Bank Lending Networks and Employment Dynamics following Natural Disasters*

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Abstract

We use confidential loan-level regulatory data to show that lending dynamics affect employment responses to natural disasters at both the local and national level. Following a disaster, bank credit contracts as perceived default risk increases. Lending volume and terms tighten more for financially constrained firms, and counties with more ex-ante constrained firms experience worse employment outcomes. Using a novel measure of firms' indirect exposure to disasters through undrawn bank credit lines, we show that disasters propagate through the banking system. Disasters tighten credit access in unaffected areas, even when controlling for firm-level credit demand, and reduce local employment growth.

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

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

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1 Introduction

When a firm experiences a negative shock, pre-committed credit lines ensure access to financing when external funding might otherwise be prohibitively expensive or unavailable (Holmström and Tirole, 1998). While this can mitigate the real effects of the shock for the directly affected borrower, it can also create spillovers, because a shock that pushes one firm to draw down their credit lines can also crowd out lending to other borrowers (Greenwald et al., 2025). For large banks with nationwide operations, this mechanism allows local shocks to affect lending—and, ultimately, real activity—on the other side of the country. In this paper, we build on recent work including Cortes and Strahan (2017), Brown et al. (2021), and Ivanov et al. (2022) to study how financial frictions affect local recoveries following natural disasters and how bank lending networks generate real and financial spillovers through undrawn credit line commitments.

We study natural disasters because they impose tremendous financial burdens on affected communities. The National Oceanic and Atmospheric Administration estimates that in 2024 alone the US experienced 27 distinct disasters that each caused at least 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). Bank lending plays an important role in funding these recovery efforts, particularly when the disasters simultaneously reduce revenues by depressing local demand and destroying productive capital. All else equal, providing more credit on better terms to firms in affected areas should mitigate the consequences of the disaster on real outcomes like employment, and thus areas with more financially constrained firms should experience worse employment outcomes. At the same time, because disasters cause affected firms to draw down their credit lines, they can also force banks to adjust lending in unaffected areas, which in turn could distort employment far from the disaster site. Quantifying these mechanisms is crucial, not only for policymakers overseeing recovery efforts, but for understanding how local shocks propagate through bank lending networks.

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

Our analysis uses confidential loan-level regulatory data to show that firms' access to credit shapes employment dynamics following natural disasters both locally and nationally. We first show that firms with direct exposure to a disaster obtain less credit at higher interest rates, and that this credit contraction is more severe for small, risky, and private firms relative to otherwise-similar firms exposed to the same disaster. We then show that areas with ex-ante riskier firms experience worse employment outcomes following a disaster, suggesting that the local employment response depends on the financial condition of local borrowers. Finally, we show that even *indirect* exposure to disasters via banks' undrawn credit lines can affect credit and employment outcomes. Firms in non-disaster areas who borrow from banks with greater disaster exposure experience a credit contraction relative to their peers who borrow from less-exposed banks, and areas with a greater share of these firms experience economically significant declines in employment. Our findings highlight an important tradeoff: While channeling additional credit to disaster areas could help mitigate its immediate effects on local labor markets, doing so could come at the cost of distorting credit supply and employment in unaffected areas.

We begin by studying the firm-level consequences of disaster exposure. Following a disaster, banks' perceived probability of default for the average firm in a disaster-stricken county rises by about 10 basis points, which represents more than 10 percent of its median value in our sample. This increase in perceived risk is accompanied by a decline in lending of about a half percent and a slight increase in interest rates. While disasters likely weigh on both supply and demand for credit, the fact that this decline in lending is accompanied by increases in interest rates and perceived borrower riskiness suggests that at least part of the decline in lending results from a contraction in credit supply. Consistent with this interpretation, we find that exposed firms also increase utilization of their pre-committed revolving lines of credit following a disaster.

Next, we aggregate firm characteristics to the county level to argue that banks' lending responses matter for employment dynamics. Following a disaster, local employment declines immediately before gradually recovering. Counties that go on to experience higher subsequent default rates or lower inflows of credit following a disaster tend to have worse ex-post employment outcomes: A 1 standard deviation decrease in credit growth in the aftermath of a disaster is associated with a 1 percent decrease in employment. While not causal, these results provide suggestive evidence for a link between financial and employment outcomes.

To provide more direct evidence for this mechanism, we show that ex-ante constrained firms experience worse financial outcomes following a disaster, and that areas with more of these firms immediately prior to a disaster experience worse subsequent employment outcomes. Firm lending displays striking heterogeneity across several dimensions—perceived riskiness, public status, and size—all of which are commonly used as proxies of financial constraint in the literature. Relative to small or private firms, large or public firms increase their total borrowing by roughly 1 percent and their credit utilization rate by 2 percent while paying about 5 fewer basis points in interest. In addition, in areas with higher average ex-ante firm default risk, employment exhibits a larger decline and a slower recovery relative to counties with less-risky firms. These results suggest that firms' financial constraints affect their ability to obtain credit following a disaster, which in turn matters for the disaster's real effects.

However, because the banks in our sample operate across hundreds of counties, disaster-induced changes in credit can also affect borrowers thousands of miles away. We find that committed credit lines, which often sit unused but are frequently drawn down by exposed firms following disasters, are a key driver of these spillovers. In this spirit, we construct a novel measure of borrowers' *indirect* disaster exposure based on their lenders' committed-but-undrawn credit lines to firms in other disaster-affected counties. We show that indirect disaster exposure via undrawn credit lines has economically significant real effects: A 1 standard deviation increase leads to a decline of almost 2 percent in employment. Crucially, when we run a horse race between our measure of indirect lending exposure and an analogously constructed measure based on banks' deposit networks, we find that the lending network drives all of the employment effects. These results suggest that large banks' committed credit lines—which, unlike many other measures of banks' activity, are not directly observable in publicly available data—play a key role in propagating local shocks.

Finally, we provide evidence that these employment spillovers are driven in part by exposed banks cutting back their lending to firms in unaffected areas. Indirect disaster exposure leads to a reduction in lending volume and a modest increase in interest rates that mirrors the direct effects of a disaster. When estimating regressions with firm-time fixed effects that control for unobservable factors that affect credit demand, we find similar increases in interest rates along with increased probabilities of firm-bank separations, suggesting that indirect disaster exposure causes banks to lend less and charge higher interest rates relative to other banks lending to the same firm.

Overall, our paper provides two key contributions. First, we provide direct evidence for an intricate link between firms' financial outcomes and local employment recoveries following natural disasters. And second, we illustrate how local shocks can propagate throughout bank lending networks to affect both real and financial outcomes in otherwise-unaffected areas. Beyond natural disasters, our results emphasize the unique role of banks' network of committed credit lines relative to other measures of banks' geographical footprint, and provide a broader framework for studying how a range of local shocks can propagate through bank lending networks to generate spillovers nationwide.

Related Literature. Our paper contributes to three strands of literature. The first studies the role of credit lines, which provide firms with pre-committed capital and are therefore an important tool for corporate liquidity management (Holmström and Tirole, 1998) that banks are uniquely well-suited to provide (Kashyap et al., 2002). Our analysis builds on several recent papers who use the Y-14Q data to show that firms draw down their credit lines in response to adverse shocks. Brown et al. (2021) show that firms increase credit line utilization following severe snowfall, while Greenwald et al. (2025) show that firms drew down credit lines during COVID. Relative to these papers, we provide two major contributions. First, we use county-level employment data to study how access to financing mitigates the *real* effects of an adverse local shock, which builds on recent work showing how financial frictions can affect employment outcomes (Chodorow-Reich, 2014). And second, we leverage the rich borrower detail in the Y-14Q to study the role of credit lines in propagating local shocks through the banking system to areas with no direct exposure to the shock.

Second, we contribute to the literature analyzing how shocks propagate through the banking system. Several recent papers also study this question using natural disasters. Cortes and Strahan (2017) 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 lender, the vast majority of lending in our sample of C&I loans flows to firms borrowing from multiple banks at once, which provides rich within-firm-time variation in lender exposure. We use this feature to trace out shocks through banks' lending networks and study their real effects. Koetter et al. (2020) and Ivanov et al. (2022) also study corporate lending spillovers in response to natural disasters in Germany and the US, respectively. We build on these papers by studying the effects of both direct and indirect disaster exposure on employment outcomes and emphasizing the role of credit lines in driving these results. Our data include many small and private firms and contain detailed borrower characteristics, which allows us to more accurately map out banks' lending networks and study how firm characteristics affect shock propagation.

Finally, beyond the study of natural disasters specifically, we also build on the extensive literature using 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. 2025).

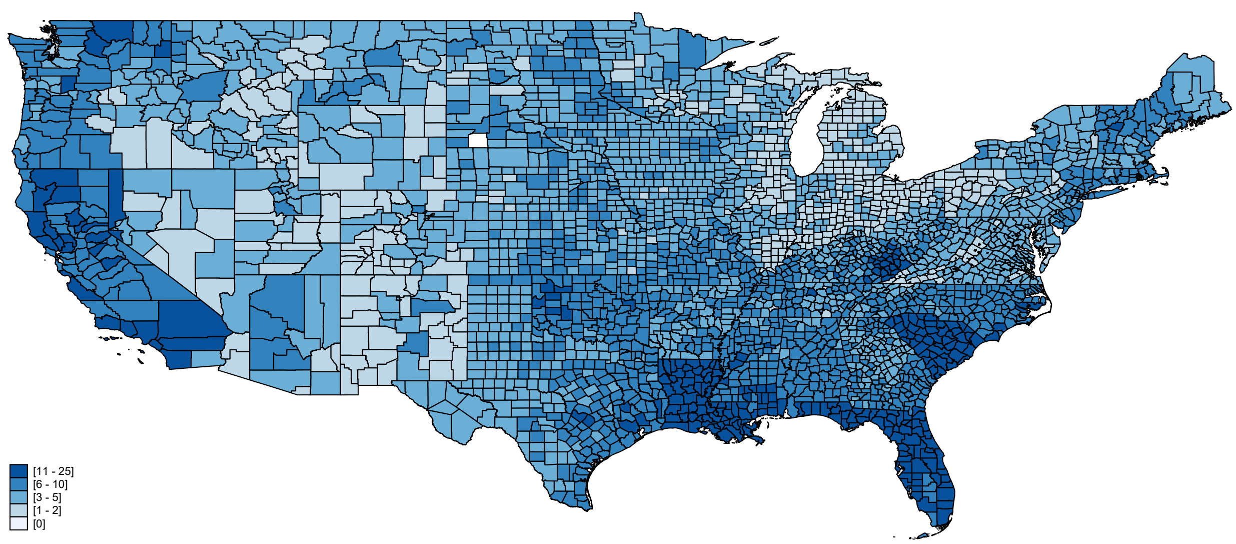
The remainder of the paper is structured as follows. Section 2 describes our data. Section 3 documents local financial and employment responses to natural disasters. Section 4 shows that firm-level lending outcomes depend on the financial constraints of firms and that areas with more ex-ante financially constrained firms experience worse employment outcomes following a disaster. Section 5 shows that disasters propagate through the banking system and distort credit supply and employment in unaffected areas. Finally, 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.[2]

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. Due to the COVID-19 outbreak, almost every county has been subject to at least one disaster.

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.*

Table 1 provides a summary of the frequency and government support for various types of disasters over the sample period. Government support comes from FEMA's Public Assistance program, which provides funds to state and local governments to remove immediate threats

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

and rebuild infrastructure, though these funds are not directed towards for-profit firms.[3] *Storm* events are the most common disaster type, followed by *Biological* disasters based on the total number of incidents, though *Biological* disasters, which include the COVID-19 outbreak, affected more counties. The table also illustrates considerable variation in Public Assistance as measured in total assistance divided by the total population in affected areas. For example, the median assistance following a storm disaster is about $14 per person in Public Assistance, whereas the 99th percentile is $579 per person. In our subsequent analysis, we aggregate over all disasters. A further breakdown of disaster types by states and time is available in Table A1 and Figure A1 in the Appendix.

