FLASH DROUGHTS AND BANK STABILITY IN THE UNITED STATES

Maxime Fajeau[a] ✉ Rémi Generoso[ab] Clément Mathonnat[c]

January 30, 2026

Abstract

Climate change increasingly manifests through short-lived but intense shocks rather than gradual shifts in long-run averages. This paper studies the financial stability implications of flash droughts—rapid-onset episodes of severe soil moisture depletion that develop within weeks and often escape standard drought monitoring systems. While droughts are among the costliest climate hazards worldwide, their effects on banks at the institutional level remain poorly understood. We combine high-resolution meteorological data with granular U.S. banking data covering more than three decades, over 10,000 banks, and tens of thousands of branches. Flash drought exposure is identified using soil-moisture-based indicators and aggregated to the bank level using deposit-weighted branch exposure. Exploiting the plausibly exogenous and localized nature of flash droughts, we estimate their dynamic effects on bank stability using local projections. We find that flash droughts significantly and persistently reduce bank stability, operating primarily through declines in profitability and a gradual buildup of credit risk, with no evidence of a liquidity channel. Effects are strongly seasonal and markedly larger for spring and summer droughts. These results identify flash droughts as a distinct and underappreciated source of physical climate risk for the banking system.

JEL Classification Flash droughts · Bank stability · Climate risk · Local projections
Keywords G21 · G01 · Q54

[a] University of Lille, LEM-CNRS, France.
✉ Corresponding author: maxime.fajeau@univ-lille.fr
[b] Macroeconomic and Forecasting Chair, UQAM, Montreal, Canada.
[c] University of Lorraine, BETA-CNRS, France.

ACKNOWLEDGEMENT – The authors thank Michael Brei, Étienne Dagorn, Nicolas Debarsy, and Jan Fidrmuc for valuable discussions and comments. We are also grateful to participants at the WIP Seminar at the University of Lille for helpful feedback.

1 Introduction

Climate and weather profoundly influence economic activity across multiple channels, affecting productivity, income, asset values, and the spatial organization of production. As the climate warms, the focus of both policy and research has shifted from long-run average changes to the economic consequences of climate variability. This shift recognizes that short-lived shocks stemming from climatic variations, rather than large-scale natural disasters, can generate disproportionate losses when interacting with sectoral specialization, limited adaptive capacities, and financial frictions. While empirical work consistently documents that various weather shocks have persistent effects on output and welfare (Dell et al., 2014; Burke et al., 2015; Kotz et al., 2024), a central and pressing challenge remains: to comprehensively understand how these diverse physical hazards are transmitted to the financial system.

Historically, research on climate-related financial risk has focused on acute, rapid-onset events, often categorized as natural disasters such as floods and hurricanes (Garmaise and Moskowitz, 2009; Cortés and Strahan, 2017; Schüwer et al., 2019; Noth and Schüwer, 2023). While these studies show that extreme events can indeed affect bank performance—reducing lending, increasing loan defaults, and weakening overall financial health—, results vary widely across hazards and institutional settings (Klomp, 2014; Noth and Schüwer, 2023). Despite droughts being consistently ranked among the costliest natural hazards globally, causing billions in economic damage annually and profoundly affecting real economic activity, their implications for bank stability at the institutional level remain comparatively poorly understood (Brei et al., 2025). This critical gap hinders our understanding of how drought-related shocks, despite their significant economic footprint, translate into bank fragility, particularly when contrasted with the more extensively studied impacts of floods and hurricanes.

A major limitation is that standard drought measures capture gradual moisture deficits and are poorly suited to episodes that develop too quickly for agents to adjust. We focus on a specific hazard: flash droughts. These episodes intensify rapidly, often transitioning from normal conditions to acute soil-moisture stress within days or weeks. Growing evidence from climate science suggests that anthropogenic warming is increasing the likelihood of such rapid-onset drying events by strengthening land–atmosphere feedback and accelerating soil moisture depletion (Yuan et al., 2023). These features make flash droughts particularly challenging from economic and financial perspectives: their speed limits anticipatory responses, compresses adjustment margins, and increases the risk that localized shocks propagate before agents and institutions can adapt.

The economic disruption caused by flash droughts is severe and multisectoral. The agricultural sector is the first and most severely affected. Flash droughts can cause abrupt yield losses, crop failures, and livestock stress, with immediate knock-on effects on input suppliers, agro-processing, and rural employment (Lesk et al., 2016; Deryugina and Hsiang, 2017; Diffenbaugh et al., 2017). Beyond agriculture, water stress can disrupt energy generation, hinder transportation along inland waterways, and depress activity in regions specialized in climate-sensitive production (Hsiang et al., 2017; Kahn et al., 2021). Due to their rapid onset, flash droughts often bypass early warning systems, making them a potent yet underexplored source of physical risk for banks (Otkin et al., 2018).

We focus our analysis on the United States, which serves as a critical laboratory for two reasons. First, the U.S. is a global hotspot for flash droughts, with a documented increase in their frequency and intensity (Otkin et al., 2018; Christian et al., 2019). Second, the geographically dispersed and fragmented structure of the U.S. banking sector is uniquely exposed to such localized hazards. Unlike more centralized financial systems, the U.S. market relies on a vast network of community and regional banks whose

stability is intrinsically tied to the economic health of specific locales. This fragmentation creates a direct transmission channel between local physical shocks—such as flash droughts—and the resilience of financial intermediaries. The depth and consistency of U.S. regulatory data allow us to exploit this spatial variation to study how localized climate shocks interact with the banking system (Cortés and Strahan, 2017; Noth and Schüwer, 2023).

To capture the rapid-onset nature of flash droughts, we rely on recent advances in drought monitoring that emphasize high-frequency, high-resolution soil moisture dynamics. Specifically, flash drought events are identified using soil-moisture-based indicators derived from reanalysis products produced by the National Oceanic and Atmospheric Administration (NOAA) and related land-surface datasets, following the framework proposed by (Osman et al., 2024). These indicators allow us to track abrupt declines in root-zone soil moisture at fine spatial and temporal scales, capturing the surprise component of flash droughts that is often missed by traditional drought metrics. This feature is essential for our analysis, as it is precisely the speed of intensification that limits anticipatory responses by banks and borrowers.

We combine these high-resolution meteorological data with granular banking information covering the U.S. financial system. Regulatory balance-sheet and income-statement data are drawn from U.S. Call Reports, while branch-level deposits and locations are obtained from the FDIC Summary of Deposits. Merging these datasets allows us to construct bank-level exposure measures based on the geographic distribution of banks' branch networks. Our sample spans nearly three decades and includes thousands of flash drought episodes, more than 10,000 banks, and tens of thousands of bank branches, providing extensive variation in exposure across space and time.

To quantify the dynamic effects of flash droughts on bank stability and balance-sheet outcomes, we employ a local projection framework (Jordà, 2023). This approach is well suited to tracing the response of financial variables to plausibly exogenous climate shocks over time and has been widely used in recent work on macroeconomic and financial responses to environmental disturbances (Fajeau et al., 2025).

Our analysis shows that exposure to flash droughts has significant and economically meaningful effects on bank stability. Banks operating in areas affected by flash droughts experience a persistent deterioration in standard measures of financial stability, with effects that unfold over several quarters rather than dissipating quickly. These impacts are not driven by balance-sheet size alone but reflect deterioration in underlying financial conditions, operating through declines in profitability and a gradual buildup of credit risk. The dynamic response of banks suggests that rapid-onset droughts compress adjustment margins and translate localized economic disruptions into sustained financial stress. A series of complementary exercises confirms that these effects are robust across alternative measures of drought exposure, bank characteristics, and empirical specifications. Taken together, our results indicate that relatively common but rapidly developing climate hazards—such as flash droughts, despite being less visible than major disasters—can generate persistent and heterogeneous effects on financial institutions, with important implications for the resilience of the banking sector to physical climate risk.

2 Data and methods

2.1 Flash droughts data

What makes a drought a "flash" drought. Unlike conventional droughts, flash droughts are characterized by rapid deterioration in moisture conditions over very short time horizons—often within a few

weeks—driven by the interaction of precipitation shortfalls and anomalously high atmospheric evaporative demand (Otkin et al., 2018; Christian et al., 2019). In many cases, flash droughts develop from near-normal antecedent conditions, making them difficult to anticipate with standard drought monitoring tools that rely on slowly evolving moisture anomalies

This rapid onset has important economic and financial implications. Because flash droughts compress the time available for adjustment, they limit the scope for anticipatory responses by households, firms, and financial intermediaries. In contrast to slow-developing droughts, which may allow gradual adaptation through changes in production plans or financial arrangements, flash droughts can lead to abrupt deteriorations in borrowers' cash flows and collateral values. For banks, this implies that credit risk and profitability may be affected before loan pricing, portfolio composition, or liquidity buffers can be adjusted, making flash droughts particularly relevant for the analysis of short- to medium-run financial stability.

Stylized facts on flash drought exposure in the United States. The continental United States has emerged as a documented hotspot for rapid drought intensification. Several well-studied episodes illustrate the defining features of flash droughts and motivate our empirical focus. The flash droughts affecting the Southern Plains in 2011 and the Central Great Plains in 2012 are widely cited as paradigmatic cases. In particular, the 2012 event evolved from near-normal moisture conditions in late spring to severe drought across large parts of the Corn Belt by mid-summer, reflecting an exceptionally rapid intensification driven by precipitation deficits and elevated atmospheric evaporative demand. This abrupt transition translated into severe agricultural losses, exceeding $30 billion, and highlighted the limited capacity of existing monitoring systems to anticipate such rapid changes (Hoerling et al., 2014; Otkin et al., 2018).

