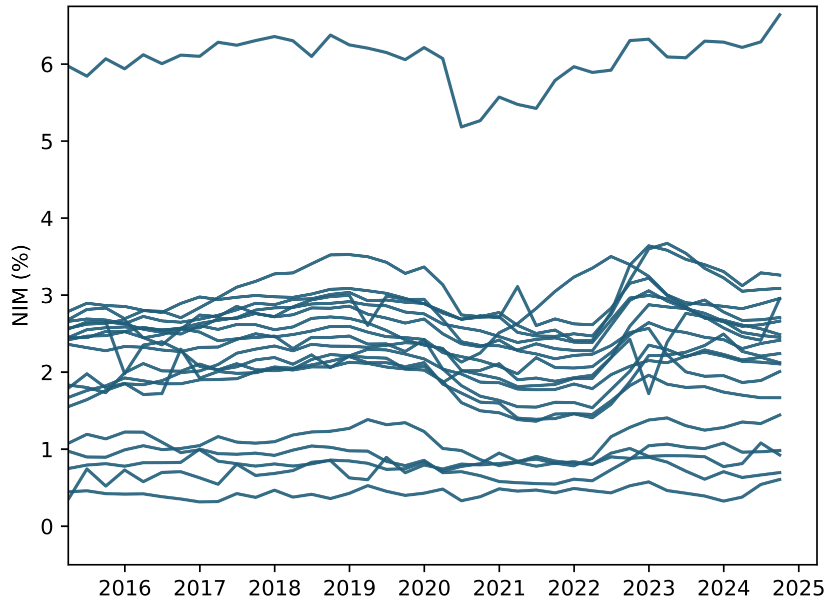
Table 2 reports summary statistics for NIM in our sample. The average Y-14 bank operated with a NIM of 2.1 percent, while the 10th and 90th percentile values were 0.6 percent and 3.0 percent, respectively. Figure 7 shows that differences in net interest margins across banks tend to be very persistent and relatively stable during our sample period. As documented in past work such as Chodorow-Reich (2014), differences in bank health can have real effects on a firm's response to a negative shock if they impact its ability to obtain credit; we test this prediction in the next section.

4.2 Local Effects of Bank Profitability

To study how lender profitability affects a firm's response to a natural disaster, we re-estimate equation (2) where the state variable is an indicator equal to one if the loan volume-weighted average NIM from the perspective of the borrower was above or below the median across all borrowers in the prior quarter. As before, we include county-quarter fixed effects, so our identifying variation comes from observing different responses to the same disaster at the same time for firms matched to different combinations of lenders. We plot the difference between high-NIM (more profitable) versus low-NIM (less profitable) lenders, and trace out the effect for total utilized credit and the average interest rate in Figure 8.

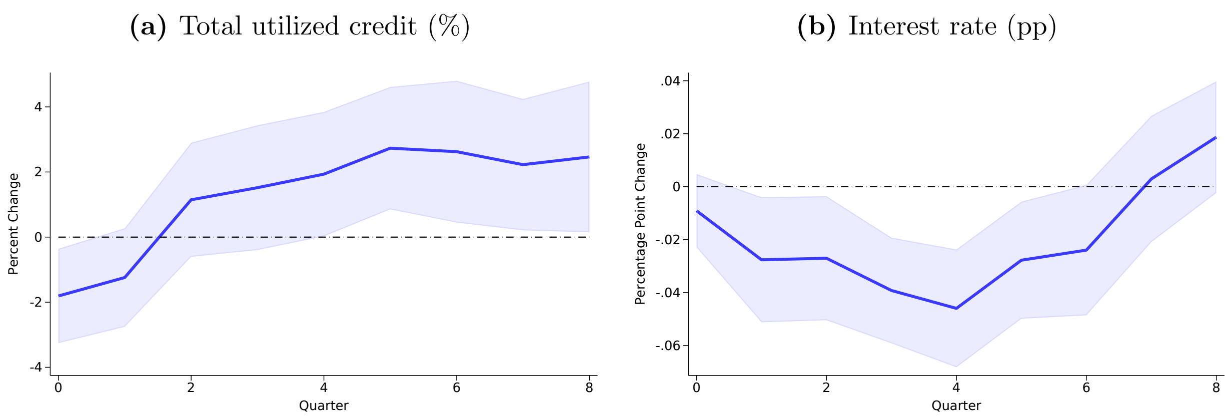
Consistent with our results in Section 3.1, we find that firms benefit financially from relationships with more profitable lenders. The left panel shows that credit utilization briefly declines for firms with more profitable lenders relative to those with unhealthy lenders following the disaster—consistent

Figure 7: Bank-Level Net Interest Margins Over Time



Notes: *The plot shows bank-level net interest margins for reporting Y-14 banks. The sample is restricted to only Y-14 banks which have at least 40 reported quarters. Sample: 2015 Q1 - 2023 Q4.*

Figure 8: Profitable versus Unprofitable Lenders

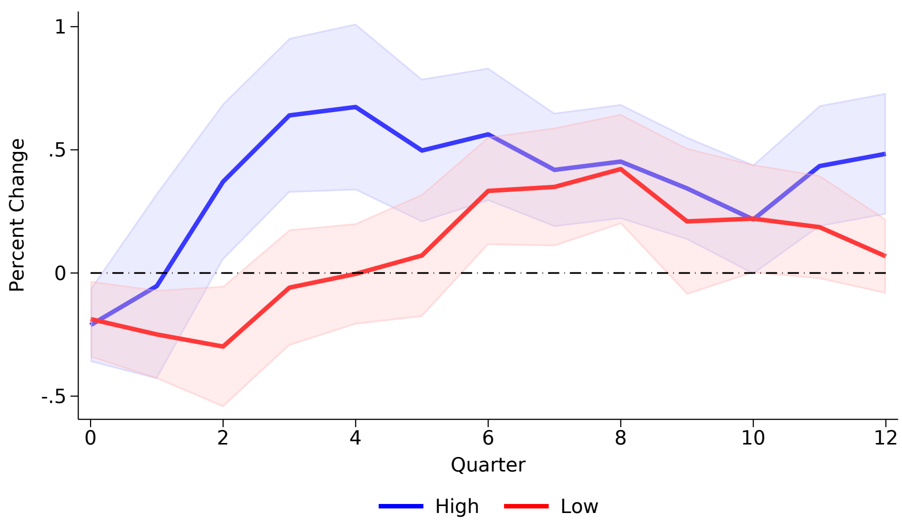


Notes: *The charts show the impact of a natural disaster in* $t = 0$ *on utilized credit (Panel (a)) and interest rates (Panel (b)) measured at the firm-level depending on the profitability of the lending bank. The classification is based on the quarterly median in NIMs. The local projection is specified in equation* (2). *Shaded areas indicate 95 percent confidence intervals. Sample: 2015 Q1 - 2023 Q4.*