Table 1: Disasters: Type and Public Assistance

Incident Type	# Events	# Counties	Total Aid	25th Percentile	50th Percentile	75th Percentile	99th Percentile
Fire	297	473	6,210	0.9	10.4	75.2	1,875
Storm	291	5,590	24,408	4.5	14.2	32.8	579
Flood	121	1,886	5,184	7.9	22.4	49.2	668
Biological	81	3,528	76,990	19.4	63.3	122.2	359
Cold	39	997	984	3.6	6.7	15.8	306
Other	14	48	526	25.4	51.9	92.1	959

Notes: *Column 2 counts the total number of disasters for each disaster category over the years 2015-2023. Column 3 displays the number of counties that were affected by disasters of that type. Column 4 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-per-person county distribution for each disaster category (in dollars per person).*

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 or local authorities, and loans by the Small Business Administration 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, they can take several months to pay out and generally will not cover all expenses, making them imperfect substitutes for bank credit.[4] Nonetheless, to

[3]The support from the program is therefore not a suitable proxy for losses/damages of firms in our sample.
[4]A full distribution of large insurance claims can take several months (see `https://www.philadelphiafed.`

the extent that these programs are at least partially able to satisfy firms' financing needs following a disaster, they suggest that our estimated effects on employment are conservative.

Y-14 Banks. Our primary data source for bank lending is the Y-14Q report. Data are 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. Table 2 reports descriptive statistics for the Y-14 banks at the bank-quarter level, and over the sample period 2015-2023. The two rows provide a sense of coverage for the Y-14Q data. Reported Y-14 loans, on average, account for nearly 90 percent of the total commercial and industrial (C&I) lending for each bank. 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
Y-14 Loan / Total C&I (%)	960	88.6	71.5	77.2	89.7	97.7	98.9
# Lending Counties	960	312	15	58	257	665	879

***Notes**: Column 2 shows the number of bank-quarter observations. Column 3 the mean of the corresponding variable, and columns 4-8 the respective 5th, 10th, 50th, 90th and 95th percentile. Sample: 2015 Q1 - 2023 Q4.*

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. For several exercises, we also construct firm-bank level and county-level datasets following the same conventions.

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.

Table 3 provides firm-level descriptive statistics for 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-14 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.

Table 3: Y-14 Firm-Quarter Summary Statistics

Object	N	Mean	5p	10p	50p	90p	95p
Total Loan Commitments ($mil)	1.1m	67.0	1.0	1.1	4.5	94.7	224.8
Share of Revolving Loans (%)	1.1m	57.2	0	0	98.8	100	100
Revolving Utilization Rate (%)	719k	34.7	0	0	22.4	100	100
Firm Assets ($mil)	948k	1,583	1.83	3.27	29.5	1,604	5,319
Firm Sales ($mil)	947k	1,095	1.83	7.1	52.7	1,318	3,811
Public Firm Indicator	1.1m	0.08	0	0	0	0	1
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
Interest Rate (%)	889k	4.5	1.75	2.19	4.08	7.49	8.5

Notes*: Column 2 shows the number of firm-quarter observations. Column 3 the mean of the corresponding variable, and columns 4-8 the respective 5th, 10th, 50th, 90th and 95th percentile. 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.*

The median values of assets and sales 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-14 data uniquely well suited to analyzing how the real effects of natural disasters depend on firms' financial constraints. The inclusion of these small and private firms, who are distributed far more evenly across counties than public firms, is also what enables us to comprehensively map each bank's lending network.

In addition to borrower and loan characteristics, we also observe banks' internal risk assessments for each loan, including an estimated a default probability for each borrower. 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.

3 Direct Disaster Effects

This section examines the direct local effects of natural disasters. We first 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. To partially offset this effect, eligible firms draw down pre-committed credit lines. We then document a strong correlation between financial outcomes and employment in the aftermath of a disaster.

3.1 Firm-Level Disaster Responses

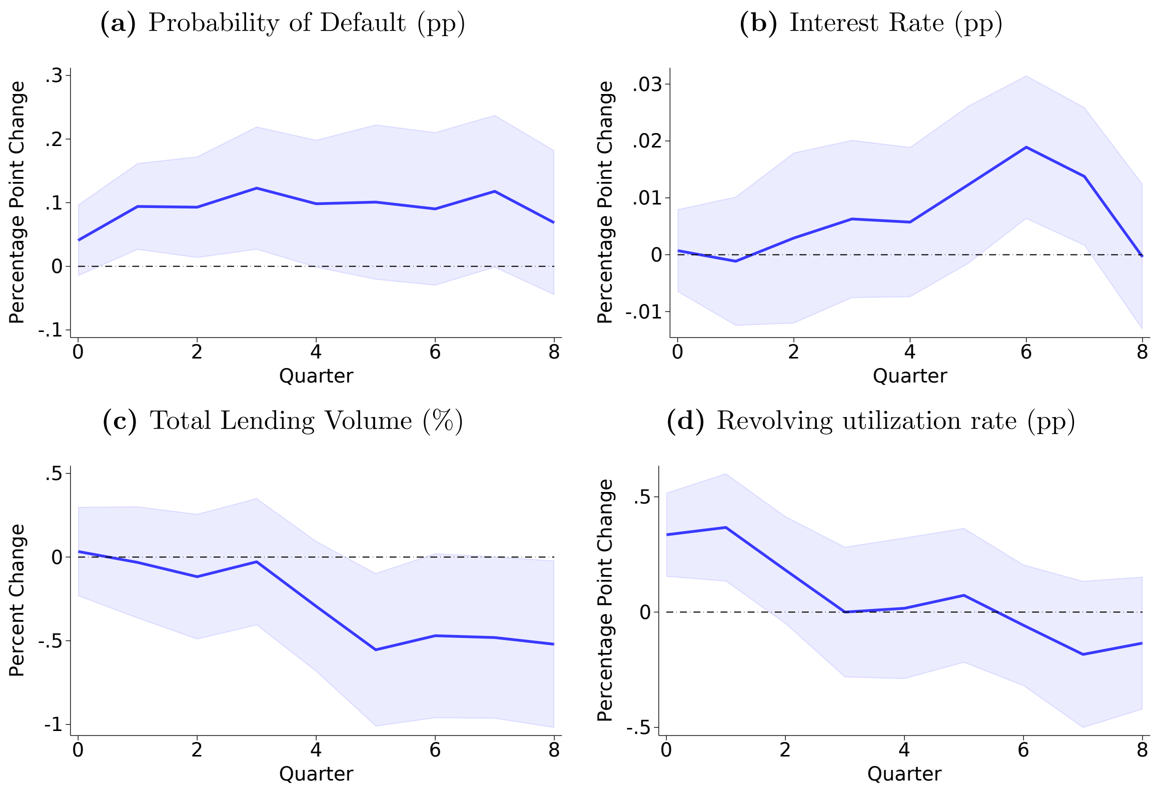
We begin by estimating average firm-level effects of disaster exposure based on the following local projection (Jordà, 2005):

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

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 in areas prone to more frequent disasters. The time fixed effect accounts for national trends. We include one lag of the dependent variable to control for conditions prior to the disaster and 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).[5] This regression tracks the same firm i over time starting at $t-1$. The coefficient of interest γ^h is therefore unaffected by firm entry following the disaster, but may include different sets of firms at each horizon depending on which ones survive. Standard errors are clustered by county. The results are shown below in Figure 2.

Figure 2: Lending, Interest Rates, and Default Risk



Notes: *These figures plot estimates of γ^h from equation (1), which is estimated using a firm-quarter panel, and display the effect on the firm-level financial outcome shown above in response to a natural disaster (measured by the binary indicator $D_{i,c,t}$) at $t = 0$. Shaded areas indicate 95 percent confidence intervals calculated using standard errors clustered by county. Sample: 2015 Q1 - 2023 Q4.*

The top-left panel shows that banks increase their perceived probability of default (PD)

[5]We assign each firm to the county in which it had the highest total committed loan volume across all loans in our sample for purposes of fixed effects and clustering. 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.

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 a small but statistically significant increases of roughly 2 basis points on their average interest rates. 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.

Firms can partially mitigate a credit contraction by drawing down pre-existing credit lines. The bottom-right panel shows that firms respond by increasing their revolving credit utilization rate by more than 30 basis points, which represents roughly $110k for the average firm in our sample. While not sufficient to fully offset the loss in committed credit shown in the bottom-left panel, these results suggest that firms with access to credit lines—which, as Greenwald et al. (2025) show, tend to exhibit the fewest symptoms of being financially constrained—have greater financial flexibility in responding to shocks. On this front, our results are consistent with the findings of Brown et al. (2021), who show that firms draw down credit lines in response to contractionary demand shocks caused by severe snowfall. However, many of the disasters in our sample also cause much greater economic damages—and thus have a larger effect on banks' willingness to supply credit—than snowfall. This is consistent with our finding that firms' drawdowns are accompanied by less-favorable risk assessments, higher interest rates, and lower lending volumes.

We examine additional variables in Figure A2 in the appendix. There we show that disasters also lead to higher anticipated losses conditional on default, higher expected losses, a higher default rate, and higher firm exit rates. In the next section, we show that firms' financial responses have important implications for the real effects of disasters.

3.2 County-Level Disaster Responses

In this section, we first show that employment in counties exposed to natural disasters declines immediately before gradually recovering. We then document a strong ex-post correlation between real and financial outcomes in the disaster's aftermath, providing suggestive evidence for the importance of financial frictions in driving the pace of local recoveries. To study the average effect of a disaster on employment, we estimate the following regression:

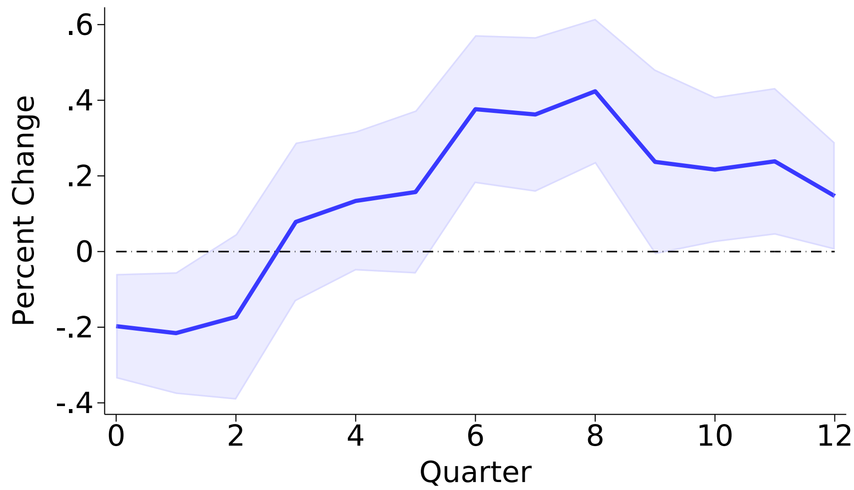
$$y_{c,t+h} = \sum_{j=1}^{4} \delta_j^h y_{c,t-j} + \gamma^h D_{c,t} + \alpha_c^h + \beta_t^h + \epsilon_{c,t+h}. \tag{2}$$

The dependent variable $y_{c,t+h}$ is the h-quarter ahead realization of total nonfarm employment in logs for county c. The independent variable of interest is the binary disaster indicator $D_{c,t}$, which is equal to one if county c experiences a disaster at time t. Relative to the previous firm-level regression, this specification aggregates all firms operating in county c in a quarter and therefore also captures firm entry. We add county fixed effects α_c and time fixed effects β_t. As before, the time fixed effects absorb aggregate trends, while the county fixed effects absorb persistent county-specific characteristics like average disaster exposure. We also include four lags of the dependent variable to account for trends in local employment prior to the disaster. 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 at the county level after h periods and is plotted below in Figure 3.