Subsequent events underscore that flash droughts are neither isolated nor confined to specific regions. The 2017 Northern High Plains flash drought developed rapidly following a wet spring, leading to substantial reductions in wheat yields and widespread livestock forage losses in the Dakotas and Montana before mitigation measures could be implemented Hoell et al. (2021). Similarly, the 2016 Southeast U.S. flash drought illustrates how rapid soil moisture depletion can generate cascading risks beyond agriculture. Case and Zavodsky (2018) document how the swift transition from moist to extremely dry conditions—driven by record-high temperatures—created favorable conditions for wildfire ignition and spread, contributing to the destructive Gatlinburg fires. These episodes highlight the role of land–atmosphere feedback in amplifying drought impacts over very short horizons.

These episodes highlight three stylized facts central to our analysis. First, flash droughts often intensify abruptly from otherwise benign baseline conditions, compressing adjustment margins and limiting anticipatory adaptation. Second, their spatial footprint varies widely across episodes: some events remain geographically contained, while others expand across large agricultural regions. In either case, damages can be economically significant because impacts concentrate in areas specialized in climate-sensitive activities. Third, flash droughts can generate indirect effects through interconnected systems—agricultural supply chains, water-dependent energy production, and wildfire risk—suggesting plausible transmission channels to the financial sector.

Measuring flash droughts with the Soil Moisture Volatility Index (SMVI). To operationalize this rapid-onset behavior, we use the recent framework proposed by Osman et al. (2024) to construct an indicator of root-zone soil moisture (RZSM) volatility. The approach is designed to detect uninterrupted accelerations in drying rather than gradual background fluctuations: analogous to high-frequency volatility filters in finance, it emphasizes sharp, persistent departures consistent with rapid intensification. A key

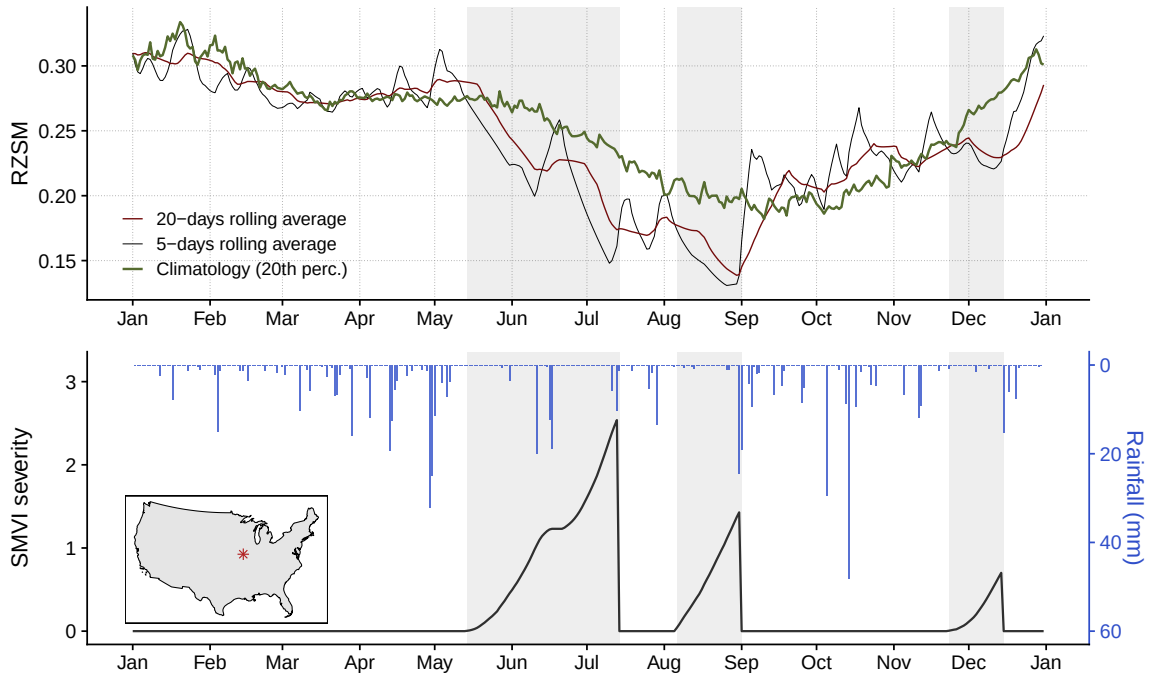


Figure 1: SMVI-based flash drought detection at 91°W - 39°N location during year 2012.

Note: The figure illustrates the dynamic of the Soil Moisture Volatility Index (SMVI) calculated from the NLDAS-2 dataset at a single grid cell in Ralls County, Missouri. The top panel shows the daily time series of root-zone soil moisture (RZSM, 0-10cm layer) during year 2012. The thin black line plots the 5-day moving average of RZSM, capturing short-term soil moisture fluctuations, while the dark red line represents the 20-day moving average, which serves as a slower "background" state. The green line plots the 20th percentile climatology of RZSM for each day of the year, providing a drought threshold consistent with "Moderate Drought – D1" conditions. Shaded grey intervals indicate periods during which (i) the 5-day mean remains below the 20-day mean for at least four consecutive pentads (20 days) and (ii) the 5-day mean falls below the 20th percentile threshold; these intervals are classified as flash-drought onset periods according to the SMVI criteria. The bottom panel shows the corresponding SMVI-based severity index, defined as the cumulative deficit of the 5-day mean RZSM relative to the 20th percentile climatology over each identified event (in $m^3 \cdot m^{-3}$ summed over time). Shaded grey bands are repeated to show the temporal alignment between onset periods and the build-up of event severity.

feature is its sensitivity to interruptions—rainfall events break drying sequences and attenuate the volatility signal—so the metric preferentially flags sustained drying spells most relevant to acute agricultural impacts.

Soil moisture is a particularly relevant state variable from an economic perspective, as it directly affects crop growth, pasture conditions, and water availability, and responds quickly to both precipitation anomalies and elevated evaporative demand. In contrast, widely used drought indicators such as the Standardized Precipitation Index (SPI) or the Standardized Precipitation–Evapotranspiration Index (SPEI) are designed to capture cumulative anomalies over longer horizons and therefore primarily reflect slow-onset drought conditions (Vicente-Serrano et al., 2010). While these indices are well-suited for assessing long-run water stress, they are less effective at identifying rapid-onset events that unfold over weeks rather than seasons.

We compute this volatility indicator from daily soil moisture series derived from two complementary gridded products. First, we use NCA-LDAS to characterize rapid moisture changes in the near-surface layer (0–10 cm), which provides a high-frequency signal closely tied to land–atmosphere exchanges governing

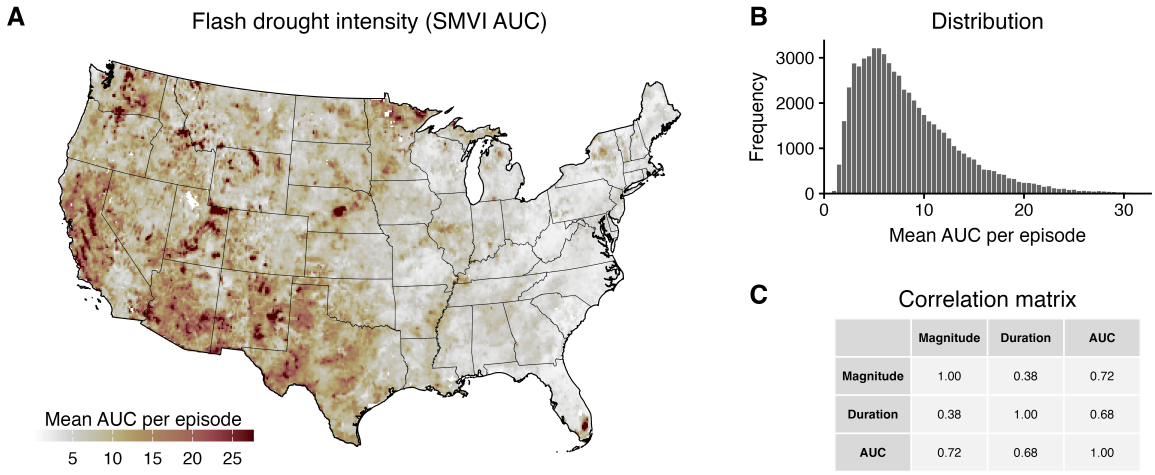


Figure 2: Panel A maps the average flash drought intensity across the continental United States using the area-under-the-curve (AUC) of the Soil Moisture Volatility Index (SMVI). Panel B shows the distribution of flash drought episodes over the 30-year sample by intensity. Panel C reports the correlation matrix across the three dimensions of the SMVI indicator.

rapid desiccation. Second, to capture dynamics at agronomically relevant rooting depths, we compute our index from deeper soil-moisture conditions (0–40 cm) using the SMERGE 2.0 product. In both cases, flash-drought onset is detected by contrasting a fast soil-moisture signal (a 5-day running mean) with a slow baseline (a 20-day running mean) that summarizes antecedent conditions. An episode is triggered when the fast signal declines sharply and persistently below the slow baseline. We also impose a local deficit requirement by requiring the fast signal to fall below the 20th percentile of the historical distribution for the corresponding calendar date, which normalizes for local seasonality and aligns with operational drought-monitoring practice (e.g., the U.S. Drought Monitor convention, where "moderate drought (D1)" is associated with the 20th-percentile range).[1]

For each grid cell, we construct a continuous intensity measure by cumulating soil-moisture deficits from onset to termination. The daily deficit (in volumetric units) is defined as the shortfall of the fast soil-moisture signal relative to the local 20th-percentile benchmark for the corresponding calendar date. Figure 1 illustrates, for a representative grid cell, the soil-moisture trajectory and the associated cumulative deficit.