with Ivashina and Scharfstein (2010), who show that firms quickly draw down their credit lines when concerned about their lenders' health—but steadily and persistently increases roughly 2 percent over the following years. Similarly, we find that firms matched to more-profitable lenders experience a decline of roughly 4 basis points in their average interest rate relative to firms matched to less-profitable lenders following the disaster. Thus, firms with high-NIM lenders obtain more credit at better prices than their peers exposed to the same disaster.

We argued previously that these firm-level financial responses could help rationalize differences in county-level employment responses. We find a similar effect when conditioning on bank profitability rather than firm financial constraints. For Figure 9, we re-estimate equation (4) with bank profitability as the relevant state variable. The chart plots two county-level employment responses conditional upon whether the average NIM exposure of borrowers in a county was above or below the national median across counties in the period prior to the natural disaster. The chart shows that the initial decline in employment after a natural disaster is driven by counties in which borrowers rely more on low-NIM lenders, and that the subsequent recovery of employment is slower and weaker than areas in which more lending comes through high-NIM banks.

Figure 9: Employment Response and Lender Profitability



Notes: *The plot shows the impact of a natural disaster in $t = 0$ on employment conditional on different NIM levels at $t-1$. The classification of the state variable into a 'high' or 'low' regime is based on the quarterly median. The local projection is specified in equation (4). Shaded areas indicate 95 percent confidence intervals. Sample: 2015 Q1 - 2023 Q4.*

These results provide further evidence that financial frictions are an important determinant of the real effects of a natural disaster: If firms experiencing a disaster have relationships with profitable lenders, they are able to obtain more credit while paying lower interest rates. One corollary of this fact is that less-profitable lenders respond to natural disasters by providing less credit on worse terms to disaster areas. In the next section, we show that these adjustments are not restricted to directly affected areas, and that less-profitable banks also respond to disasters by adjusting their lending behavior in other unaffected areas.

5 Spillovers

In this section, we show that disasters in one area propagate through the banking system and affect lending in areas without any direct disaster exposure. This approach builds on past work such as Cortes and Strahan (2017), Gilje et al. (2016), Wang (2021) and Ivanov et al. (2022) in documenting bank spillovers from *affected* markets to *unaffected* markets. We begin by providing descriptive statistics on banks' disaster exposure in Section 5.1. Next, consistent with financial constraints causing shocks to propagate through firms' internal capital markets (see Giroud and Mueller (2015) and Giroud and Mueller (2019)), we show in Section 5.2 that these spillovers are driven by lenders with low profitability: For firms with below-median lender profitability that are *not* exposed to a disaster, we find that an increase in lender disaster exposure *in all other counties* causes firms to obtain less credit and pay higher interest rates. In Section 5.3 we highlight that spillovers from low profitability banks are concentrated among financially constrained borrowers. Then we show that these spillovers have temporary real effects on employment.

5.1 Bank Disaster Exposure

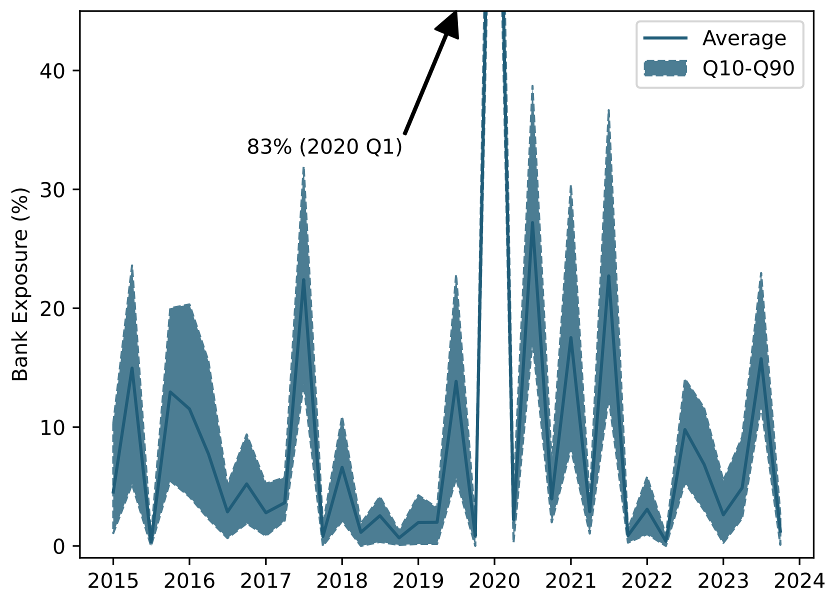
Y-14 banks operate expansive branch and loan networks that span many geographic markets; as Table 2 highlighted, the average Y-14 bank reported business lending across 312 counties in each quarter. These broad geographic footprints suggest that a natural disaster affecting one area could generate spillovers across many others. To quantify this effect, we construct a loan-weighted measure of a bank's exposure to natural disasters via its loan network $E_{b,t}$:

$$E_{b,t} = 100 * \frac{\sum_c L_{c,b,t-1} D_{c,t}}{\sum_c L_{c,b,t-1}}.$$

As before, $D_{c,t}$ is a binary disaster indicator. $L_{c,b,t-1}$ is the loan volume of bank b in county c. We lag the loan volume by one quarter to mitigate endogeneity concerns, as banks adjust lending in response to a disaster (see Figure 2). The exposure ranges between $[0, 100]$ percent. For example, a value of 100 percent would mean that all counties receiving a loan from bank b at time $t-1$ were subject to a disaster at time t. Figure 10 plots the average bank exposure over time along with the 10th and 90th percentiles.