Following a disaster, employment briefly declines by about 0.2 percent before steadily growing over the following two years. This is qualitatively consistent with Roth Tran and Wilson (2025), who also aggregate across many disaster types.[6] 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 Roth Tran and Wilson (2025) that much of the employment recovery is driven

[6] Past work focusing exclusively on hurricanes, including Deryugina (2017) and Jerch et al. (2023), finds more persistently negative effects on aggregate employment.

Figure 3: Employment Response to a Disaster



***Notes**: This figure plots estimates of γ^h from equation (2), which is estimated using a county-quarter panel, and displays the cumulative percent change in county-level employment after a natural disaster (measured by the binary indicator $D_{c,t}$) at $t = 0$. Shaded areas indicate 95 percent confidence intervals calculated using standard errors clustered by county. Sample: 2015 Q1 - 2023 Q4.*

by the construction sector.[7]

Next, we provide some suggestive evidence that the *ex-post* response of financial variables shapes 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, including the scale of damage caused by the disaster, we emphasize that such a relationship need not be causal. Nonetheless, understanding the unconditional correlations between real and financial outcomes following a disaster is useful for understanding how financial frictions drive recoveries. To test this mechanism, we estimate the following county-level regression:

$$\Delta_h y_{c,t(d)} = \gamma^h \Delta_h x_{c,t(d)} + \epsilon_{c,t(d)+h}, \tag{3}$$

where h refers to the horizon (in quarters) after a disaster d at time t. $\Delta_h y_{c,t(d)}$ is the

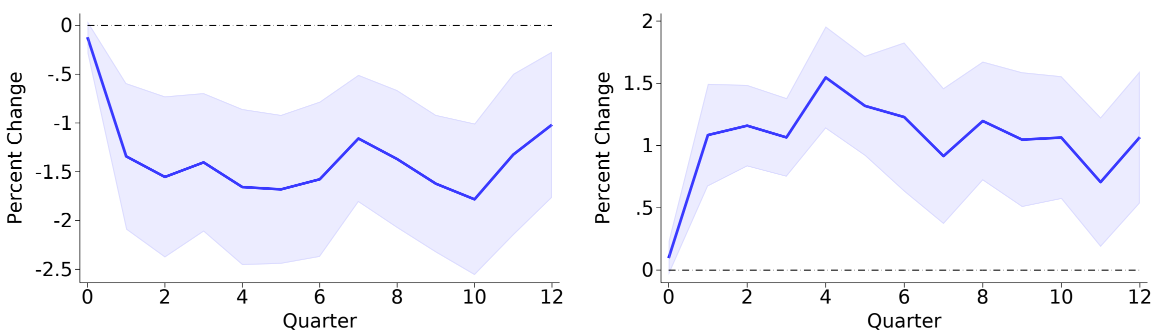
[7] Crucially, these results do not imply that disasters are beneficial on net, particularly when they lead to destruction of the capital stock.

cumulative change in log employment during the first h quarters after the disaster at $t(d)$ in county c. We use the notation $t(d)$ to emphasize that we, for this exercise only, zoom in on data in the immediate aftermath of a disaster. The counterfactual is hence not the absence of a disaster, but a disaster with a different response of some financial variable x.

For the independent variable x, we aggregate two Y-14 variables to the county level: banks' loan volume-weighted average probability of default (PD), and total committed loan volume in logs. $\Delta_h x_{c,t(d)}$ is then defined as the cumulative change in x during the first h quarters after a disaster. We standardize the independent variable for comparison and estimate this regression separately for each h, weight estimates by employment in the period prior to a disaster, and report heteroskedastic-robust standard errors. Because $x_{c,t(d)}$ is itself endogenous, we reiterate that γ^h cannot be interpreted in a causal sense; instead, it simply captures whether counties with better ex-post financial outcomes are, on average, the same ones with better ex-post employment outcomes.

Figure 4: Employment and Financial Outcomes after the Disaster

(a) Probability of Default **(b)** Total Lending Volume



Notes: *These figures plot γ^h from equation (3), which is estimated using a county-quarter panel, and show the relationship between the standardized cumulative change in banks' estimated probability of default (left panel) or the standardized cumulative growth in total committed lending volume (right panel) between $t = 0$ and $t = h$ on cumulative employment growth between $t = 0$ and $t = h$. Shaded areas indicate 95 percent heteroskedastic-robust confidence intervals. Sample: 2015 Q1 - 2023 Q4.*

The left panel of Figure 4 shows that disasters which cause banks to become more pessimistic in their risk assessments also unsurprisingly lead to lower employment: A one standard deviation increase in borrowers' perceived probability of default *after* a disaster leads to an additional decline of roughly 1.5 percent in employment. In contrast, the right panel shows that areas which subsequently receive more credit tend to have better employment outcomes: A one standard deviation increase in ex-post loan growth is associated with an additional 1 percent increase in employment. On their own, these results cannot tell us whether lower perceived risk or higher lending volumes were the causes of the increase in employment, the consequences, or simply the joint result of a shock affecting both simultaneously. Nonetheless, to the extent that some firms will be better positioned to obtain financing in the aftermath of a disaster than others, these findings suggest that greater *ex-ante* financial flexibility may help mitigate the negative employment effects of a disaster. We provide evidence supporting this hypothesis in the next section.

4 Financial Heterogeneity and Employment Dynamics

To study how firm financial constraints affect local employment responses to disasters, we first show in Section 4.1 that firms more likely to be financially constrained ex-ante go on to obtain fewer loans and pay higher interest rates than their unconstrained counterparts following a disaster. Crucially, because these regressions include county-time fixed effects, they allow us to identify the difference in responses to constrained versus unconstrained firms exposed to the exact same disaster. In Section 4.2, we show that areas with more ex-ante financially constrained firms experience worse employment outcomes following natural disasters, suggesting that these results survive aggregation.

4.1 Firm Financial Heterogeneity

To test whether financial frictions generate firm-level heterogeneity in disaster responses, we estimate the following state-dependent regression:

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

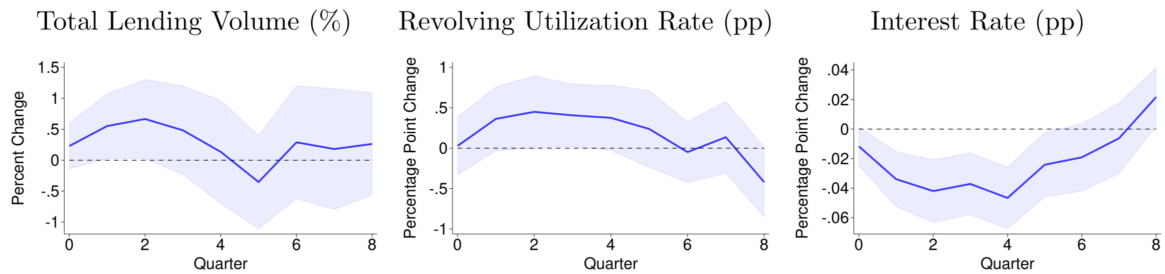
Relative to equation (1), this specification adds two features. First, a binary state variable $S_{i,t-1}$ allows us to test for heterogeneity in firm-level disaster responses. Second, county-time fixed effects $\beta_{c,t}$ absorb the average effect of a disaster common to all firms in the county and allow us to estimate whether firms with different values of $S_{i,t-1}$ respond differently to the exact same disaster at the exact same time. We restrict the sample to firms observed in at least 12 quarters and to county-quarters with at least 10 firms to precisely estimate α_i and $\beta_{c,t}$. The primary object of interest is the difference between $\gamma^h_{s=1}$ and $\gamma^h_{s=0}$, which captures the differential effect of *the same* disaster for a firm with $S_{i,t-1} = 1$ relative to $S_{i,t-1} = 0$. Crucially, $S_{i,t-1}$ is always measured in the quarter *before* the disaster strikes to avoid reverse causality. As before, we cluster standard errors by county. In Figure 5 below, we report the responses of loan volume, interest rates and credit utilization.

We consider three different measures of financial constraint for $S_{i,t-1}$. In the top row, $S_{i,t-1}$ is an indicator equal to 1 if a firms' loan volume-weighted average probability of default (PD) was below the median across all firms in that quarter. This measure serves as our baseline indicator of financial constraint for two reasons. First, it is a much stronger predictor of loan performance than other firm characteristics in practice (Howes and Weitzner, forthcoming), and is thus highly relevant for banks' credit allocation decisions. And second, it maps directly to theoretical measures of financial constraint in the class of macro models that define financial constraint by distance to default, including Bernanke et al. (1999) and Ottonello and Winberry (2020). For comparison, the middle and bottom rows report results from specifications in which $S_{i,t-1}$ is defined based on whether a firm had assets above the median across all borrowers in that quarter (middle row) or was publicly traded (bottom row). In each of these specifications, a value of $S_{i,t-1} = 1$ represents a firm that is less likely to be financially constrained.

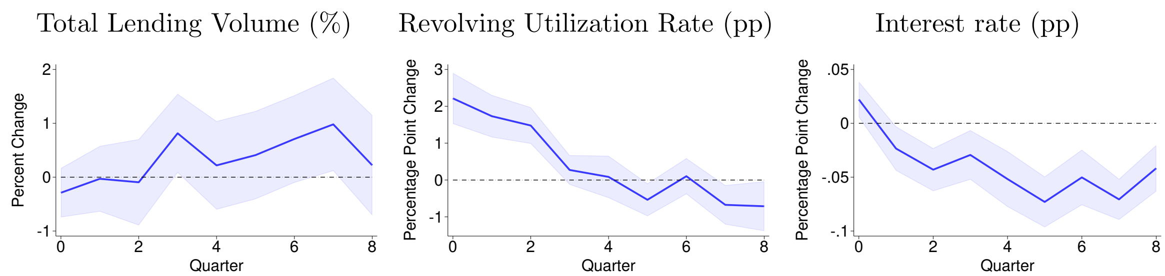
Following a disaster, the left panels show that total committed loan volume increases by about 0.5 percent for firms with below-median default risk and about 1 percent for firms with above-median assets, relative to firms with above-median default risk or below-median assets. Both effects are statistically and economically significant, considering that lending in

Figure 5: Lending Terms and Borrower Characteristics

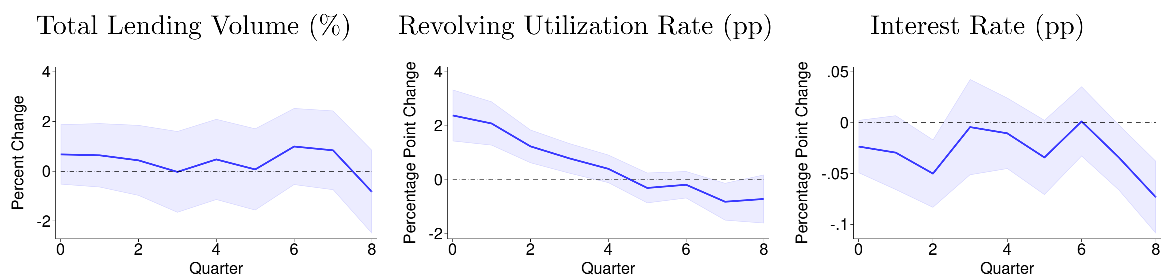
(a) Low-Risk versus High-Risk Firms



(b) Large versus Small Firms



(c) Public versus Private Firms



Notes: *These figures plot the difference between* $\gamma^h_{s=1}$ *and* $\gamma^h_{s=0}$ *from equation* (4)*, which is estimated using a firm-quarter panel, and measure how the impact of a natural disaster at* $t = 0$ *on total firm-level committed credit (left panels), revolving credit utilization rates (middle panels), and interest rates (right panels) vary across firms with different values of the state variable* $S_{i,t-1}$*. In the top row,* $S_{i,t-1}$ *is an indicator equal to one if a firm's loan volume-weighted average PD was below the median across all firms in a quarter. In the middle row,* $S_{i,t-1}$ *is an indicator equal to one if a firm's reported assets were above the median across all firms in a quarter. In the bottom row,* $S_{i,t-1}$ *is an indicator equal to one if a firm is publicly traded. Shaded areas indicate 95 percent confidence intervals calculated using standard errors clustered by county. Sample: 2015 Q1 - 2023 Q4.*

response to a disaster contracts by about 0.5 percent on average as shown previously. The point estimates are similar for public firms, though these estimates are much noisier. In addition to obtaining more total credit, the middle panel shows that unconstrained firms also increase their use of revolving credit across all three constraint measures, with utilization rates rising by around 0.5pp for low-risk firms and 2pp for large and public firms. These results suggest that unconstrained firms increase their borrowing and utilize more of their pre-existing lines of credit relative to constrained firms following the disaster.