Applying this procedure over 1980–2019 yields a flash-drought event dictionary at 0.125° spatial resolution for both the NLDAS-based fields and SMERGE 2.0. In each case, the dictionary assigns to every grid cell a sequence of distinct episodes, indexed by onset and termination dates, which we use as the event-level input for our exposure construction. From each episode's cumulative-deficit path, we extract three indicators. Duration is the number of days between onset and termination. Magnitude is the peak cumulative deficit reached during the episode. Because flash droughts differ in their within-episode dynamics—some are short and steep, while others are longer with gradual accumulation—Duration and Magnitude can be only weakly correlated. We therefore use the area under the cumulative-deficit curve (AUC) as our benchmark severity measure, as it integrates both the speed of deficit build-up and its

[1]Following Osman et al. (2024), we apply duration and pooling rules to exclude transient dry spells; all parameter choices are reported in Appendix A1.

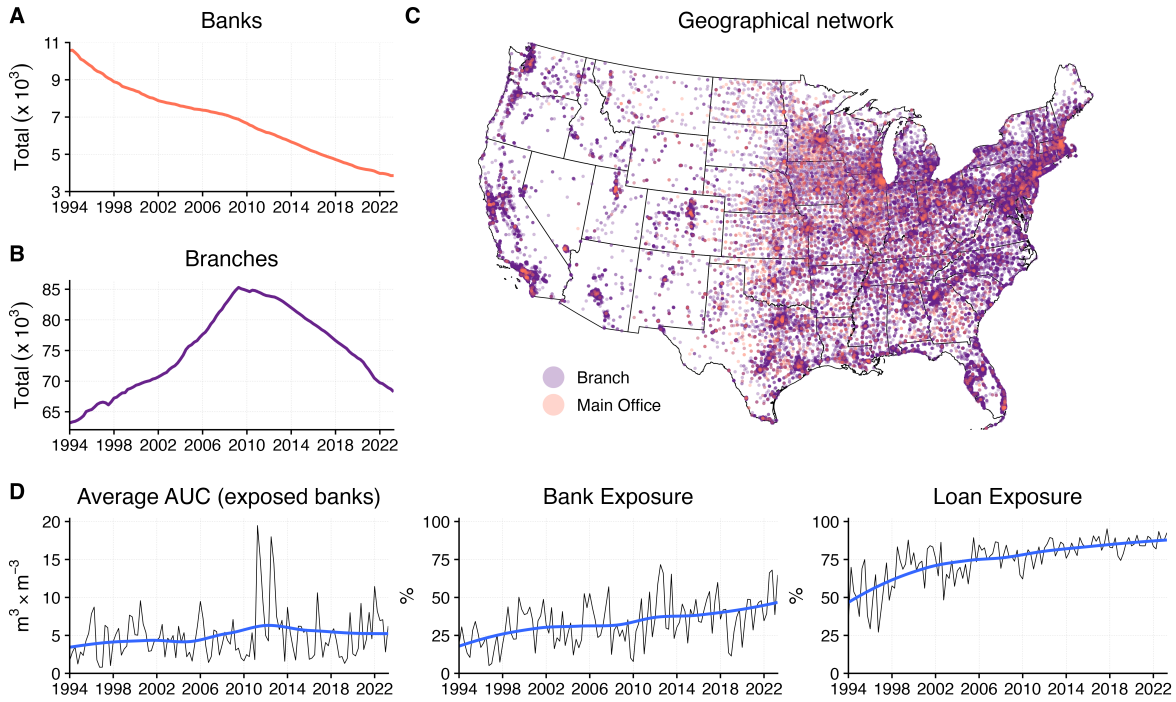


Figure 3: U.S. Banking sector from 1994 to 2023 (panel A & B) and its geographical network in 2023 (panel C).

Note: Spatial distribution of bank branches and headquarters based on FDIC Summary of Deposits data. Branch locations are geocoded using a three-step process incorporating OpenStreetMap, U.S. Census, and ZIP code-level approximations to address missing geographic coordinates. Headquarters locations are sourced from Call Reports and mapped according to official registry data.

persistence, distinguishing episodes that share a similar peak (or length) but differ in how long and how intensely soil moisture remains depressed (Figure 2).

2.2 Bank data

Why branch-level exposure matters. Banks operate as spatial networks rather than as point entities located at their headquarters. While balance sheets are consolidated at the bank level, lending, deposit-taking, and customer relationships are conducted locally through branch networks that are unevenly distributed across space. A large literature in banking emphasizes that geographic proximity between banks and borrowers plays a central role in credit allocation, monitoring, and relationship lending, implying that local economic conditions are directly relevant for banks' financial performance (Degryse and Ongena, 2005; Petersen and Rajan, 2002). In line with Petersen and Rajan (2002) and more recent analyses (Nguyen, 2019; Abecasis and Walker, 2023), firms typically borrow from nearby lenders, with median borrower–lender distances of 4 miles, remaining under 10 miles in most cases today, emphasizing the continued importance of branch-based intermediation.

This distinction is particularly important for climate-related shocks, which are inherently spatial and often highly localized. A flash drought affects banks only insofar as it disrupts economic activity in the areas where they maintain operational presence. Treating banks as geographically undifferentiated entities

would therefore obscure substantial heterogeneity in exposure, especially in a setting where institutions differ widely in the size, density, and dispersion of their branch networks. Recent work shows that the geographic footprint of banks shapes how localized shocks propagate through the financial system and translate into balance-sheet outcomes (Cortés and Strahan, 2017; Noth and Schüwer, 2023).

Accordingly, our analysis relies on branch-level information to map localized flash drought exposure into bank-level measures of climate risk. This approach allows us to capture how identical physical shocks can generate heterogeneous financial effects across banks depending on the spatial configuration of their operations.

Constructing bank-level flash drought exposure. We combine granular banking data with high resolution climate information to construct bank-level exposure to flash droughts. Bank balance-sheet and income-statement variables are obtained from U.S. regulatory *Call Reports*, filed quarterly with federal banking authorities and made available through the Federal Financial Institutions Examination Council (FFIEC). Branch-level information on geographic location and deposits is drawn from the FDIC *Summary of Deposits*, which provides annual data on the universe of U.S. bank branches. Banks are consistently identified across datasets using unique regulatory identifiers from the National Information Center (NIC).

Flash drought exposure is measured at a fine spatial resolution using gridded climate data defined on tiles of $0.1^\circ \times 0.1^\circ$ (approximately $9, \text{km} \times 9, \text{km}$ at the equator). Each bank branch b is assigned the flash drought exposure of the grid cell in which it is located. For each bank i and period t, branch-level exposures are then aggregated into a bank-level measure using deposit-weighted averages. Let $d_{i,b,t}$ denote flash drought exposure at branch b of bank i at time t, and let $\delta_{i,b,t}$ denote the share of branch deposits in total bank deposits, defined as:

$$\delta_{ibt} = \frac{\text{branch deposits}_{bt}}{\text{bank deposits}_{it}} \qquad \text{s.t.} \quad \sum_b \delta_{ibt} = 1. \tag{1}$$

The resulting bank-level flash drought exposure is given by:

$$d_{it} = \sum_b (d_{ibt} \cdot \delta_{ibt}). \tag{2}$$

Using deposits as aggregation weights reflects the relative economic importance of different branch locations within a bank's operations. Deposits provide a broad and consistently measured proxy for local banking activity, capturing both retail and commercial presence and remaining available for all banks throughout the sample period. This approach circumvents the limitations of activity-specific proxies—such as *Community Reinvestment Act* data for agricultural lending or *Home Mortgage Disclosure Act* data for mortgage origination—which often provide incomplete coverage due to asset-based reporting thresholds and product segmentation. By relying instead on branch-level deposit shares, the aggregation procedure offers a comprehensive measure of each bank's regional footprint and allows exposure to be measured independently of subsequent lending or funding adjustments.

Accurate geolocation of branches is essential for this mapping exercise. We therefore rely on a comprehensive geocoding procedure to assign precise geographic coordinates to branch locations and ensure full coverage of branch-level deposits over the sample period. All details regarding data sources, geocoding methods, and validation exercises are reported in the Appendix (see Section A2). The resulting exposure measure provides a consistent and time-varying representation of banks' vulnerability to localized flash drought shocks, reflecting the spatial structure of the U.S. banking system (see Figure 3).