Average exposure hovers between slightly above zero to 30 percent, with a notable spike during Covid-19. This figure also illustrates meaningful dispersion across banks at each point in time,

Figure 10: Bank Exposure to Natural Disasters



Notes: *The plot shows average bank-level exposure to natural disasters across counties along with the 10th and 90th percentile of the cross-section quarter. Sample: 2015 Q1 - 2023 Q4.*

with about 8.4 percentage points on average separating the 10th and 90th percentiles. We showed previously that direct disaster exposure leads to more defaults and credit line drawdowns, both of which constrain bank lending. We next show that the dispersion in disaster exposure and bank profitability can generate variation in lending responses to natural disasters, even for the borrower that is not hit by a disaster.

5.2 Impact on Unaffected Firms and the Role of Bank Profitability

To show that bank profitability generates lending spillovers, we estimate the following regression:

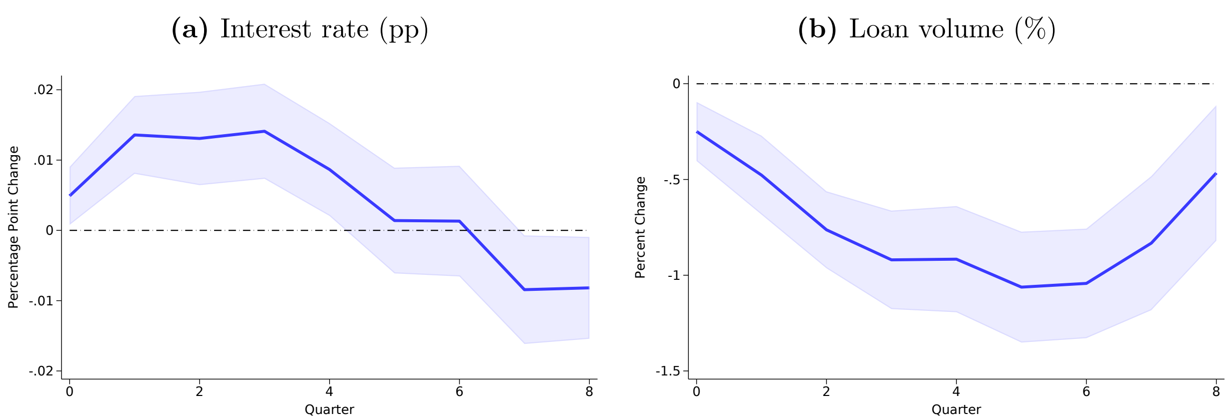
$$y_{i,t+h} = \delta^h y_{i,t-1} + \gamma^h E_{i,t}^{-c} H_{i,t-1} + \eta^h H_{i,t-1} + \omega^h E_{i,t}^{-c} + \alpha_i^h + \beta_{c,t}^h + \epsilon_{i,t+h}^h. \tag{6}$$

$H_{i,t-1}$ is a loan volume-weighted profitability measure of firm i's lenders, which we calculate based on a loan-level indicator that is one, if the loan is associated with a bank with *below*-median profitability across all loans in the previous period. $E_{i,t}^{-c}$ is the loan volume-weighted diaster exposure of banks serving firm i across all counties *excluding* c in which firm i operates. Excluding disasters in a firm's home county from this calculation allows us to trace out the purely indirect effects of a disaster through the banking system.

The coefficient of interest is γ^h, which captures the interaction between bank profitability and external disaster exposure. We define treatment in terms of firms' exposure to banks that have both low profitability and high external disaster exposure. The measure $E_{i,t}^{-c}H_{i,t-1}$ takes on values between 0 and $E_{i,t}^{-c}$. For borrowers with a single low-profitability lender, the two measures will be identical. For borrowers with multiple lenders, however, this measure will increase with firms' exposure to banks that have both below-median health and high exposure to natural disasters in other areas. For interpretability, we subsequently plot the effect from a one standard deviation increase in exposure. The remaining conventions are identical to equation (2). In particular, we include firm fixed effects α_i^h and county-quarter fixed effects $\beta_{c,t}^h$. We also restrict the sample to firms with at least 12 observations and counties with at least 10 firms to precisely estimate the fixed effects. Standard errors are clustered by county.

The results are shown in Figure 11. Note that the measure of bank profitability is flipped relative to the previous subsection; there, we plotted the marginal effects for an exposed firm with more profitable lenders. Here, because the shock is defined entirely by exposure to less-profitable banks, we would expect the effects to go in the opposite direction. Our estimates suggest that a firm which obtains all of its lending from banks with below-median profitability relative to a firm which obtains all of its lending from banks with above-median profitability experiences a statistically significant 1-2 basis point increase in interest rates and a decline of more than 1 percent in loan volumes when the lenders experience a one standard deviation increase in disaster exposure.

Figure 11: Spillovers to Unaffected Firms



Notes: *The charts show spillovers from a natural disaster in $t = 0$ on interest rates (Panel (a)) and loan volume (Panel (b)) at the firm-level depending on bank exposure and profitability as measured by NIMs (γ^h). See text for definitions. The local projection is specified in equation (6). Shaded areas indicate 95 percent confidence intervals. Sample: 2015 Q1 - 2023 Q4.*

Ultimately, while operating across a large geographic area can diversify a bank's risk, these results show that it can also allow disasters in one area affect lending in other unaffected areas. We next show that spillovers from low profitable and highly exposed banks are concentrated among more financially constrained borrowers.