Despite this increase in credit, the right panel shows that unconstrained firms simultaneously experience a decline in their average interest rate relative to constrained firms. These effects are statistically significant across all three measures, though the difference of 5 basis points is economically small. Nonetheless, the fact that these firms pay *lower* interest rates despite increasing their borrowing relative to constrained borrowers is consistent with the idea that banks shift credit from constrained to unconstrained borrowers following disasters. While we cannot rule out the possibility that these effects may be driven in part by changes in credit demand for financially unconstrained firms relative to constrained firms, these estimates come from specifications that employ county-time fixed effects, and thus compare firms exposed to the exact same disaster at the exact same time. Hence, to the extent that the changes in credit demand due to a disaster were common across all exposed firms, this mechanism could not explain our results. We next analyze the real effects of this financial heterogeneity.

4.2 Financial Constraints and Employment Outcomes

The previous section showed that unconstrained firms obtain more and cheaper credit relative to constrained firms following a disaster. To the extent that this influx of credit allows exposed firms to avoid reducing output or employment in the disaster's aftermath, areas in which firms display more signs of being financially constrained should 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 at the county level:

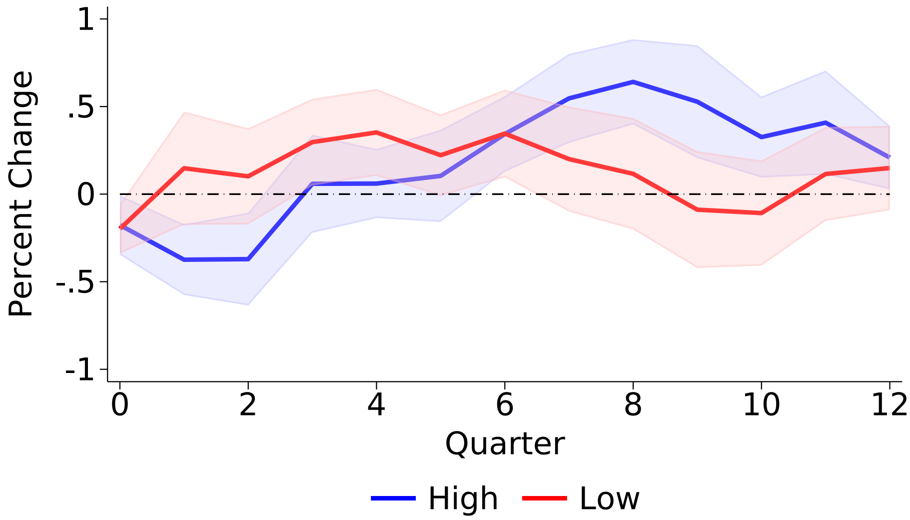
$$y_{c,t+h} = S_{c,t-1}\left[\delta^h_{s=1} Y_{c,t-} + \gamma^h_{s=1} D_{c,t}\right] + (1 - S_{c,t-1})\left[\delta^h_{s=0} Y_{c,t-} + \gamma^h_{s=0} D_{c,t}\right] + \alpha^h_c + \beta^h_t + \epsilon_{c,t+h}. \quad (5)$$

The key difference relative to equation (2) 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 county c 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 (2). In particular, we summarized the four lags of the dependent variable into a vector $Y_{c,t-}$. The primary objects of interest are the coefficients $\gamma^h_{s=1}$ and $\gamma^h_{s=0}$, which capture the employment response for a county with a low or high *ex-ante* share of financially constrained firms. Because this regression is estimated at the county level, and because we include county and time fixed effects, the coefficients are identified based on variation in firms' average financial conditions within a county over time.

Figure 6 plots the results when $S_{c,t-1}$ is an indicator equal to 1 if the average volume-weighted probability of default for firms in a county was below the median across all counties in that quarter, which is the same measure reported in the top row of Figure 5. In response to a disaster, employment in counties with ex-ante riskier firms (blue) declines by roughly 0.5 percent in the first year following a disaster before gradually rebounding. In counties with less-risky firms (red), employment declines by almost the same magnitude on impact, but recovers almost immediately. 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.

For this exercise, we focus on a PD-based measure of financial constraint because, in addition to their use as a crucial input to banks' lending decisions and their close link to theoretical measures of financial constraint, banks' estimated probabilities of default have the added benefit of displaying far more geographical variation than the other constraint measures reported in Figure 5. While almost 80 percent of counties in our sample have at least one quarter each with above- and below-median borrower default risk, this number drops to 40 percent for borrower assets, and less than one-third of counties ever report having any publicly traded firms. In Figure A3 in the appendix, we report similar results using alternative measures of firm-level financial constraints that display meaningful geographic

Figure 6: Employment Response: High-Risk versus Low-Risk Firms



Notes: *This figure plots $\gamma^h_{s=1}$ and $\gamma^h_{s=0}$ from equation (5), which is estimated using a county-quarter panel, and measures the impact of a natural disaster at $t = 0$ on total county-level employment depending on whether the loan volume-weighted average probability of default for firms in a given county was below (red) or above (blue) the median across all counties at time $t - 1$. Shaded areas indicate 95 percent confidence intervals calculated using standard errors clustered by county. Sample: 2015 Q1 - 2023 Q4.*

variation, including the firms' average interest rates and banks' estimates of firms loss given default, both of which should be higher for more financially constrained firms.

To summarize, this section shows that firm-level financial constraints matter for employment dynamics following natural disasters. Inflows of credit to disaster-stricken counties through less financially constrained firms may help stimulate labor market recoveries in directly affected areas. However, to the extent that this redirects credit that would under normal circumstances go to other areas, such inflows may also have negative consequences for labor markets elsewhere. We test for these spillovers in the next section.

5 Spillovers

In this section, we show that disasters in one area propagate through the banking system and affect lending and employment outcomes 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. By emphasizing the importance of banks' committed (but undrawn) credit lines as a crucial transmission vector for these shocks, we also complement past work showing that credit line drawdowns for some firms can affect bank lending for others, including Ivashina and Scharfstein (2010), Chodorow-Reich (2014), and Greenwald et al. (2025).

We begin by providing descriptive statistics on banks' disaster exposure in Section 5.1. Next, in Section 5.2, we show that firms' indirect exposure to natural disasters through undrawn credit lines causes statistically and economically significant declines in local employment, and that these patterns are consistent with the response of firms' financial outcomes.

5.1 Bank Disaster Exposure

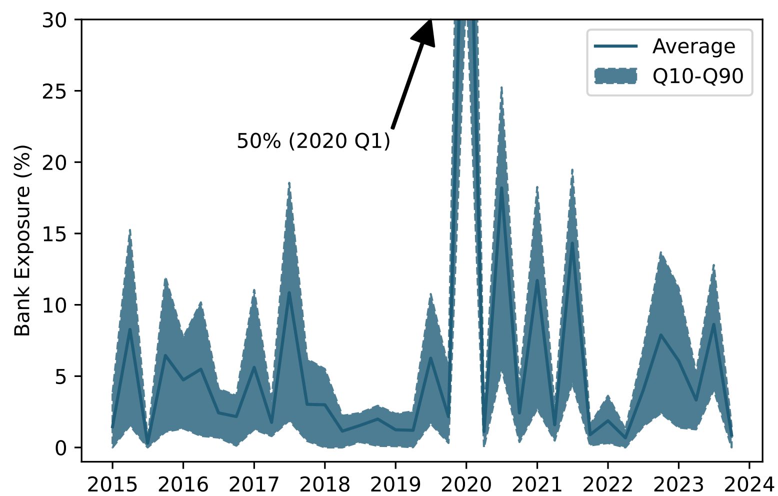
Relative to other US datasets, the Y-14Q data are uniquely well suited to constructing measures of bank exposure to natural disasters for two reasons. First, the banks in our sample operate expansive branch and loan networks that span many geographic markets; as Table 2 highlighted, the average bank lends to 312 counties per quarter. The inclusion of small and private firms allows us to capture the geography of bank lending relationships in greater detail than datasets that rely on large or publicly traded firms. The inclusion of these borrowers is crucial given that many disasters do not affect areas with publicly traded firms; as we showed in Table 3, more than 90 percent of the firms in our sample are private, and most counties have zero public firms that receive loans. Second, the Y-14Q data include information about both committed and utilized revolving credit, which allows us to construct measures of exposure based on undrawn credit that are not captured in public datasets like DealScan.

To quantify whether a banks' exposure to a natural disaster in one area could distort lending in many others, we begin by constructing a loan-weighted measure of a bank's exposure to natural disasters via undrawn credit lines $E_{b,t}$:

$$E_{b,t} = 100 \times \frac{\sum_c U_{c,b,t-1} D_{c,t}}{\sum_c L_{c,b,t-1}}. \tag{6}$$

As before, $D_{c,t}$ is a binary disaster indicator. $L_{c,b,t-1}$ is the volume of total committed exposure, and $U_{c,b,t-1}$ is the volume of total undrawn revolving credit, from bank b in county c. We lag both of these measures by one quarter to mitigate endogeneity concerns given that both the numerator and denominator respond to disasters (see Figure 2). Exposure ranges between $[0, 100]$ percent, with a value of 100 implying that all committed lending from bank b at time $t-1$ consisted of unused revolving credit lines to firms in counties that were subject to a disaster at time t. Figure 7 plots the average bank exposure over time along with the 10th and 90th percentiles. Average exposure hovers between zero and 20 percent in most quarters, with a notable spike during COVID-19. This figure also illustrates meaningful dispersion in disaster exposure across banks at each point in time, with about 7.4 percentage points on average separating the 10th and 90th percentiles.

Figure 7: Bank Exposure to Natural Disasters



Notes: *The plot shows the average bank-level exposure to natural disasters as defined in equation* (6) *over time along with the 10th and 90th percentile of the cross-section quarter. Sample: 2015 Q1 - 2023 Q4.*

We measure disaster exposure via undrawn revolving credit because, in contrast to term loans or previously drawn credit lines, banks typically cannot adjust the quantity or terms of previously committed credit lines. Following an adverse shock, a firm who obtained such a commitment during good times may thus be able to borrow even if they otherwise might not be able to obtain a new loan. The corollary of this insurance effect is that such drawdowns can force banks to commit additional capital precisely when they would otherwise be most hesitant to do so, which could crowd out borrowers elsewhere. As shown in Figure 2, firms exposed to disasters respond by drawing down on their credit lines, even as total lending volumes decline; this supports the findings of Brown et al. (2021), who use the same data to show that firms draw down credit in response to adverse weather shocks. This result is also consistent with Greenwald et al. (2025), who show that credit lines serve as an important source of insurance for large firms, but that these drawdowns disproportionately crowd out lending to smaller and more financially firms without access to credit lines.