Dependent variables and financial transmission channels. Our primary dependent variable is the widely recognized bank Z-score, a standard measure of financial stability. The Z-score is defined as the sum of a bank's return on assets (ROA) and equity-to-assets ratio (EQ), standardized by the standard deviation of ROA (see Laeven and Levine, 2009; Dafermos et al., 2018). This metric compares a bank's resilience, as reflected in its returns and equity, with the volatility of those returns, providing an indicator of the distance-to-default. Specifically, it represents the number of standard deviations a bank's returns need to drop to exhaust its capital, making it a measure of insolvency likelihood (Hannan and Hanweck, 1988). A higher Z-score indicates greater financial stability, while a lower Z-score reflects heightened fragility. Formally, it is calculated as:

$$z_{it} = \frac{\text{ROA}_{it} + \text{EQ}_{it}}{\sigma_{it}^{\text{ROA}}}, \tag{3}$$

where σ_{it}^{ROA} is the standard deviation of ROA computed over a backward looking rolling window of eight quarters. This approach captures recent volatility in bank performance while smoothing out short-term fluctuations (Noth and Schüwer, 2023). To ensure comprehensive data coverage, we extend Call Reports data for ROA back to 1992, allowing full availability of all variables starting from 1994.

To refine our analysis and investigate the channels through which financial stability is affected, we decompose the Z-score into profitability and risk metrics. Climate shocks may impair borrowers' ability to service debt, leading to an increase in non-performing loans (NPLs) and foreclosures. The NPL ratio, calculated as the sum of loans 90+ days past due and non-accrual loans divided total assets, serves as a key indicator of loan book quality. Similarly, the foreclosure ratio (FOR), which measures foreclosed properties relative to total assets, highlights the burden of problematic loans on a bank's balance sheet. Rising NPLs and foreclosures erode capital ratios, impair profitability, and threaten solvency.

The cumulative effects of credit risks directly impact profitability. Metrics such as Return on Assets (ROA) evaluate financial performance, while the cost-to-income ratio (CIR) measures operational efficiency by comparing expenses to revenue. Declines in these profitability metrics indicate stress on a bank's financial health. Summary statistics are presented in Table A2 in the Appendix.

2.3 Empirical strategy

Flash droughts as plausibly exogenous shocks. Our empirical strategy exploits the meteorological nature of flash droughts to identify their effects on bank stability. Flash droughts originate from rapid and unexpected shifts in atmospheric conditions—such as abrupt increases in temperature, evaporative demand, and precipitation deficits—that lead to sharp declines in soil moisture over short horizons. These processes are driven by large-scale climate dynamics and land–atmosphere interactions that are exogenous to local economic activity and, a fortiori, to individual bank behavior (Otkin et al., 2018; Hoell et al., 2021).

A defining feature of flash droughts is their speed of onset. Unlike conventional droughts, which evolve gradually over seasons and may allow for anticipatory adjustments, flash droughts typically intensify within weeks. As a result, they frequently escape early-warning systems and are poorly captured by standard drought classifications that focus on accumulated precipitation deficits or long-run moisture anomalies Otkin et al. (2018); Ford and Labosier (2017). At the quarterly frequency of our analysis, this rapid evolution sharply limits the scope for anticipation by banks, borrowers, or regulators. In particular, banks have little time to reprice credit, adjust collateral requirements, rebalance portfolios, or alter branch-level operations in response to emerging drought conditions.

Moreover, flash drought exposure is orthogonal to banks' strategic decisions. Banks do not choose the timing, location, or intensity of flash droughts, nor can they influence the climatic mechanisms that generate them. While banks do choose where to locate branches, these decisions are made years in advance and reflect long-run considerations unrelated to short-run weather realizations. Conditional on bank and time fixed effects, variation in flash drought exposure arises from within-bank differences in the geographic distribution of branches and from time variation in local climate conditions, providing plausibly exogenous variation in exposure across institutions and over time.

Together, the meteorological origin, rapid onset, and limited predictability of flash droughts underpin our identification strategy and support their interpretation as plausibly exogenous shocks to banks' operating environments.

Dynamic estimation framework. To estimate the dynamic effects of flash drought exposure on bank stability, we rely on local projections (LPs) as introduced by Jordà (2005). LPs estimate a sequence of horizon-specific regressions, allowing us to trace the response of bank-level outcomes to flash drought shocks over time without imposing strong parametric assumptions on the data-generating process. Compared to vector autoregressive models, LPs are more robust to model misspecification and are well suited for settings with heterogeneous units, multiple controls, and relatively short time series (Montiel Olea and Plagborg-Møller, 2021; Plagborg-Møller and Wolf, 2021; Jordà, 2023; Olea et al., 2025).

This framework is well adapted to our context because flash droughts may generate both immediate disruptions and persistent effects on bank balance sheets through credit quality and profitability channels. LPs allow us to quantify these short- and medium-run dynamics flexibly, without constraining responses to follow a specific autoregressive structure. Moreover, flash drought exposure varies continuously across space and time rather than occurring as a one-off binary treatment, and LPs naturally accommodate such continuous shocks and heterogeneous exposure profiles across banks (Jordà, 2023). For each horizon $h = 0, \ldots, H$, we estimate:

$$\Delta_h y_{it+h} = \lambda_h y_{it-1} + \omega_h d_{it} + \Gamma_h X_{it} + \phi_i + q_t + u_{h,it}, \tag{4}$$

where y_{it} denotes a bank-level outcome for bank i at time t, $\Delta_h y_{it+h} \equiv y_{it+h} - y_{it}$ is the h-period-ahead change, and d_{it} is the bank-level flash drought exposure measure constructed from branch-level exposure. The vector X_{it} includes a parsimonious set of bank and regional controls. Bank fixed effects ϕ_i absorb time-invariant heterogeneity across institutions, and time fixed effects q_t capture common shocks. Standard errors are clustered at the bank level to account for serial correlation in bank outcomes.

Overall, the LP framework provides a transparent characterization of both the magnitude and persistence of flash drought effects on the banking sector, using within-bank variation over time while controlling for aggregate and bank-specific confounders.

3 Flash droughts destabilize the banking sector

Average effect on bank stability. Figure 4 presents the dynamic response of bank stability, measured by the distance-to-default (Z-score), to a strong flash drought shock, defined as an increase in exposure equal to the mean plus two standard deviations. Panels A and B report impulse responses estimated using local projections for the three dimensions of the SMVI index—magnitude, duration, and a composite intensity metric that jointly accounts for both severity and persistence of soil-moisture stress. Panel A

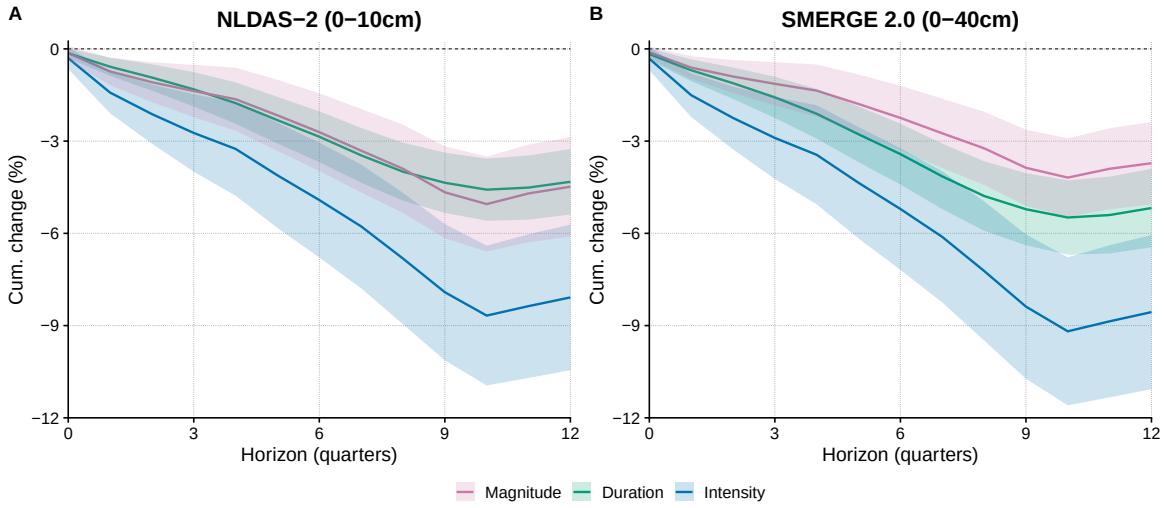


Figure 4: Impulse responses of bank stability to flash drought shocks: surface (Panel A) and root-zone (Panel B) soil moisture.

Note: Panel A is based on surface soil moisture (0–10 cm) from the North American Land Data Assimilation System, Phase 2 (NLDAS-2), while Panel B relies on root-zone soil moisture (0–40 cm) from the SMERGE 2.0 dataset, which combines satellite observations and land-surface modeling. Flash drought exposure is measured using the Standardized Moisture Volatility Index (SMVI), constructed following Otkin et al. (2018) to capture rapid soil moisture declines characteristic of flash droughts. Impulse responses are estimated using local projections. Shaded areas denote 90% confidence intervals. Robust standard errors are clustered at the bank level. All specifications include bank and time fixed effects.

relies on surface soil moisture measured over the 0–10 cm layer, while Panel B uses a deeper 0–40 cm soil profile. We focus on the latter as our preferred specification, as it provides a smoother and more informative measure of drought intensity, whereas surface soil moisture tends to saturate quickly during extreme events. Nonetheless, the similarity of the estimated responses across soil depths highlights the robustness of the destabilizing effect of flash droughts on bank stability.