5.3 Spillovers, Borrower Characteristics and Real Effects

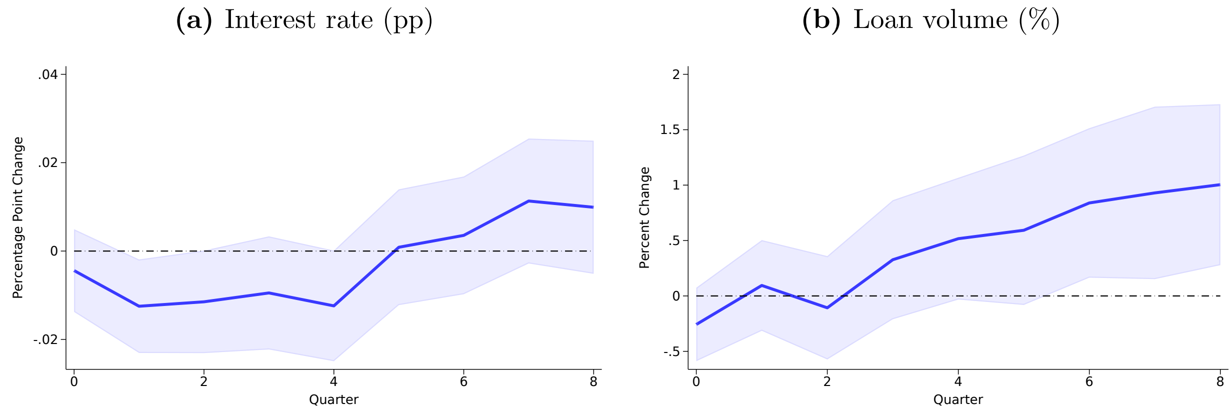
Here we show that disaster spillovers through less profitable banks vary with firms' financial constraints, and that these spillovers affect real outcomes. We begin by estimating the following regression:

$$\begin{aligned} y_{i,t+h} =& S_{i,t-1}\left[\delta^h_{s=1} y_{i,t-1} + \gamma^h_{s=1} E^{-c}_{i,t} H_{i,t-1} + \eta^h_{s=1} H_{i,t-1} + \omega^h_{s=1} E^{-c}_{i,t}\right] \\ &+ (1 - S_{i,t-1})\left[\delta^h_{s=0} y_{i,t-1} + \gamma^h_{s=0} E^{-c}_{i,t} H_{i,t-1} + \eta^h_{s=0} H_{i,t-1} + \omega^h_{s=0} E^{-c}_{i,t}\right] + \alpha^h_i + \beta^h_{c,t} + \epsilon^h_{i,t+h}. \end{aligned} \tag{7}$$

The difference relative to equation (6) is that we now also condition on heterogeneity at the firm level as captured by the binary state variable $S_{i,t-1}$. Similar to the local effects of a disaster, we test whether spillovers differ if a firm (i) is above median size, (ii) publicly traded, or (iii) perceived as above median risky from the perspective of the lending banks. As before, we include county-quarter fixed effects and firm fixed effects, and cluster standard errors by county. We also restrict the sample to firms with at least 12 observations and counties with at least 10 firms to precisely estimate the fixed effects. The objective of interest is the difference between $\gamma^h_{s=1}$ and $\gamma^h_{s=0}$ conditional on time-invariant heterogeneity at the firm-level and the same mix of low-profitable disaster exposed banks. In the case of firm size, for example, this measure tells us whether the spillover effects of natural disasters through less profitable banks on firms' credit supply are disproportionately larger for small firms relative to large firms.

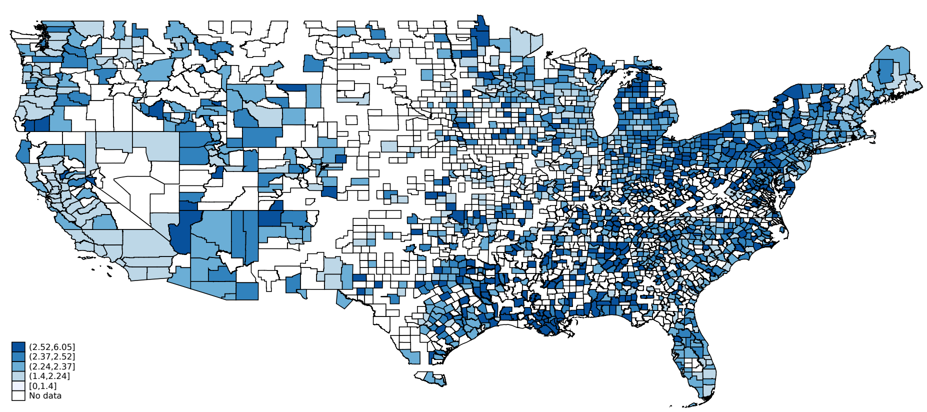
The results are shown in Figure 12. Our estimates suggest that, for two borrowers in unaffected areas who are both matched to low-profitability banks hit with a one standard deviation increase in disaster exposure, the large firm will experience a decline of 2 basis points in their interest rates and an increase in lending volume of roughly 1 percent relative to the small firm. These effects are sizeable relative to the average spillover effects of a 1 basis point increase in interest rates and a 1 percent reduction in lending reported in Figure 11, suggesting that these spillovers are driven by small firms. In the appendix, we show similar effects if we vary the bank profitability measure, or if we condition on differences in banks' perceived firm default probabilities or whether a firm is publicly traded.