Beyond credit lines, other types of lending could also generate spillovers if disasters caused banks to substantially revise their assessments. However, because the capital for term loans has already been distributed at the time of the disaster, the effect on a bank's balance sheet is likely to be smaller than if they are forced to provide a large influx of additional credit through pre-committed credit lines. Consistent with this idea, we find qualitatively similar—though quantitatively smaller—results when we measure banks' disaster exposure using total committed exposure in the Appendix.[8]

To study the spillover effects of disaster exposure for firms in unaffected areas, we build a measure of purely *indirect* disaster exposure by excluding county c. We construct this indirect disaster measure as follows:

$$E_{b,t}^{-c} = 100 \times \frac{\sum_{j \neq c} U_{j,b,t-1} D_{j,t}}{\sum_{j \neq c} L_{j,b,t-1}}. \tag{7}$$

Relative to our measure of total bank-level exposure $E_{b,t}$ defined in equation (6), the measure in equation (7) excludes county c from the calculation and therefore captures the indirect disaster exposure of a firm borrowing from bank b in county c. We create two variants of this

[8]For this alternative measure, we calculate the exposure of a bank as $100 \times \frac{\sum_c L_{c,b,t-1} D_{c,t}}{\sum_c L_{c,b,t-1}}$. Based on this committed credit exposure we then calculate indirect disaster exposure measures analogous to equations (7) - (9). Figures A4 - A6 provide details.

measure for subsequent use: $E_{i,t}^{-c}$ is the average indirect disaster exposure (weighted by total borrowing) from the perspective of firm i operating in county c across all of its lenders b:

$$E_{i,t}^{-c} = \frac{\sum_b L_{i,b,t-1} E_{b,t}^{-c}}{\sum_b L_{i,b,t-1}}. \tag{8}$$

Similarly, $E_{c,t}^{-c}$ is the indirect disaster exposure from the perspective of county c, calculated as the total loan volume-weighted indirect disaster exposure of all firms in county c:

$$E_{c,t}^{-c} = \frac{\sum_{i \in c} L_{i,t-1} E_{i,t}^{-c}}{\sum_{i \in c} L_{i,t-1}}. \tag{9}$$

Table 4 reports descriptive statistics for the indirect disaster exposure. Indirect exposure averages around six percent—meaning that, for every \$1 of total committed exposure in a given quarter, a bank has roughly 6 cents of committed-but-undrawn credit outstanding to firms in areas experiencing a natural disaster—but varies considerably over time: the indirect exposure at the 10th percentile is almost 10pp lower than at the 90th percentile.

Table 4: Indirect Exposure: Summary Statistics

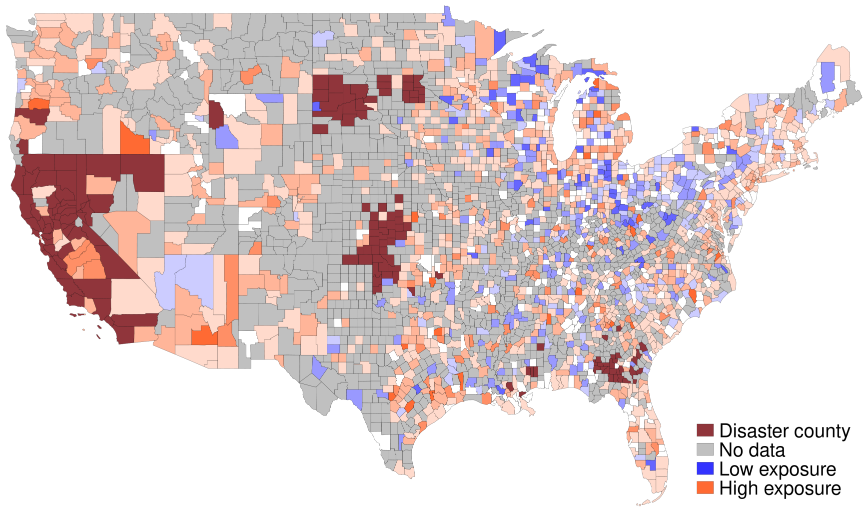
Level	N	Mean	SD	5p	10p	50p	90p	95p
Firm-Quarter ($E_{i,t}^{-c}$)	1.1m	6.0	9.5	0.4	0.7	2.6	12.4	19.3
County-Quarter ($E_{c,t}^{-c}$)	60.3k	5.9	9.1	0.5	0.8	2.9	11.8	17.3

***Notes**: This table shows summary statistics for indirect exposure measures at the firm-quarter and county-quarter levels. Firm-quarter exposure is defined in equation* (8) *and county-quarter exposure is defined in equation* (9).

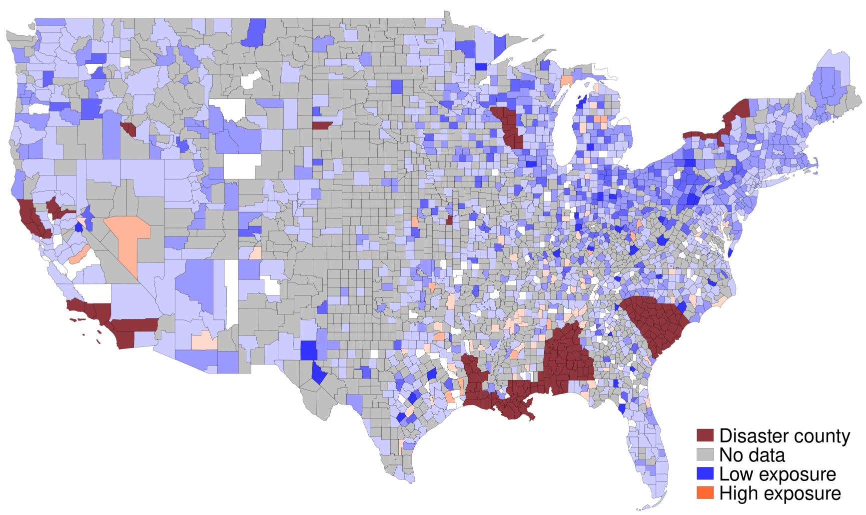
In Figure 8, we plot $E_{c,t}^{-c}$ across the US in the first and fourth quarter of 2017 for illustration. The maroon counties are those that directly experienced a disaster. The remaining counties are shaded from blue (low indirect exposure) to orange (high indirect exposure), both of which are relative to the average across all county-quarters in the sample. Gray counties are those with no observed Y-14 borrowers in that quarter.

These figures show two important properties of our indirect exposure metric. First, indirect exposure varies substantially over time: 36.8% of counties in the Y-14Q data had a high indirect exposure in 2017Q1, as disasters were concentrated in markets with substantial

Figure 8: Indirect Borrower Exposure to Natural Disasters



(a) 2017 Q1



(b) 2017 Q4

Notes: *The map shows county-level indirect exposure to natural disasters ($E^{-c}_{c,t}$) using equation (9). For each quarter/panel, disaster counties are highlighted in maroon and the remaining counties are shaded by a color gradient from low indirect exposure (blue) to high indirect exposure (orange).*

corporate borrowing. Though a similar number of total disasters struck in 2017Q4, banks had less exposure to them, and the share of counties with a high indirect exposure was only 3.3%. Second, a county's proximity to disasters via the banking system does not require geographical proximity to the disaster itself. For example, most of the counties in southeast

Texas were classified as having high exposure in Q1 but low exposure in Q4, even though the latter period featured far more nearby disaster counties. This rich variation in indirect exposure across both space and time allows us to identify its effects on both financial and employment outcomes for firms in unaffected areas.

5.2 Spillovers to Employment and Firm Financial Outcomes

Here we show that indirect exposure to natural disasters has negative effects on both real and financial outcomes in unaffected areas. We first test whether indirect disaster exposure affects employment at the county level by estimating the following regression:

$$y_{c,t+h} = \sum_{j=1}^{4} \delta_j^h y_{c,t-j} + \gamma^h E_{c,t}^{-c} + \alpha_c^h + \beta_t^h + \epsilon_{c,t+h}. \tag{10}$$

This regression resembles equation (2), except that we now estimate the employment effect from indirect spillovers through the banking network $E_{c,t}^{-c}$, rather than focusing on the direct employment response to a disaster. As mentioned before, we construct our independent variable of interest $E_{c,t}^{-c}$ as the loan-weighted average indirect disaster exposure of all banks serving firms in county c. We standardize the indirect disaster exposure for the regression. As in equation (2), we include four lags of the dependent variable to account for pre-trends, include county and time fixed effects, weight estimates by lagged employment to facilitate aggregation, and cluster standard errors by county. The coefficient of interest is γ^h and measures the effect of a one standard deviation increase in indirect bank exposure on employment at the county level. The trajectory of employment is shown in Figure 9.

The left panel shows that a one standard deviation increase in a county's indirect exposure to natural disasters via the banking network causes employment to decline by almost two percent in the first two quarters before gradually returning to its pre-disaster level after two years. While this effect is larger than in the corresponding estimates from Figure 3, there are two important caveats to keep in mind. The first is that the shock considered here is large: A one standard deviation increase in outside exposure corresponds to an increase of about 9 percentage points, which totals roughly the difference in exposure between the 90th and 10th percentile across all county-quarter observations (see Table 4). The second caveat is that directly affected areas can benefit from increases in labor demand that accompany rebuilding efforts, whereas indirect exposure is less likely to generate these effects. Even taking these caveats into account, however, the results suggest that banking networks generate statistically and economically significant spillovers to employment in unaffected areas.

The right panel shows that these spillovers are driven by banks' lending networks rather than other measures of their operational footprint. For this exercise, we first construct an analogous measure of indirect disaster exposure based on the lenders' *deposits* in each county rather than their undrawn revolving credit commitments ($\tilde{E}^{-c}_{c,t}$).[9] We then estimate the following regression at the county-quarter level that allows us to compare the effects of indirect disaster exposure through both loan and deposit networks:

$$y_{c,t+h} = \sum_{j=1}^{4} \delta_j^h y_{c,t-j} + \gamma^h E^{-c}_{c,t} + \eta^h \tilde{E}^{-c}_{c,t} + \alpha_c^h + \beta_t^h + \epsilon_{c,t+h}. \quad (11)$$

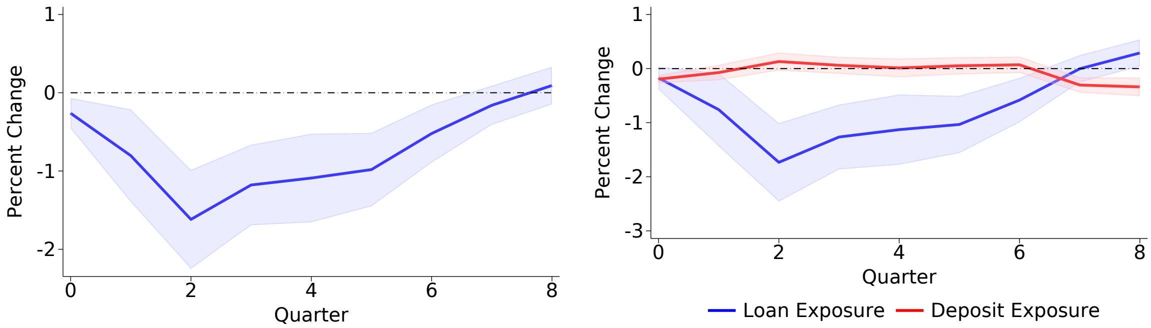
An increase in indirect disaster exposure via deposit networks has only a negligible effect on county-level employment in the following year, as shown by the right panel of Figure 9. In contrast, the effect of the banks' lending networks is almost unchanged from the estimate in the left panel and suggests that it is specifically banks' exposure to undrawn but committed credit lines that facilitate the spillovers of disasters to employment in unaffected areas.