Across all SMVI dimensions, flash droughts lead to a pronounced and persistent decline in bank stability. The estimated responses indicate that a strong flash drought shock reduces the Z-score by roughly 9 percent relative to its pre-shock level. Importantly, this destabilization is not short-lived: bank stability continues to deteriorate for up to ten quarters following the shock, before gradually recovering. This dynamic pattern suggests that flash droughts generate cumulative stress on bank balance sheets rather than transitory disruptions, consistent with delayed effects operating through borrower distress, credit quality, and profitability.

From an economic perspective, these effects are sizable. Flash droughts are rapid-onset events that often go undetected by standard drought monitoring systems and early-warning frameworks, yet the results show that they translate into meaningful and lasting financial fragility. Despite their relatively low visibility compared to more salient natural disasters, flash droughts pose a significant threat to the stability of the banking sector. These findings motivate a closer examination of the underlying transmission mechanisms through which localized climate shocks propagate to banks' balance sheets, which we explore next.

Decomposing the stability effect. Figure 5 decomposes the destabilizing impact of flash droughts on bank stability by examining key profitability, capitalization, and credit-risk channels following a strong flash drought shock, measured using the SMVI intensity metric that jointly accounts for drought mag-

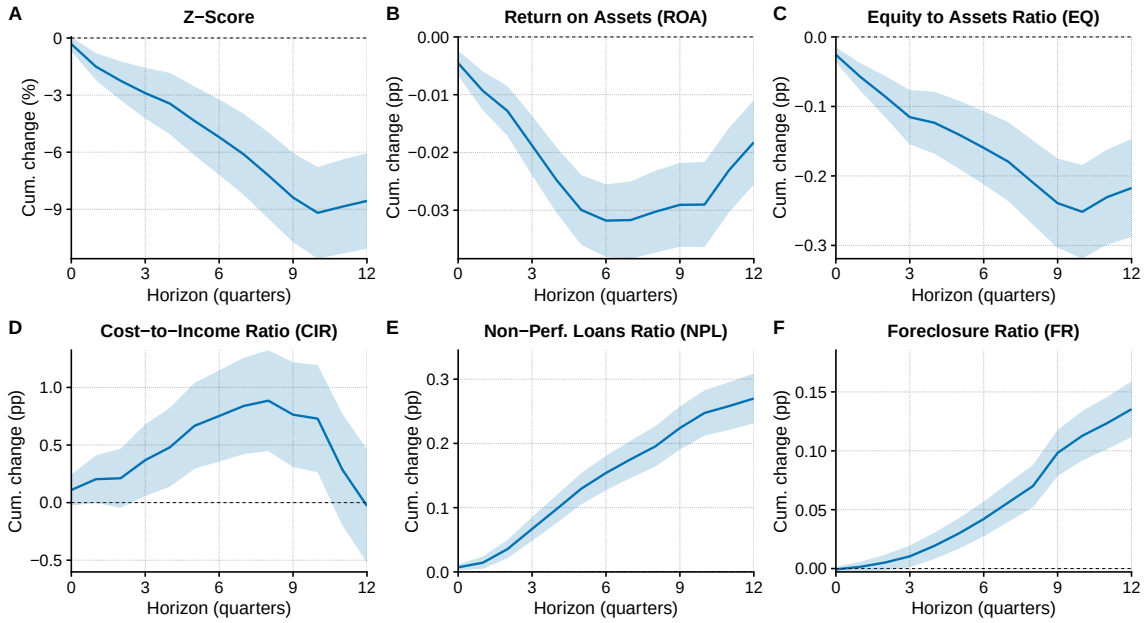


Figure 5: Credit and profitability channels following a strong magnitude flash drought shocks.

Note: this figure reports impulse responses of bank-level profitability, capitalization, and credit-risk indicators to a strong flash drought shock, defined as an increase in SMVI-based drought intensity equal to the mean plus two standard deviations. Flash drought exposure is measured using the Standardized Moisture Volatility Index (SMVI) constructed following Otkin et al. (2018) to capture rapid soil moisture declines characteristic of flash droughts and based on root-zone soil moisture (0–40 cm) from the SMERGE 2.0 dataset, which combines satellite observations and land-surface modeling. Responses are estimated using local projections at quarterly frequency. Shaded areas denote 90% confidence intervals. Robust standard errors are clustered at the bank level. All specifications include bank and time fixed effects.

nitude and duration. The figure shows that the decline in overall bank stability previously documented reflects a broad-based deterioration in banks' financial conditions rather than a single margin of adjustment.

On the income and solvency side, flash droughts lead to a sustained deterioration in profitability and operating efficiency (see panels B and D), accompanied by a gradual erosion of capital buffers (panel C). Returns on assets decline and cost-to-income ratios increase, indicating that banks face both weaker revenues and higher operating frictions in the aftermath of drought-induced local economic disruptions. Capitalization responds more slowly, but the persistent nature of profitability losses ultimately translates into reduced equity ratios, consistent with cumulative balance-sheet stress rather than transitory shocks.

Credit risk plays a central role in driving these effects. Measures of loan performance (panel E and F) deteriorate following flash drought exposure, with increases in non-performing loans and foreclosure activity reflecting stress on borrowers' repayment capacity. These dynamics highlight how localized climate shocks propagate through banks' loan portfolios, as income losses and asset-value declines in affected regions impair credit quality and raise default risk.

The timing of the responses reveals a clear sequencing of effects. Profitability and operating performance deteriorate relatively quickly after the shock, while credit risk indicators peak with a delay, reflecting the institutional features of loan classification and foreclosure processes. Capital ratios adjust only gradually, suggesting that banks absorb the initial shock through income channels before balance-sheet repair takes place. Overall, the figure illustrates how flash droughts generate persistent financial stress through inter-

acting profitability and credit-risk mechanisms, helping to explain the prolonged decline in bank stability observed in the aggregate results.

Finally, we find no evidence that flash droughts trigger a liquidity channel. Balance-sheet indicators related to funding conditions, including deposit-based measures, remain largely unaffected following drought exposure, suggesting that banks do not experience significant withdrawal pressure or short-run funding stress. This pattern is consistent with the stability of retail deposits and the presence of deposit insurance in the U.S. banking system (Brei et al., 2024). More broadly, the sequence of effects—initial profitability losses, followed by a gradual deterioration in credit quality and delayed balance-sheet adjustment—closely mirrors the transmission mechanisms documented in previous works on ENSO-driven climate shocks (Fajeau et al., 2025; Damette et al., 2026), reinforcing the view that rapid-onset climate disturbances propagate to banks primarily through income and credit-risk channels rather than liquidity stress.

4 When and where flash droughts matter most

Seasonal intensity: spring and summer shocks. The timing of flash droughts plays a central role in shaping their economic and financial consequences. Flash droughts occurring during the warm season—particularly in spring and summer—coincide with periods of heightened economic activity and biological sensitivity. In these months, water stress directly affects agricultural production through crop growth, pasture conditions, and livestock forage, but also propagates more broadly through local economies by reducing farm incomes, depressing agribusiness activity, increasing input costs, and weakening demand in rural service sectors. Beyond agriculture, warm-season droughts can disrupt construction activity, reduce hydroelectric generation, increase energy demand for cooling, and elevate wildfire risk, all of which can impair local income and employment dynamics.

By contrast, flash droughts can also occur during autumn or winter, typically driven by anomalously warm and dry conditions. However, these off-season droughts tend to be less economically damaging. During colder months, vegetation is largely dormant, agricultural water demand is lower, and many climate-sensitive activities are less exposed. As a result, winter droughts are less likely to trigger immediate income losses or widespread borrower distress, even if soil moisture conditions deteriorate temporarily.

Figure 6 confirms the importance of this seasonal dimension for bank stability. The responses of profitability, operating efficiency, and credit risk following flash droughts are substantially weaker when shocks occur during autumn and winter. In these periods, bank returns remain largely unaffected, cost-to-income ratios do not rise meaningfully, and overall bank stability shows no significant deterioration. We observe only a modest increase in non-performing loans, consistent with delayed credit-risk materialization linked to earlier warm-season drought exposure rather than contemporaneous winter conditions.

In contrast, flash droughts occurring in spring and summer generate markedly stronger and more persistent effects. Bank stability declines sharply following warm-season droughts, with the distance-to-default falling by approximately 13 percent—an increase of nearly 45 percent in magnitude relative to the baseline average response. This amplification extends uniformly across transmission channels, with larger declines in profitability, sharper increases in operating costs, and more pronounced deterioration in credit quality. The dynamic pattern mirrors the baseline responses but at a significantly higher intensity, underscoring that the economic relevance of flash droughts critically depends on when they occur.

Overall, these results highlight that flash droughts are not only rapid but also seasonally asymmetric shocks.