Figure 12: Spillovers: Large versus Small Firms in Unaffected Areas



Notes: *The charts show spillovers from a natural disaster in $t = 0$ on interest rates (Panel (a)) and loan volume (Panel (b)) at the firm-level depending on bank exposure and profitability as measured by NIMs for large versus small firms ($\gamma^h_{s=1} - \gamma^h_{s=0}$). See text for definitions. The local projection is specified in equation (7). Shaded areas indicate 95 percent confidence intervals. Sample: 2015 Q1 - 2023 Q4.*

Figure 13: County-Level Exposures to Low-NIM Banks



Notes*: The plot shows county-level net interest margins of lending banks, weighted by loan volume. The sample is restricted to only counties with at least 50 Y-14 loans over the sample period. Sample: 2015 Q1 - 2023 Q4.*

We next examine the real effects of bank spillovers on employment. As shown in Figure 13, the average profitability of Y-14 banks varies substantially across counties, precisely because banks operate across different regions. This implies that the average borrower in one county is matched with a different set of banks than the average borrower in another county. This bank-profitability heterogeneity in turn could rationalize different employment responses in unaffected areas in response to bank disaster exposure. To investigate this channel, we estimate the following regression:

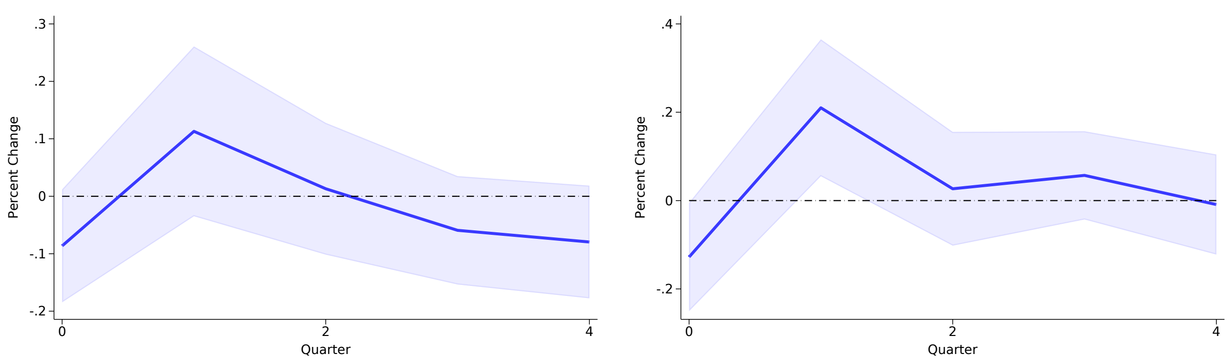
$$y_{c,t+h} = \delta^h y_{c,t-1} + \gamma^h E^{-c}_{c,t} H_{c,t-1} + \eta^h H_{c,t-1} + \omega^h E^{-c}_{c,t} + \alpha^h_c + \beta^h_t + \epsilon_{c,t+h}. \quad (8)$$

The regression is a mix between equation (6) and equation (3). In particular, the dependent variable is log nonfarm employment at county-level c. However, the coefficient of interest is the interaction between bank exposure and bank profitability, both aggregated to a loan-weighted average at the county-level. As before, we add both time and county fixed effects.

Figure 14 plots our coefficient of interest γ^h from the above equation. A one standard deviation increase in bank exposure to natural disasters elsewhere among low profitable banks cause a 0.1 percent decline in employment. However, the effect is short-lived and offset by an equivalent increase in employment in the subsequent quarter. Bank spillovers from natural disasters emerging from less profitable banks therefore have real but brief consequences whose direction is consistent with their effects on lending documented previously.

Figure 14: Employment Spillovers

(a) NIM **(b)** ROA



Notes: *The charts show spillovers from a natural disaster in $t = 0$ on employment depending on bank exposure and profitability (γ^h) as proxied by NIM or ROA. See text for definitions. The local projection is specified in equation* (8). *Shaded areas indicate 95 percent confidence intervals. Sample: 2015 Q1 - 2023 Q4.*

To conclude, natural disasters spill over to unaffected areas through the lending networks of less-profitable banks. These spillovers are heterogeneous and more acute for more financially constrained firms. Further, because banks operate across different regions, we also observe a temporary reduction in employment in counties that are primarily served by less profitable banks following disasters. Many large metro areas are served by less-proftable banks; Table 4 lists the loan-weighted average lender NIM for the 15 most populous counties in the United States with the percentile across all counties in the sample. The results indicate that borrowers in more populated areas tend to borrow from less-profitable banks, which disproportionately exposes these areas to spillovers from external disasters.

Table 4: Bank NIM Exposures for the 15 Most Populous Counties

County	Net Interest Margin	Percentile
Los Angeles County, CA	2.13	7
Cook County, IL	2.26	17
Harris County, TX	2.26	17
Maricopa County, AZ	2.25	16
San Diego County, CA	2.23	14
Orange County, CA	2.19	10
Miami-Dade County, FL	2.22	12
Kings County, NY	2.19	10
Clark County, NV	2.16	8
Dallas County, TX	2.32	24
Queens County, NY	2.37	30
Riverside County, CA	2.10	5
San Bernardino County, CA	2.15	7
King County, WA	2.17	9
Wayne County, MI	2.31	23

***Notes**: This table reports the average bank net interest margin (weighted by total loans) for the 15 most populous U.S. counties. In addition, the table reports the percentile of that county-specific NIM relative to the total cross-section of counties. Sample: 2015 Q1 - 2023 Q4.*

6 Conclusion

Financial frictions are a crucial determinant of the real effects of natural disasters, both locally and nationally. Following a disaster, local firms that exhibit fewer symptoms of financial constraints are able to obtain more loans at better interest rates than more constrained firms. At the county level, these differences in financial constraints matter for employment responses to a local disaster: Counties with more financially constrained firms experience larger initial declines and slower subsequent recoveries in employment.

We find that lender profitability is a key source of variation in firms' access to financing following a disaster. Borrowers matched to banks with higher net interest margins obtain more loans at better rates in the disaster's aftermath, and areas with less-profitable lenders suffer larger adverse employment effects following a disaster. Firms who rely on less-profitable lenders experience credit contractions when their lenders are exposed to more disasters in other areas, suggesting that these disasters can propagate through banks' lending networks and generate spillovers in unaffected areas. This effect is particularly strong among financially constrained borrowers. These spillovers also have real effects, as areas with more indirect disaster exposure via less-profitable banks experience brief declines in employment.