This distinction between lending and deposit networks is important because it suggests that the exposure of banks' *borrowers* to a disaster is what matters for employment spillovers, rather than the physical operating footprint of the bank itself. If a bank were to cut back on lending in unaffected areas purely because some of their office buildings or local branches were damaged in a disaster, for example, then that bank's deposit network should be a more useful predictor of spillover effects than their C&I lending network, because the latter will

[9] In particular, we define: $\tilde{E}^{-c}_{b,t} \equiv 100 \times \frac{\sum_{j \neq c} Deposit_{j,b,t-1} D_{j,t}}{\sum_{j \neq c} Deposit_{j,b,t-1}}$ analogous to equation (7) and then aggregate this measure to the county level in line with equation (9).

Figure 9: Employment Spillovers

(a) Indirect Disaster Exposure **(b)** Lending versus Deposit Exposure



Notes: *Panel (a) plots estimates of γ^h from equation (10), which is estimated using a county-quarter panel, and displays the cumulative percent change in county-level employment to a one standard deviation increase in outside exposure $E_{c,t}^{-c}$. Shaded areas indicate 95 percent confidence intervals calculated using standard errors clustered by county. Panel (b) plots the response from from equation (11), which in addition includes an exposure measure based on deposits and traces the response of both exposure measures. Sample: 2015 Q1 - 2023 Q4.*

have a much weaker correlation with banks' physical operations.[10] This result also highlights the limitations of quantifying potential spillover risks using publicly available measures of banks' geographical operations, particularly since the vast majority of the lending network we construct is based on loans to small and private firms that are not visible in other datasets.

Next, we estimate the firm-level financial effects of indirect disaster exposure using the following regression, which is closely related to equation (1):

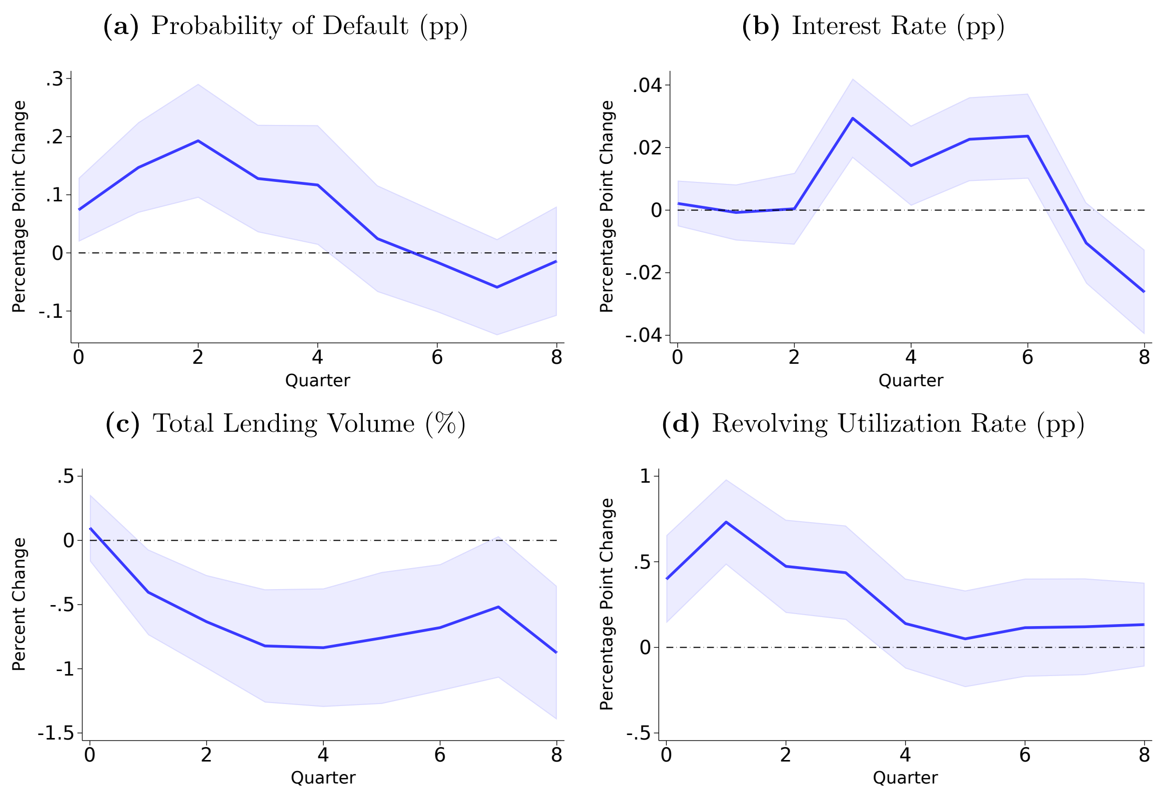
$$y_{i,t+h} = \delta^h y_{i,t-1} + \gamma^h E_{i,t}^{-c} + \alpha_i^h + \beta_t^h + \epsilon_{i,t+h}^h. \tag{12}$$

The variable of interest is $E_{i,t}^{-c}$ is the loan volume-weighted average indirect diaster exposure of banks serving firm i. The coefficient of interest γ^h captures the spillovers of this exposure on firm variable $y_{i,t+h}$. As before, we include firm fixed effects, time fixed effects, and the lagged dependent variable to control for pre-trends. We also restrict the sample to firms with at least 12 observations and cluster standard errors by county. We standardize the indirect

[10]Banks' C&I lending operations tend to be managed far more centrally than their retail operations, meaning that some areas with retail branches will not receive any C&I loans, and conversely that some C&I loans flow to counties in which the bank holds no deposits.

exposure $E_{i,t}^{-c}$, so that the coefficient γ^h represents the effect of a one standard deviation increase in indirect disaster exposure. The results are shown in Figure 10. Overall, we find that the effect of indirect disaster exposure on firms' bank lending outcomes is qualitatively similar to the effects of direct disaster exposure shown in Figure 2.

Figure 10: Spillovers to Unaffected Firms



Notes: *These figures plot estimates of γ^h from equation (12), which is estimated using a firm-quarter panel, and represent the cumulative effect on the firm-level financial outcome shown above in response to a one standard deviation increase in indirect disaster exposure at $t = 0$. Shaded areas indicate 95 percent confidence intervals calculated using standard errors clustered by county. Sample: 2015 Q1 - 2023 Q4.*

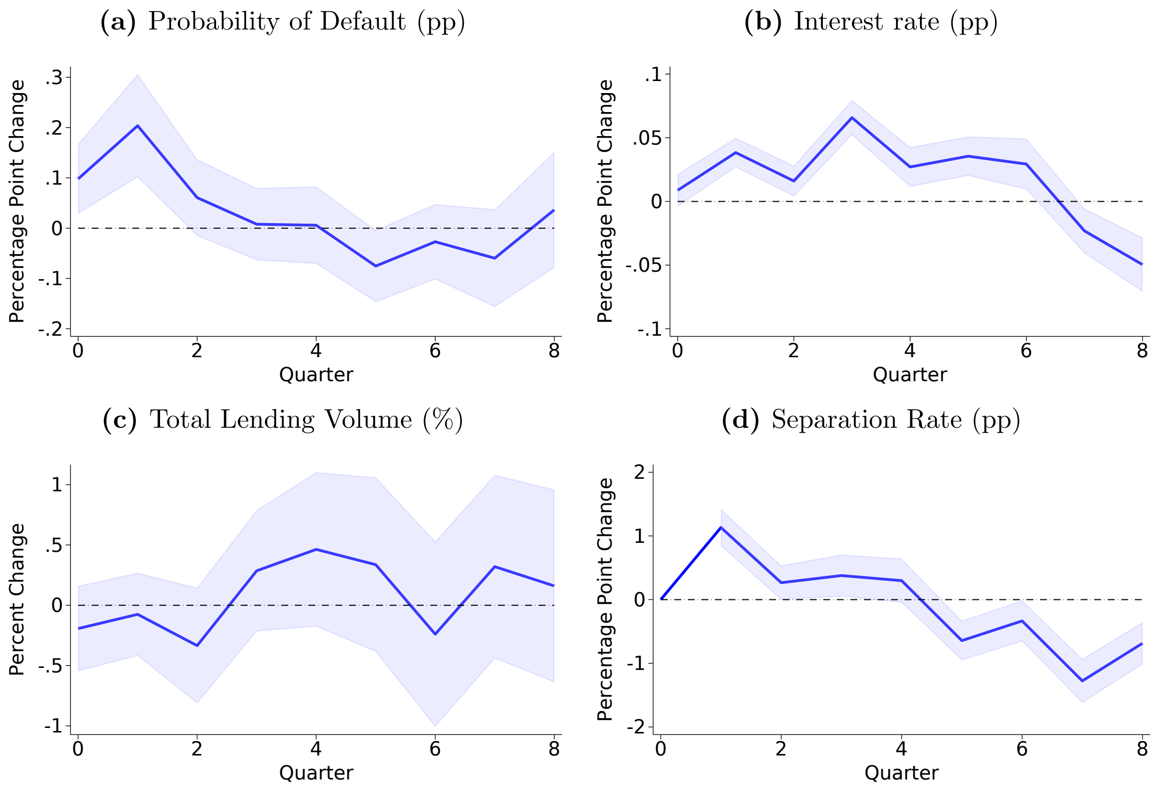
The top-left panel shows that indirect exposure leads to a statistically and economically significant increase in firm riskiness of about 20 basis points over the following year, which represents more than 20% of the median probability of default. The top-right panel shows that this elevated risk is accompanied by a small but statistically significant increase in firms' interest rates. The bottom-left panel shows that lending volume declines by about one percent in the following year and remains depressed throughout the response horizon. Finally, the bottom-right panel shows that revolving credit utilization increases by about a percentage point before gradually normalizing. This response is consistent with Ivashina and Scharfstein (2010), who show that borrowers responded to concerns about their lenders' financial stress by proactively drawing down their credit lines.

To provide sharper identification of these credit spillover effects, we leverage the fact that many of the firms in our data borrow from multiple banks. Although only about 10 percent of firms fall into this category, these firms collectively account for an average of almost three-quarters of total outstanding loan volume at any given time. This structure allows us to estimate regressions that include firm-time fixed effects as in Kwaja and Mian (2008). These specifications compare the quantity and terms of lending to the same borrower across different banks at the same time, which controls for variation in firm-level credit demand. We aggregate the data to a firm-bank-quarter panel and estimate the following regression:

$$y_{i,b,t+h} = \delta^h y_{i,b,t-1} + \gamma^h E_{b,t}^{-c} + \alpha_{b,c}^h + \beta_{i,t}^h + \epsilon_{i,b,t+h}^h. \tag{13}$$

This specification differs from the previous firm-level regressions in two ways: First, we slice the data by firms and banks, where the subscript b refers to a particular bank serving firm i. In this context, the indirect disaster exposure of a bank b serving firm i is simply $E_{b,t}^{-c}$. As before, we standardize the indirect disaster exposure. Second, we introduce firm-time fixed effects $\beta_{i,t}$, which allow us to interpret the coefficient of interest γ^h as the supply-side response of bank b in response to an increase in disaster exposure, while controlling for overall credit demand at firm i at time t. We also include bank-county fixed effects $\alpha_{b,c}$ that account for persistent features of any bank operating in any county, including the average indirect disaster exposure of a bank for a particular county. The dependent variable $y_{i,b,t+h}$ refers to outcome y at time $t + h$ for the firm-bank pair i, b. For example, for interest rates, the dependent variable corresponds to the volume-weighted average interest rate bank b charges firm i across all of their outstanding loans. As in previous regressions we include only firms observed in at least 12 quarters, add the lagged dependent variable to control for pre-trends, and cluster standard errors by county. The results are plotted below in Figure 11.