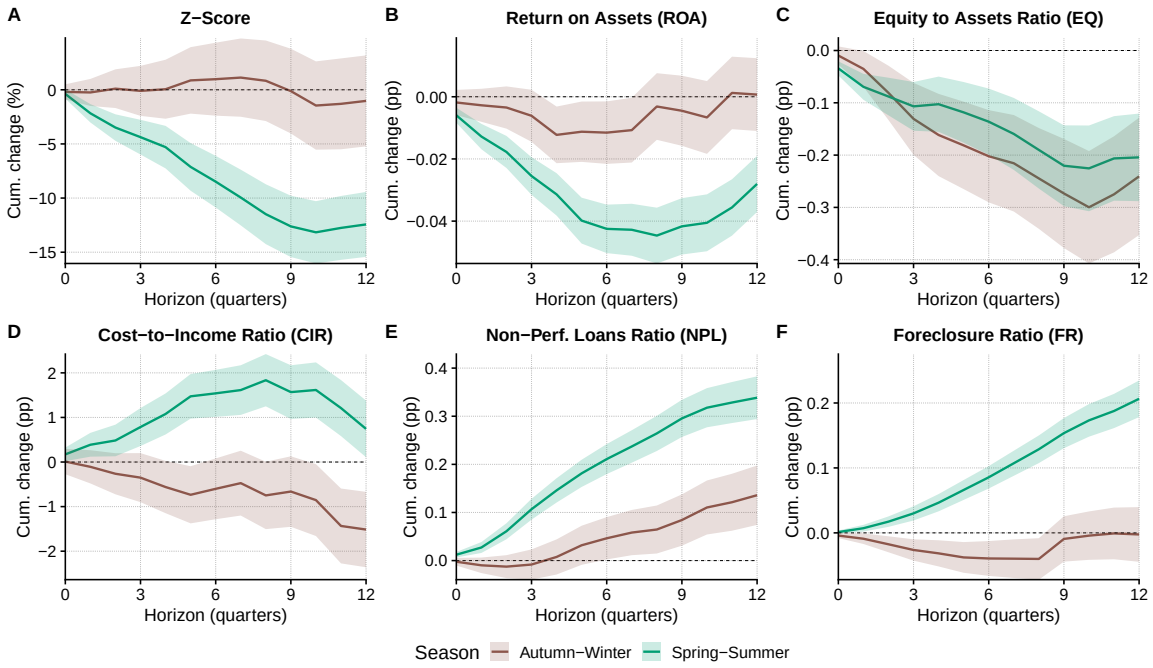


Figure 6: Seasonal heterogeneous responses of credit and profitability channels following a strong magnitude flash drought shocks.

Note: this figure reports impulse responses of bank-level profitability, capitalization, and credit-risk indicators to a strong flash drought shock, defined as an increase in SMVI-based drought intensity equal to the mean plus two standard deviations. Flash drought exposure is measured using the Standardized Moisture Volatility Index (SMVI) constructed following Otkin et al. (2018) to capture rapid soil moisture declines characteristic of flash droughts and based on root-zone soil moisture (0–40 cm) from the SMERGE 2.0 dataset, which combines satellite observations and land-surface modeling. Responses are estimated using local projections at quarterly frequency. Shaded areas denote 90% confidence intervals. Robust standard errors are clustered at the bank level. All specifications include bank and time fixed effects.

Their capacity to destabilize banks is concentrated in periods when water stress interacts most strongly with local economic activity, reinforcing the importance of timing in assessing climate-related financial risks.

`forthcoming` **Bank characteristics and resilience.** We hypothesize that the effects of flash drought exposure on bank stability are heterogeneous across institutions: larger and more geographically diversified banks should be better able to absorb localized real-economy disruptions (through portfolio diversification, broader funding bases, and greater managerial/financial buffers), while smaller and more locally concentrated banks may face stronger deterioration in profitability and asset quality. Several mechanisms can generate this heterogeneity, including (i) differences in loan-portfolio composition and concentration in climate-sensitive sectors, (ii) varying exposure to correlated local shocks due to the spatial footprint of branch networks, and (iii) differential capacity to reprice credit, provision, and manage non-performing loans. Empirically, we will test these predictions by estimating our local-projection responses separately by bank groups and/or by interacting flash-drought exposure with measures of size and geographic dispersion (e.g., total assets, number of counties/states served, concentration measures), and by comparing local versus multi-state banks; we then assess whether the key transmission channels (ROA, cost-to-income, NPLs/foreclosures, capitalization) exhibit systematically different dynamic responses across these groups.

`forthcoming` **Sectoral exposure and local economic transmission.** An important channel through which flash droughts may affect bank stability operates via the sectoral composition of local economic activity. Recent work emphasizes that the economic consequences of climate shocks depend crucially on pre-existing sectoral exposure, as different industries display markedly different sensitivities to climate stress. In particular, Coronese et al. show that climate shocks propagate unevenly across sectors, with agriculture and climate-intensive manufacturing exhibiting significantly larger output and financial responses than services, and that aggregate effects mask substantial heterogeneity driven by local production structures. Building on this insight, we will explicitly account for differentiated local sectoral exposure in our analysis of U.S. bank stability.

Specifically, we exploit county-level information on sectoral employment and value added to characterize the economic environment in which banks operate. For each bank, we construct exposure measures that reflect the sectoral composition of the counties where its branches are located, distinguishing between agriculture, manufacturing, and services. This allows us to assess whether banks operating in areas more reliant on climate-sensitive sectors experience stronger stability responses to flash drought shocks. By interacting flash drought intensity with local sectoral exposure, we can test whether the transmission of climate risk to bank balance sheets is amplified in counties where economic activity is more directly affected by rapid soil moisture depletion and heat stress.

This approach serves two purposes. First, it provides a mechanism-based interpretation of our baseline results by linking bank-level outcomes to real economic exposure rather than purely geographic variation in climate shocks. Second, it allows us to move beyond average effects and document heterogeneity in climate-financial transmission across banks operating in structurally different local economies. In line with the findings of Coronese et al., we expect flash droughts to generate stronger and more persistent effects on bank stability in counties with higher exposure to agriculture and climate-sensitive manufacturing, while effects should be attenuated in service-oriented local economies. By incorporating sectoral exposure directly into the empirical design, our analysis contributes to a more granular understanding of how localized climate shocks translate into financial instability through real economic channels.

`forthcoming` **Relieve policy** Beyond real economic exposure, public disaster relief and insurance mechanisms may critically shape how flash droughts transmit to bank stability. A growing literature highlights that government intervention following climate shocks can attenuate short-run economic losses, but may also alter incentives, risk-taking, and the persistence of financial effects. In particular, Coronese et al. emphasize that policy responses interact with underlying exposure and sectoral composition, potentially dampening aggregate impacts while redistributing risks across agents and balance sheets. In the U.S. context, the Federal Emergency Management Agency (FEMA) constitutes the primary federal channel for disaster assistance, providing direct transfers to households, support to local governments, and funding for recovery and mitigation projects.

In our analysis, we will explicitly account for heterogeneity in exposure to FEMA relief across local banking markets. Using county-level data on FEMA disaster declarations and assistance flows, we construct measures of relief intensity that capture both the occurrence and the magnitude of federal intervention following climate shocks. We then exploit variation in FEMA exposure across counties to assess whether banks operating in areas that systematically receive higher levels of disaster assistance exhibit differential stability responses to flash droughts. By interacting flash drought intensity with local FEMA relief intensity, we test whether public intervention mitigates or reshapes the transmission of climate shocks to bank balance sheets.

This approach allows us to distinguish between two competing mechanisms. On the one hand, FEMA assistance may stabilize local income and credit demand, limiting loan losses and liquidity stress for banks exposed to flash droughts. On the other hand, relief policies may weaken market discipline or delay necessary balance-sheet adjustments, potentially amplifying medium-term fragility. Importantly, flash droughts differ from conventional disasters in that they often generate diffuse, cumulative economic losses rather than discrete physical destruction, raising the possibility that relief mechanisms designed for sudden catastrophes provide only partial insurance.

By incorporating FEMA relief explicitly into our empirical design, we move beyond reduced-form estimates of climate shocks and provide evidence on the role of public policy in shaping climate-financial transmission. This analysis complements our sectoral exposure framework and contributes to a more complete understanding of how flash droughts propagate to the banking system through both real economic activity and institutional risk-sharing arrangements.

`forthcoming` **Spacial spillovers.** Even highly localized climate anomalies can generate effects that extend beyond the location where they occur, propagating through commuting zones, input–output linkages, and regional trade networks. Coronese et al. explicitly test for such propagation by augmenting their distributed-lag specification with a Spatial Lag of X (SLX) term that captures exposure in neighboring counties, thereby disentangling direct impacts in the treated county from indirect impacts in nearby counties. Motivated by this approach, and by evidence that climate shocks can spill over geographically along economic linkages (Coronese et al., 2025), we extend our baseline bank-level local projections by allowing flash drought intensity in neighboring counties to affect bank stability outcomes.