Our results have two important consequences for policy makers and regulators. First and foremost, our finding that access to credit can help mitigate the adverse employment effects of natural disasters suggests a potential role for policies that improve access to credit in their aftermath; while large and public firms are able to at least partially insure themselves through their use of credit lines, these facilities are far less common for smaller, private, and more constrained firms. Second, because our spillover results suggest that low bank profitability can turn what starts as a local disaster into potentially nation-wide disruptions in credit supply and employment, understanding who borrows from less-profitable lenders can provide valuable insights into which sorts of firms and regions are at the highest risk of suffering negative consequences from shocks originating far away.

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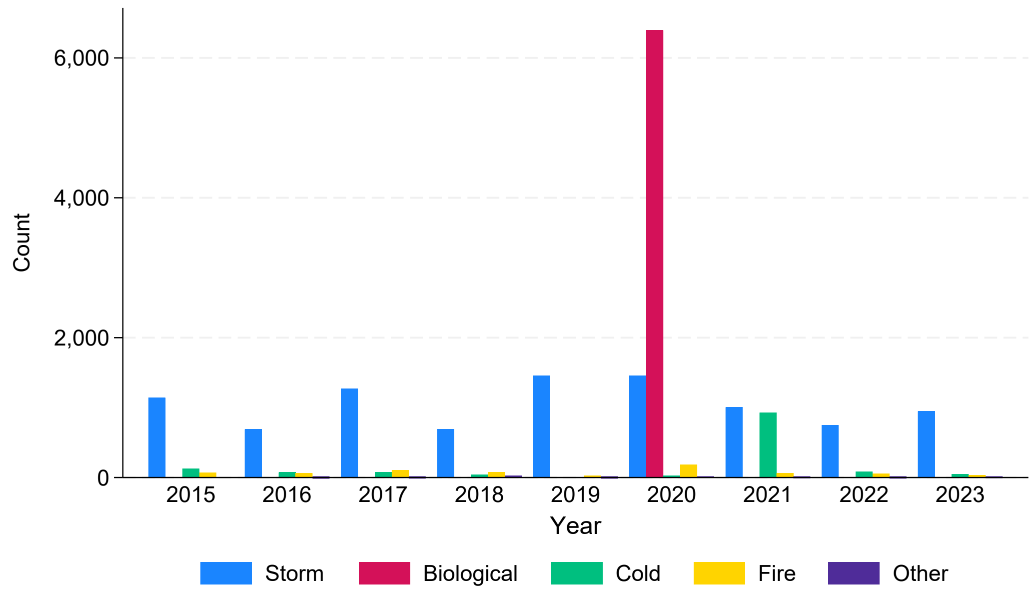
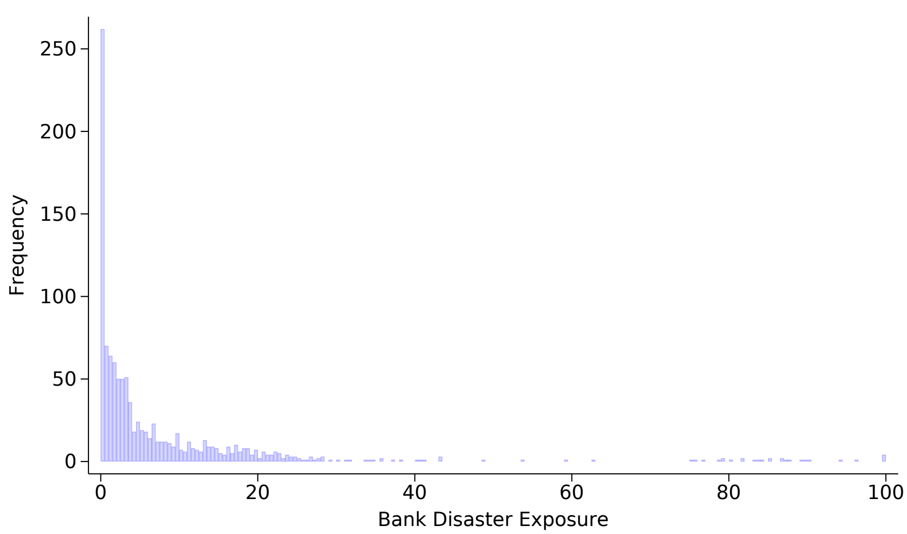
A Tables and Figures

Figure A1: Disasters over Time



Notes: *The histogram counts the number of disasters for each year split by disaster category.*

Figure A2: Exposure Measure



Notes: *Bank-quarter observations. Sample: 2015 Q1 - 2023 Q4.*

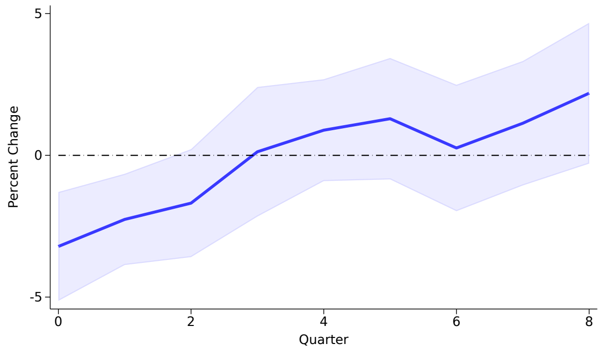
Table A1: Disaster Events by Type and U.S. State

State	Storm	Biological	Cold	Fire	Other
AK	20	55		8	14
AL	368	138			
AR	247	152	13		
AZ	9	33		26	
CA	317	116	1	203	6
CO	29	130		19	
CT	41	18			
DC		2	1		1
DE	3	6	1		
FL	774	137		9	1
GA	584	320	16	4	
HI	17	9		9	2
IA	227	201			
ID	45	89		14	
IL	66	204			
IN	44	185			
KS	260	215	67	17	
KY	519	240	86	5	
LA	907	131	128	5	5
MA	31	31	10		
MD	8	48	19		
ME	59	35	4		
MI	21	168			7
MN	180	178			
MO	444	230			
MS	503	166	37		1
MT	55	115		33	5
NC	587	202		4	
ND	144	109	20		
NE	213	192	31	4	
NH	32	20	3	1	
NJ	81	43	5		
NM	1	78		24	
NV	19	36		20	
NY	115	128	46		
OH	55	176			
OK	279	171	204	27	
OR	42	73		83	1
PA	28	134	23		
RI	15	12	6	1	
SC	533	94		2	
SD	192	134	18	4	
TN	260	190	69	7	1
TX	481	511	531	17	
UT	11	60		17	2
VA	108	268	63		
VT	98	28			
WA	122	80		104	
WI	72	146			
WV	124	110	5		21
WY	9	48		8	