Figure 11: Spillovers to Unaffected Firms: Controlling for Credit Demand



Notes: *These figures plot estimates of γ^h from equation* (13)*, which is estimated using a firm-bank-quarter panel, and represent the cumulative effect on the financial outcome shown above at the firm-bank level in response to a one standard deviation increase in indirect disaster exposure at $t = 0$. Shaded areas indicate 95 percent confidence intervals calculated using standard errors clustered by county. Sample: 2015 Q1 - 2023 Q4.*

The top two panels show responses of perceived default risk and interest rates to indirect disaster exposure that are both similar to the average firm-level responses shown in Figure 10. However, despite the decline in total firm-level lending volume shown in the bottom-left panel of Figure 10, the bottom-left panel of Figure 11 shows that total committed lending volume at the firm-bank-quarter level is unchanged. This discrepancy can be reconciled by the lower-right panel, which shows that indirect disaster exposure increases the probability that a firm-bank match dissolves, which we define as occurring if a firm-bank pair had at least one outstanding loan at time t but zero outstanding loans at time $t + h$. The increase of about one percentage point in the separation rate of a firm-bank match in the quarter following a one standard deviation increase in indirect exposure is economically significant and represents roughly 10 percent of the unconditional quarter-ahead average separation rate in our sample (see Appendix Figure A7). 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 to affect employment and credit supply in other unaffected areas.[11]

6 Conclusion

Lending dynamics are a crucial determinant for the real effects of natural disasters, both locally and nationally. Following a disaster, local firms obtain less credit at higher rates, and draw down existing credit lines. This contraction in lending is more severe for more ex-ante financially 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. In addition to these direct effects, natural disasters also propagate through the banking system to affect employment and financial outcomes in areas with no direct disaster exposure. We construct a novel indirect disaster exposure measure based on banks' committed-but-undrawn credit lines and show that this indirect disaster exposure causes statistically and economically significant contractions in employment and credit supply.

Our results have two important consequences for policy makers and regulators. First, 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. Second, because our spillover results suggest that local disasters can disrupt credit supply and employment nationwide, understanding the geography of firms' bank lending networks 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.

[11] In Figures A8 and A9 in the appendix, we show that lending at the aggregate bank level does not respond to local disasters. We also do not observe any effect on profitability as measured by return on assets, return on equity, or net interest margin.

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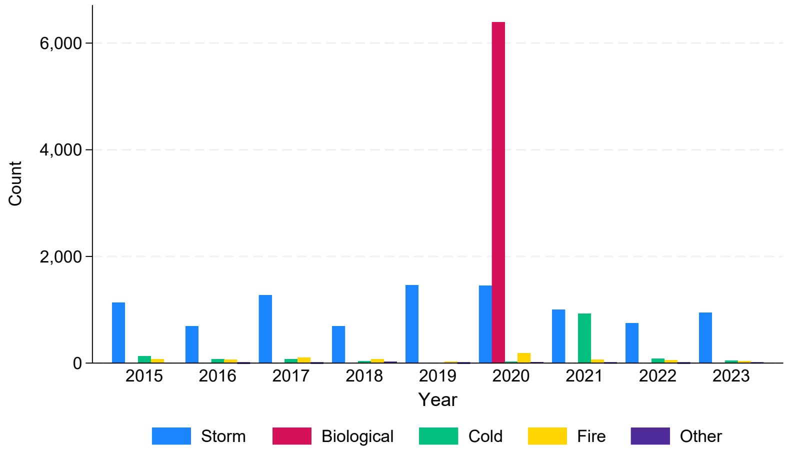
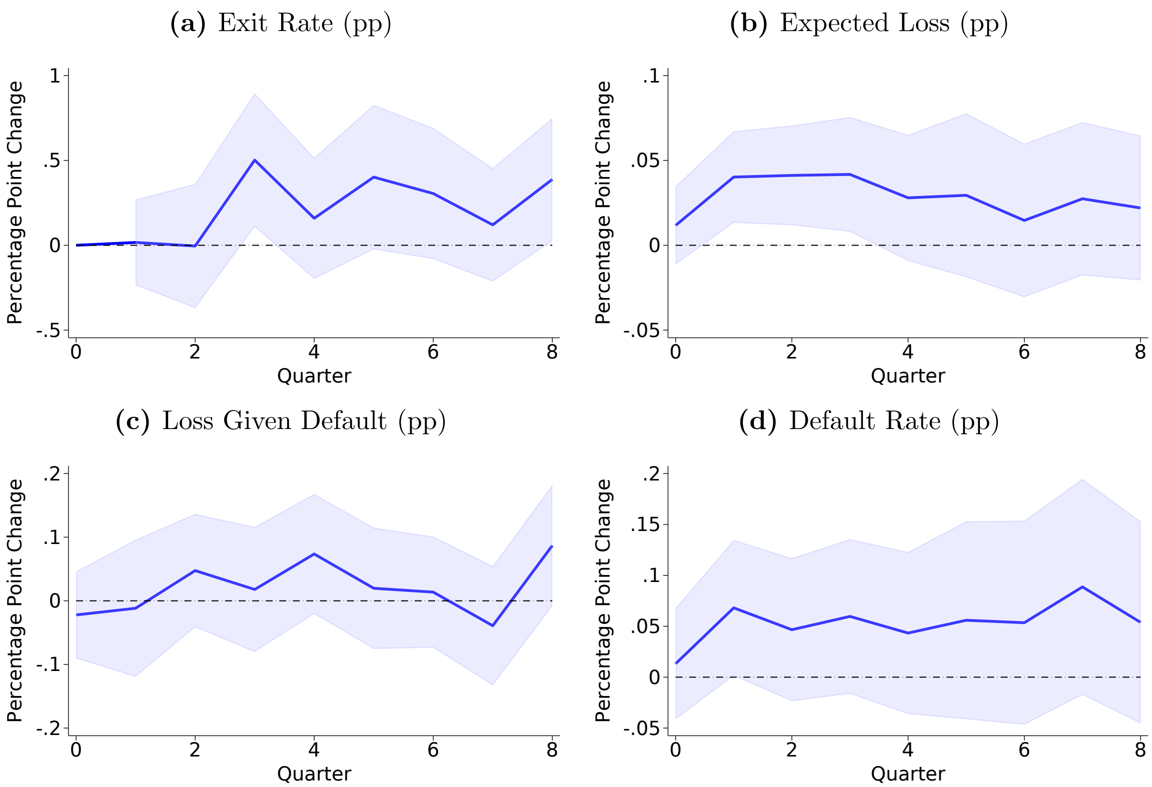
A Tables and Figures

Figure A1: Disasters over Time



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

Figure A2: Additional Firm Level Outcomes in Response to a Natural Disaster



Notes: *These figures plot estimates of γ^h from equation (1), which is estimated using a firm-quarter panel, and display the cumulative effect on the firm-level financial outcome shown above in response to a natural disaster (measured by the binary indicator $D_{i,c,t}$) at $t = 0$. Shaded areas indicate 95 percent confidence intervals calculated using standard errors clustered by county. Sample: 2015 Q1 - 2023 Q4.*

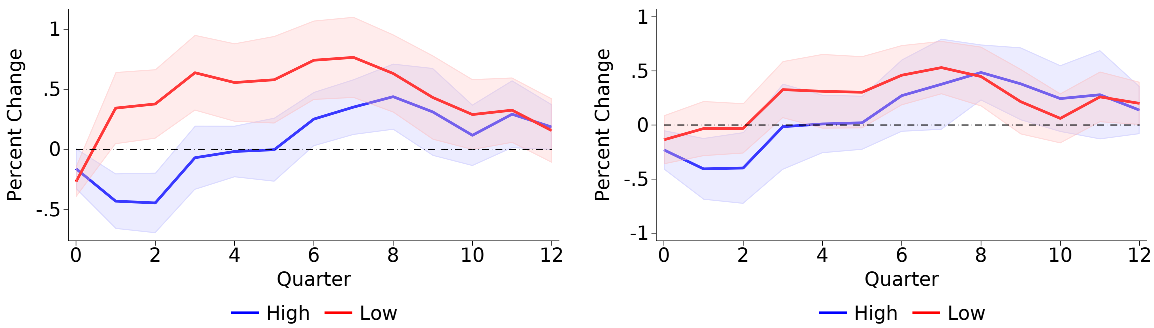
Table A1: Disaster Events by Type and U.S. State

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: State Contingent Employment Response: Additional Robustness

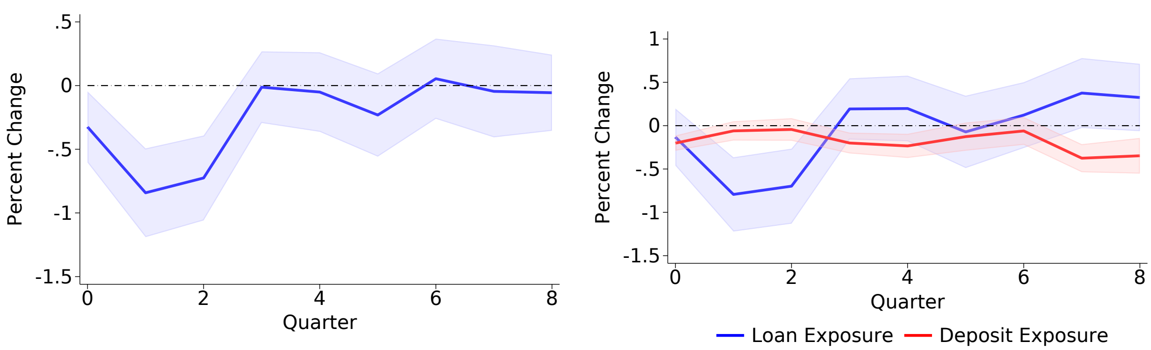
(a) Loss Given Default (pp) **(b)** Interest rate (pp)



Notes: *These figures plot* $\gamma^h_{s=1}$ *and* $\gamma^h_{s=0}$ *from equation* (5)*, which is estimated using a county-quarter panel, and measure the impact of a natural disaster at* $t = 0$ *on total county-level employment depending on whether the loan volume-weighted average loss given default (left panel) or interest rate (right panel) for firms in a given county was below (red) or above (blue) the median across all counties at time* $t - 1$*. Shaded areas indicate 95 percent confidence intervals calculated using standard errors clustered by county. Sample: 2015 Q1 - 2023 Q4.*

Figure A4: Employment Spillovers – Alternative Exposure Measure

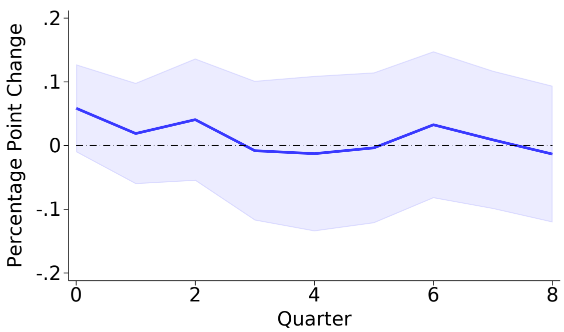
(a) Increase in Exposure **(b)** Increase in Exposure based on Loans or Deposits