Let $c(i)$ denote the county (or local market) in which bank i operates at time t, and let $d_{c,t}$ be the flash drought intensity in county c at time t. Define the neighbor exposure as a weighted average of flash drought intensity in counties neighboring c,

$$d^N_{c,t} \equiv \sum_{c' \neq c} W_{cc'}\, d_{c',t},$$

where W is a spatial weighting matrix based on inverse distance between county centroids and globally standardized, and neighbors are defined using a distance cutoff (e.g., 50km in the baseline, with robustness to 100km). The SLX-augmented local projection then takes the form:

$$\Delta_h y^k_{it+h} = \lambda^k_h y^k_{it-1} + \sum_{\ell=0}^{p} \omega^k_{h\ell}\, d_{c(i),t-\ell} + \sum_{\ell=0}^{p} \rho^k_{h\ell}\, d^N_{c(i),t-\ell} + \Gamma^k_h X_{it} + \phi^k_{i,h} + q^k_{t,h} + u^k_{it,h}, \tag{5}$$

which is the direct analog of the SLX specification used to identify direct and indirect local impacts in Coronese et al. (2025). Here, $\{\omega^k_{h\ell}\}$ capture direct effects of local flash droughts on bank stability, while $\{\rho^k_{h\ell}\}$ capture local indirect spillovers from neighboring counties. This extension serves two purposes: (i) it tests whether our baseline estimates are conservative by ignoring geographically proximate propagation, and (ii) it helps rule out spurious spatial correlation by verifying that estimated effects are not mechanically driven by broad regional co-movements. Inference uses spatially robust uncertainty measures appropriate for geographically correlated shocks.

5 Ruling-Out Alternative Explanations

Spacial dependency. A potential concern for statistical inference in our baseline specifications is spatial dependence in the error structure induced by geographically correlated climate shocks and regional

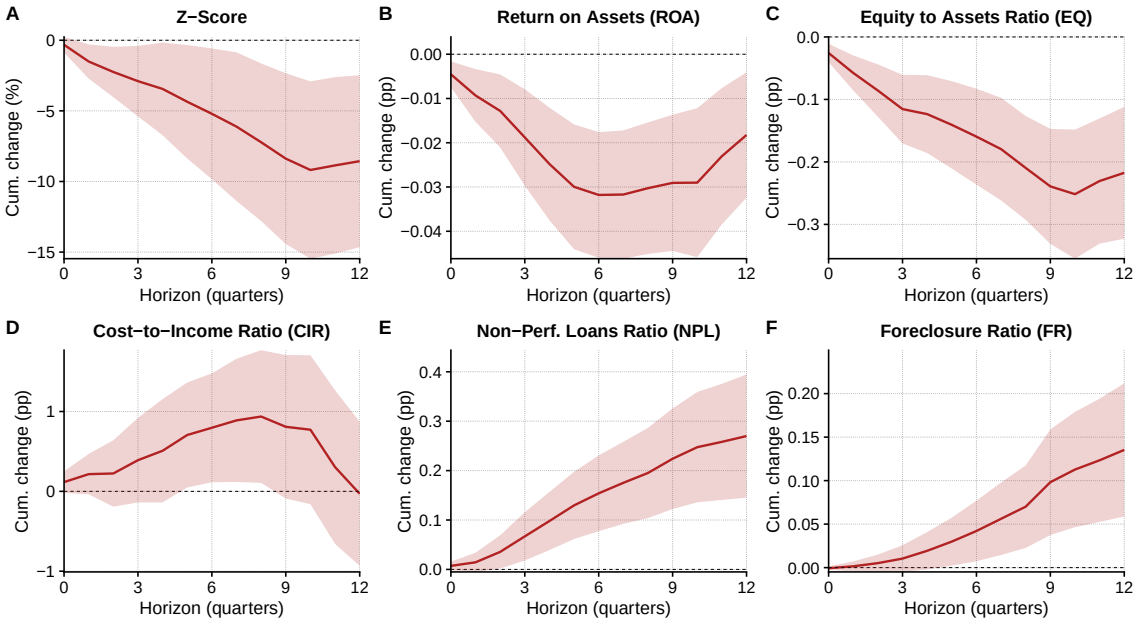


Figure 7: Impulse responses to flash drought shocks with state-level clustered inference.

Note: This figure reports impulse response functions of bank-level stability indicators to a strong flash drought shock, estimated using local projections with standard errors clustered at the state level following Cameron and Miller (2015). Flash drought exposure is measured using the Standardized Moisture Volatility Index (SMVI), capturing rapid declines in root-zone soil moisture (0–40 cm) characteristic of flash droughts, and constructed from the SMERGE 2.0 dataset as in Otkin et al. (2018). The shock magnitude corresponds to an increase in SMVI-based drought intensity equal to the mean plus two standard deviations. Shaded areas denote 90% confidence intervals. All specifications include bank and quarter fixed effects, as well as the full set of baseline controls. Compared to the baseline bank-level clustering, confidence intervals are wider, reflecting more conservative inference, but the estimated responses remain statistically significant across horizons.

economic linkages. While our main results rely on standard errors clustered at the bank level—thereby allowing for arbitrary serial correlation and heteroskedasticity within banks—this may not fully account for spatial autocorrelation across banks operating in nearby locations. Flash droughts are spatially extensive phenomena that often affect multiple counties and states simultaneously, generating common shocks to local economic conditions and potentially correlated residuals across banks with geographically proximate branch networks.

To address this concern, we follow the recommendations of Cameron and Miller (2015) and implement a more conservative clustering strategy at the state level. State-level clustering allows for unrestricted correlation of regression residuals across all banks operating within the same state, thereby capturing spatial dependence arising from common climate exposure, shared regulatory environments, and regionally synchronized economic fluctuations. As emphasized by Cameron and Miller (2015), clustering at a higher level of aggregation is appropriate when treatment variation or shocks are correlated within broader geographic units, and failure to do so may lead to downward-biased standard errors and over-rejection of null hypotheses.

Importantly, state-level clustering nests bank-level clustering and therefore provides a stringent robustness check of our baseline inference. Figure 7 presents the impulse response functions obtained under state-level clustering. While confidence intervals are mechanically wider under this more demanding inference scheme, the estimated responses remain statistically significant across horizons and are qualitatively sim-

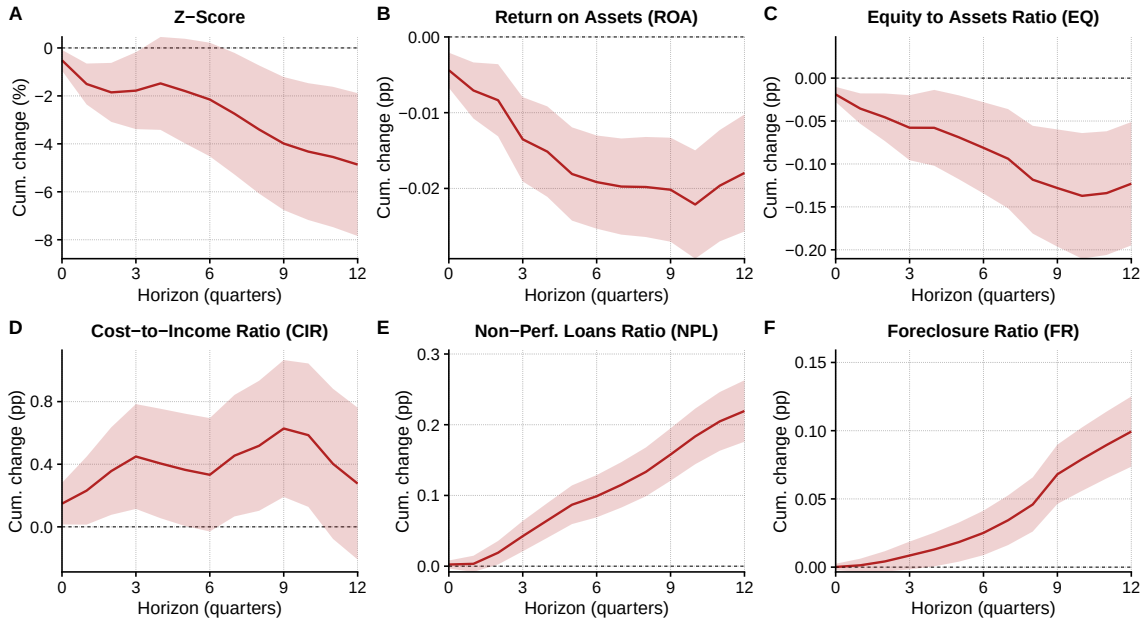


Figure 8: Impulse responses to flash drought shocks with surviving banks subsample.

Note: This figure reports impulse response functions of bank-level stability indicators to a strong flash drought shock, estimated using local projections with a surviving banks subsample. Flash drought exposure is measured using the Standardized Moisture Volatility Index (SMVI), capturing rapid declines in root-zone soil moisture (0–40 cm) characteristic of flash droughts, and constructed from the SMERGE 2.0 dataset as in Otkin et al. (2018). The shock magnitude corresponds to an increase in SMVI-based drought intensity equal to the mean plus two standard deviations. Shaded areas denote 90% confidence intervals. All specifications include bank and quarter fixed effects, as well as the full set of baseline controls. Compared to the baseline bank-level clustering, confidence intervals are wider, reflecting more conservative inference, but the estimated responses remain statistically significant across horizons.

ilar to the baseline results. The persistence of these effects strengthens confidence that our findings are not driven by unaccounted spatial correlation, but instead reflect genuine effects of flash drought shocks on bank stability.

Surviving banks. Our baseline estimates include all commercial banks operating during the sample period, including institutions that subsequently fail. Excluding failed banks would condition the analysis on ex post survival and could induce survivorship bias, potentially overstating bank resilience and attenuating the estimated effects of flash drought shocks. To assess the relevance of this concern, we re-estimate all baseline specifications on a restricted sample of banks that survive throughout the entire observation window.