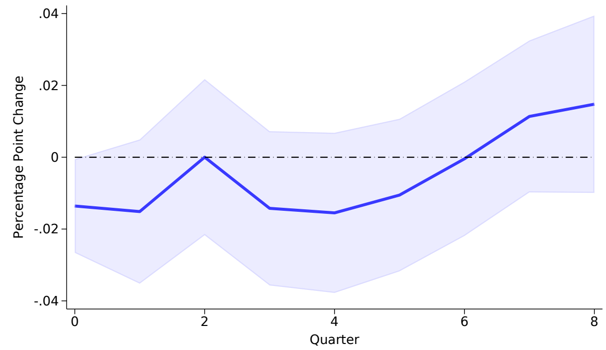
***Notes**: The table splits various disaster types by state. The number of disasters in each cell is aggregated over 2015 Q1 - 2023 Q4.*

Figure A3: Profitable versus Unprofitable Lenders: ROA

(a) Total utilized credit (%)



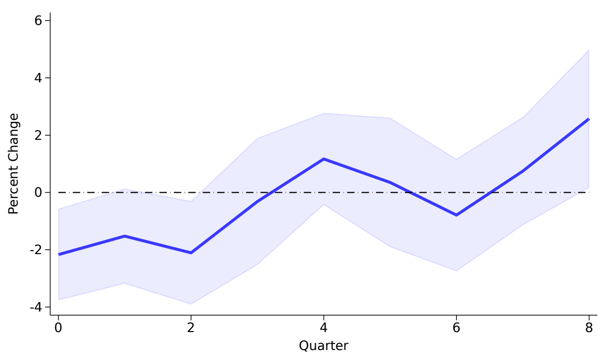
(b) Interest rate (pp)



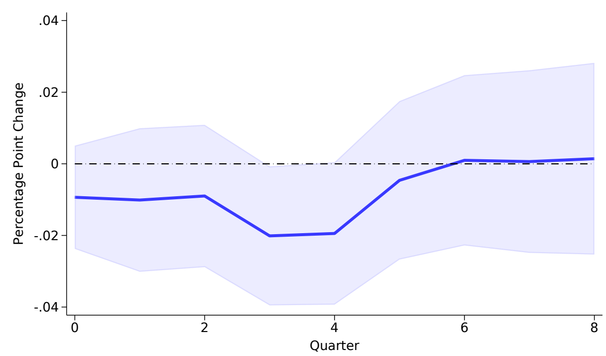
Notes: *The charts show the impact of a natural disaster in $t = 0$ on utilized credit (Panel (a)) and interest rates (Panel (b)) measured at the firm-level depending on the profitability of the lending bank. The classification is based on the quarterly median in ROAs. The local projection is specified in equation* (2). *Shaded areas indicate 95 percent confidence intervals. Sample: 2015 Q1 - 2023 Q4.*

Figure A4: Profitable versus Unprofitable Lenders: ROE

(a) Total utilized credit (%)



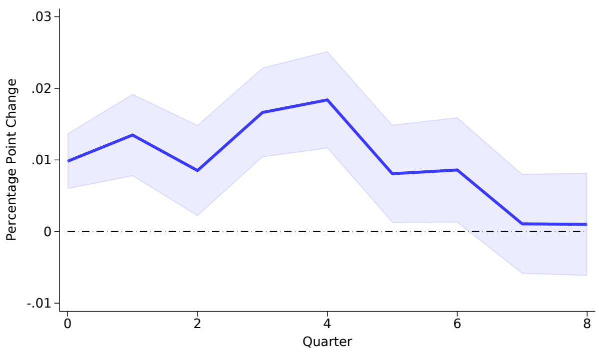
(b) Interest rate (pp)



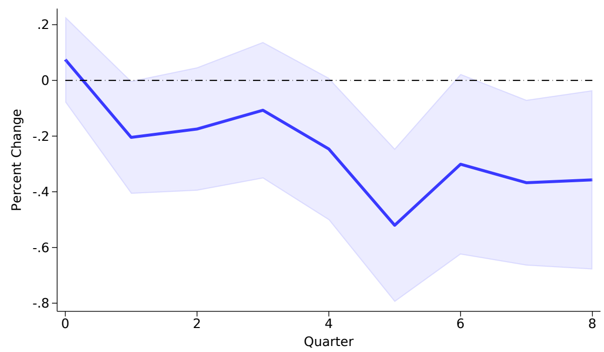
Notes: *The charts show the impact of a natural disaster in $t = 0$ on utilized credit (Panel (a)) and interest rates (Panel (b)) measured at the firm-level depending on the profitability of the lending bank. The classification is based on the quarterly median in ROEs. The local projection is specified in equation* (2). *Shaded areas indicate 95 percent confidence intervals. Sample: 2015 Q1 - 2023 Q4.*

Figure A5: Spillovers to Unaffected Firms: ROA

(a) Interest rate (pp)



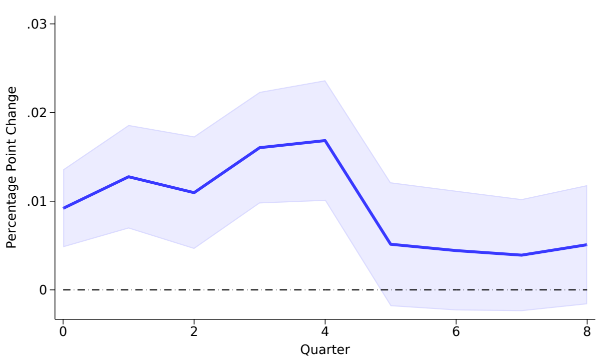
(b) Loan volume (%)