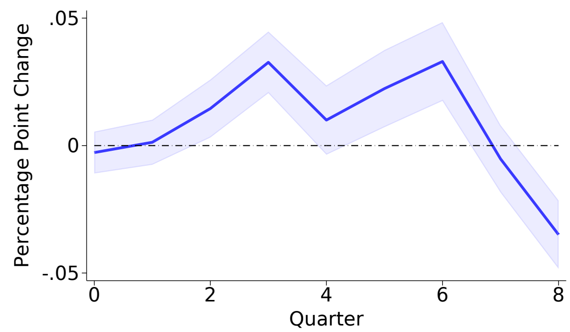
Notes: *Panel (a) plots estimates of* γ^h *from equation* (10)*, which is estimated using a county-quarter panel, and displays the cumulative percent change in county-level employment to a one standard deviation increase in our alternative outside exposure. Shaded areas indicate 95 percent confidence intervals calculated using standard errors clustered by county. Panel (b) plots the response from from equation* (11)*, which in addition includes an exposure measure based on deposits and traces the response of both exposure measures. Sample: 2015 Q1 - 2023 Q4.*

Figure A5: Spillovers to Unaffected Firms – Alternative Exposure Measure

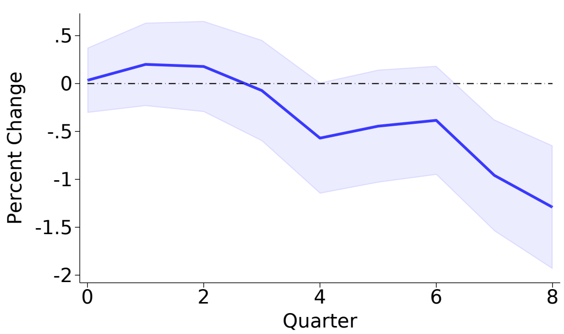
(a) Probability of default (pp)



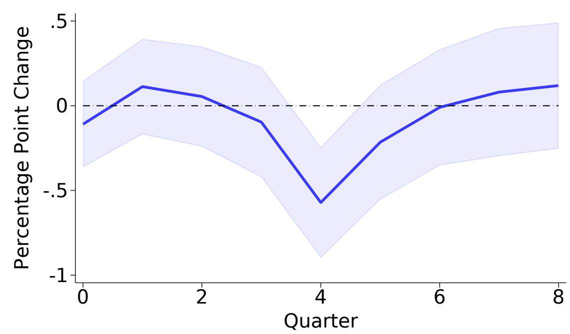
(b) Interest rate (pp)



(c) Total lending volume (%)



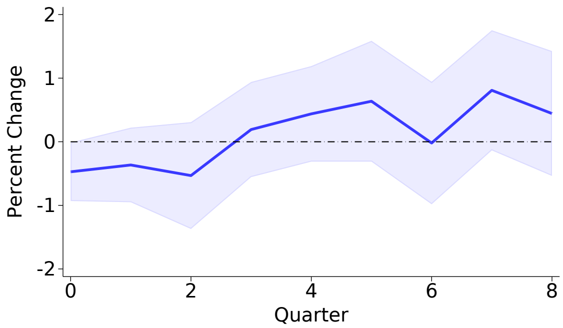
(d) Revolving utilization rate (pp)



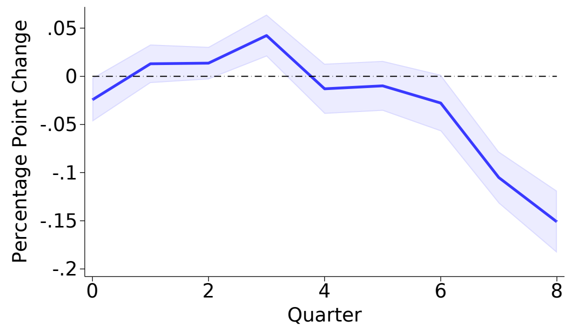
Notes: *These figures plot estimates of* γ^h *from equation* (12)*, which is estimated using a firm-quarter panel, and represent the cumulative effect on the firm-level financial outcome shown above in response to a one standard deviation increase in our alternative indirect disaster exposure at* $t = 0$*. Shaded areas indicate 95 percent confidence intervals calculated using standard errors clustered by county. Sample: 2015 Q1 - 2023 Q4.*

Figure A6: Spillovers: Controlling for Credit Demand – Alternative Exposure Measure

(a) Loan volume (%)

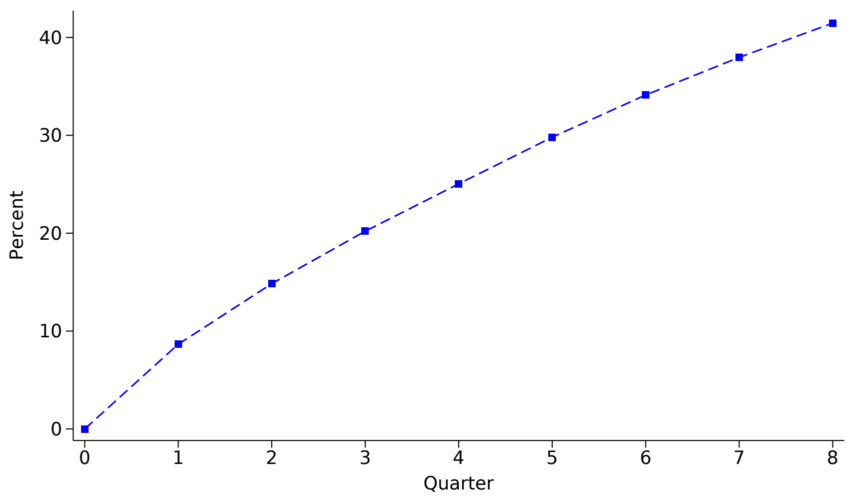


(b) Interest rate (pp)



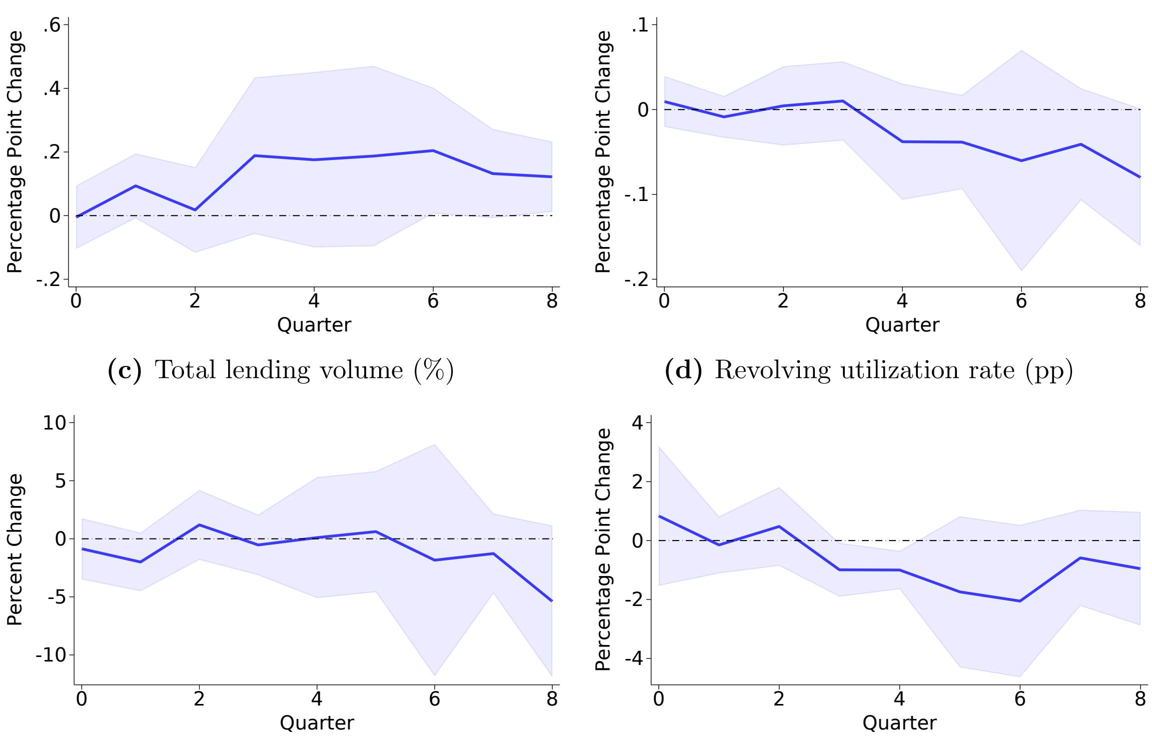
Notes: *These figures plot estimates of* γ^h *from equation* (13)*, which is estimated using a firm-bank-quarter panel, and represent the cumulative effect on the financial outcome shown above at the firm-bank level in response to a one standard deviation increase in our alternative indirect disaster exposure at* $t = 0$*. Shaded areas indicate 95 percent confidence intervals calculated using standard errors clustered by county. Sample: 2015 Q1 - 2023 Q4.*

Figure A7: Average Separation Rate for Firm-Bank Relationships



Notes*: This figure shows the unconditional probability that a firm-bank pair with at least one outstanding loan at time* t *has zero outstanding loans at time* $t + h$ *for* $h \in \{1, 2, ...8\}$*. Sample: 2015 Q1 - 2023 Q4.*

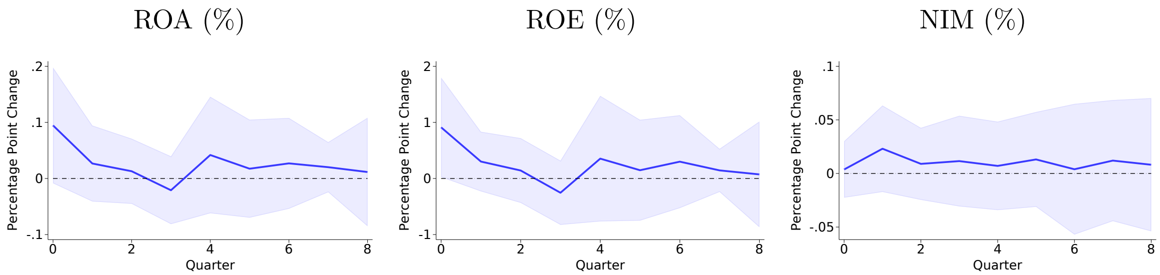
Figure A8: Aggregate Effects at the Bank Level: Financial Variables



(a) Probability of default (pp)
(b) Interest rate (pp)
(c) Total lending volume (%)
(d) Revolving utilization rate (pp)

Notes: *These figures plot estimates of γ^h from the following bank-level regression, which is estimated using a bank-quarter panel: $y_{b,t+h} = \delta^h y_{b,t-1} + \gamma^h E_{b,t} + \alpha_b^h + \beta_t^h + \epsilon_{b,t+h}^h$, where b refers to a specific bank. The dependent variable is a weighted average or sum at the bank level, obtained from individual loan level data. The total exposure measure $E_{b,t}$ includes all counties. The panels display the cumulative effect on the outcome shown above in response to a one standard deviation in total exposure at $t = 0$. Shaded areas indicate 95 percent confidence intervals calculated using standard errors clustered by bank. Sample: 2015 Q1 - 2023 Q4.*

Figure A9: Aggregate Effects at the Bank Level: Profitability Measures



Notes: *These figures plot estimates of γ^h from the following bank-level regression, which is estimated using a bank-quarter panel: $y_{b,t+h} = \delta^h y_{b,t-1} + \gamma^h E_{b,t} + \alpha_b^h + \beta_t^h + \epsilon_{b,t+h}^h$, where b refers to a specific bank. The total exposure measure $E_{b,t}$ includes all counties. The panels display the cumulative effect on the outcome shown above in response to a one standard deviation in total exposure at $t = 0$. Shaded areas indicate 95 percent confidence intervals calculated using standard errors clustered by bank. Sample: 2015 Q1 - 2023 Q4.*