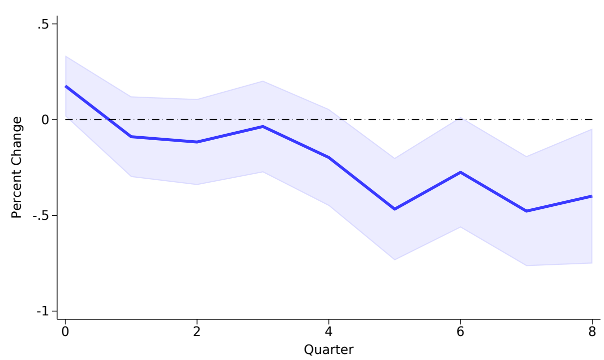
Notes:*The charts show spillovers from a natural disaster in $t = 0$ on interest rates (Panel (a)) and loan volume (Panel (b)) at the firm-level depending on bank exposure and profitability as measured by ROAs (γ^h). See text for definitions. The local projection is specified in equation* (6). *Shaded areas indicate 95 percent confidence intervals. Sample: 2015 Q1 - 2023 Q4.*

Figure A6: Spillovers to Unaffected Firms: ROE

(a) Interest rate (pp)



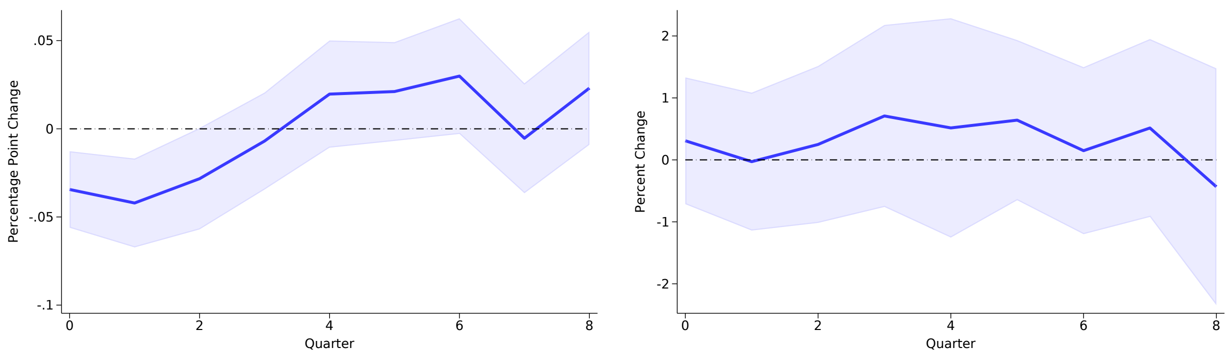
(b) Loan volume (%)



Notes: *The charts show spillovers from a natural disaster in $t = 0$ on interest rates (Panel (a)) and loan volume (Panel (b)) at the firm-level depending on bank exposure and profitability as measured by ROEs (γ^h). See text for definitions. The local projection is specified in equation* (6). *Shaded areas indicate 95 percent confidence intervals. Sample: 2015 Q1 - 2023 Q4.*

Figure A7: Spillovers: Public versus Private Firms in Unaffected Areas

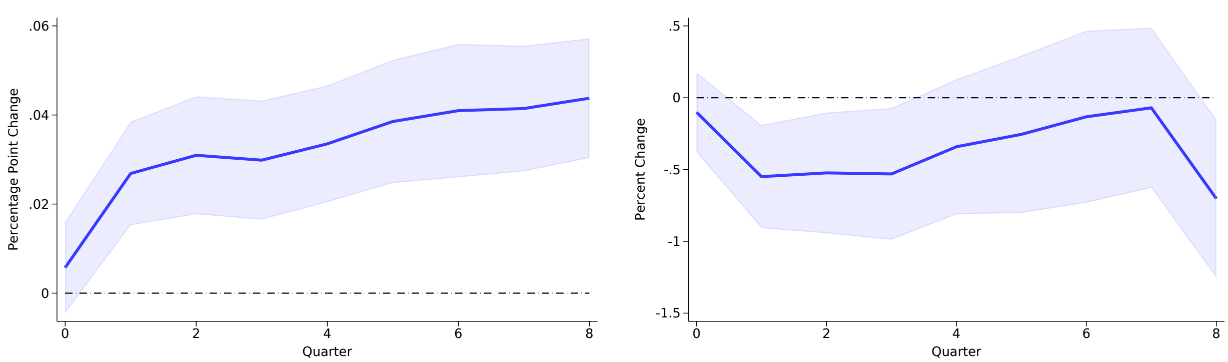
(a) Interest rate (pp) **(b)** Loan volume (%)



Notes: *The charts show spillovers from a natural disaster in* $t = 0$ *on interest rates (Panel (a)) and loan volume (Panel (b)) at the firm-level depending on bank exposure and profitability as measured by ROEs for public versus private firms (*$\gamma^h_{s=1} - \gamma^h_{s=0}$*). See text for definitions. The local projection is specified in equation* (7)*. Shaded areas indicate 95 percent confidence intervals. Sample: 2015 Q1 - 2023 Q4.*

Figure A8: Spillovers: High versus Low Risk Unaffected Firms

(a) Interest rate (pp) **(b)** Loan volume (%)



Notes: *The charts show spillovers from a natural disaster in* $t = 0$ *on interest rates (Panel (a)) and loan volume (Panel (b)) at the firm-level depending on bank exposure and profitability as measured by ROAs for large versus small firms (*$\gamma^h_{s=1} - \gamma^h_{s=0}$*). See text for definitions. The local projection is specified in equation* (7)*. Shaded areas indicate 95 percent confidence intervals. Sample: 2015 Q1 - 2023 Q4.*