The results, presented in Figure 8, remain qualitatively unchanged. Flash drought shocks continue to generate a statistically and economically significant decline in bank stability, with impulse response profiles that closely mirror those obtained in the full sample. As expected, the estimated magnitudes are slightly attenuated when restricting attention to surviving banks, reflecting the exclusion of institutions experiencing the most severe balance-sheet stress. Importantly, both the persistence and the timing of the response are preserved. These findings indicate that survivorship bias does not drive our baseline results and that bank failures are an integral part of the adjustment to climate shocks rather than a source of spurious instability.

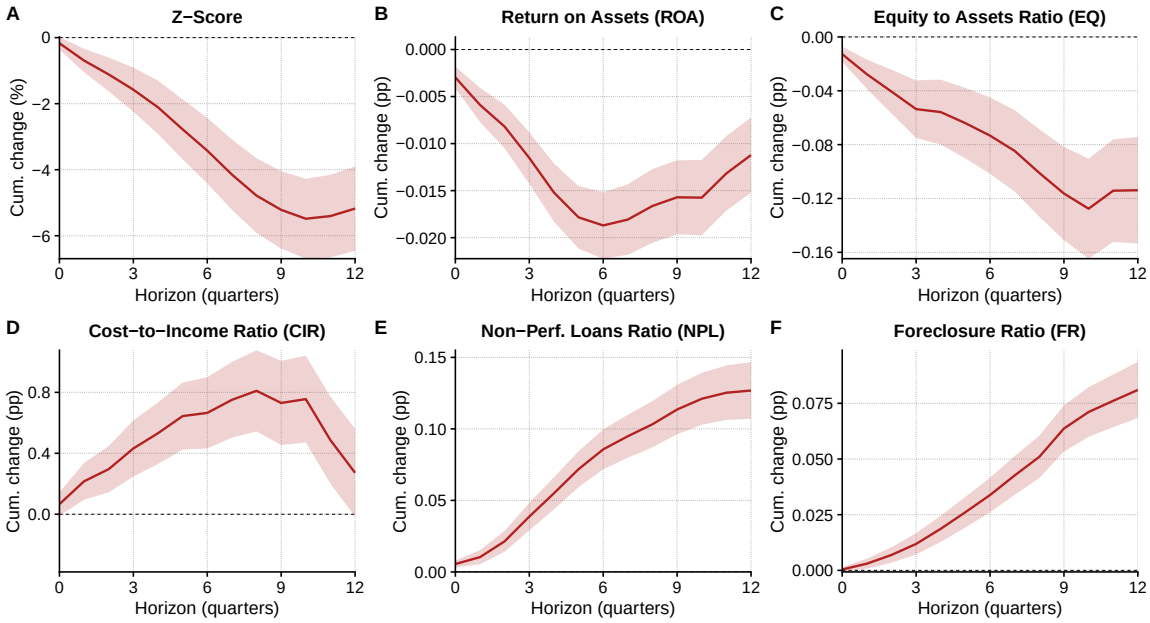


Figure 9: Impulse responses to flash drought shocks excluding the subprime crisis era.

Note: This figure reports impulse response functions of bank-level stability indicators to a strong flash drought shock, estimated using local projections excluding the subprime crisis era. Flash drought exposure is measured using the Standardized Moisture Volatility Index (SMVI), capturing rapid declines in root-zone soil moisture (0–40 cm) characteristic of flash droughts, and constructed from the SMERGE 2.0 dataset as in Otkin et al. (2018). The shock magnitude corresponds to an increase in SMVI-based drought intensity equal to the mean plus two standard deviations. Shaded areas denote 90% confidence intervals. All specifications include bank and quarter fixed effects, as well as the full set of baseline controls. Compared to the baseline bank-level clustering, confidence intervals are wider, reflecting more conservative inference, but the estimated responses remain statistically significant across horizons.

Subprime confounding factor. Because our sample spans the 2008 financial crisis, a natural concern is that the estimated effects of flash droughts could be confounded by the subprime mortgage crisis. While all baseline specifications include time fixed effects that absorb aggregate business-cycle fluctuations, we further assess this issue by re-estimating the models after excluding the subprime crisis period based on NBER recession dating.

The results, reported in Figure 9, remain qualitatively unchanged. Flash drought shocks continue to exert a statistically and economically significant negative effect on bank stability, with dynamic responses that closely resemble those obtained in the full sample. This robustness check confirms that our findings are not driven by crisis-specific dynamics and are distinct from the effects associated with the subprime mortgage crisis.

Peak events of 2011–2012. A further concern is that our baseline results could be disproportionately driven by a small number of extreme flash drought episodes. In particular, the years 2011 and 2012 are widely documented as exceptional flash drought events in the continental United States, with the 2011 Southern Plains drought and the 2012 Central Great Plains drought often cited as paradigmatic cases of rapid-onset climate stress. The 2012 event is especially notable for its abrupt intensification, evolving from near-normal conditions in late spring to widespread severe drought across the Corn Belt within a few weeks, and generating agricultural losses exceeding $30 billion (Hoerling et al., 2014; Otkin et al., 2018). As shown in Figure 3, Panel C, these years correspond to peaks in flash drought exposure in our

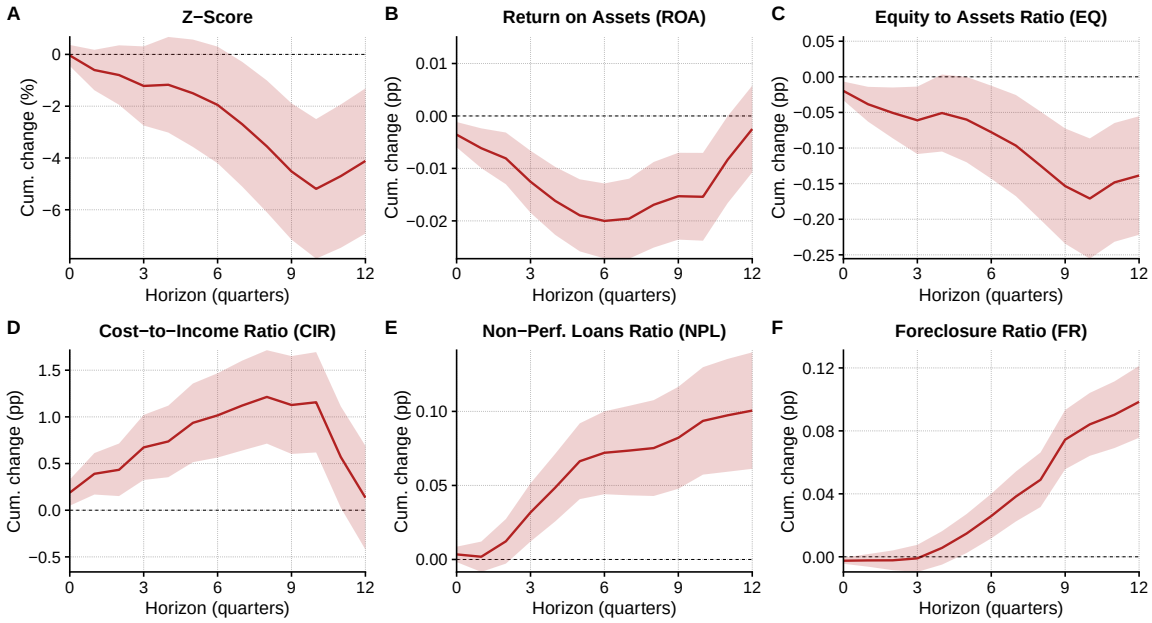


Figure 10: Impulse responses to flash drought shocks excluding the 2011-2012 peak flash drought events.

Note: This figure reports impulse response functions of bank-level stability indicators to a strong flash drought shock, estimated using local projections excluding the 2011-2012 peak flash drought events. Flash drought exposure is measured using the Standardized Moisture Volatility Index (SMVI), capturing rapid declines in root-zone soil moisture (0–40 cm) characteristic of flash droughts, and constructed from the SMERGE 2.0 dataset as in Otkin et al. (2018). The shock magnitude corresponds to an increase in SMVI-based drought intensity equal to the mean plus two standard deviations. Shaded areas denote 90% confidence intervals. All specifications include bank and quarter fixed effects, as well as the full set of baseline controls. Compared to the baseline bank-level clustering, confidence intervals are wider, reflecting more conservative inference, but the estimated responses remain statistically significant across horizons.

sample.

To ensure that our findings are not driven by these extreme episodes alone, we re-estimate our baseline specifications excluding the years 2011 and 2012. This exercise assesses whether the estimated destabilizing effects reflect a systematic relationship between flash droughts and bank stability, rather than the influence of a small number of highly salient events.

The results, reported in Figure 10, remain qualitatively unchanged. Flash drought shocks continue to generate a statistically significant and persistent decline in bank stability, with impulse response profiles that closely resemble those obtained in the full sample. The order of magnitude of the estimated effects is smaller than in the baseline specification, as expected when excluding the most extreme events, but the response profile remains similar and statistically significant across horizons. The timing and persistence of the response are preserved. Taken together, these findings indicate that our results are not driven by peak flash drought episodes, but instead capture a broader and recurring channel through which rapid-onset droughts affect the stability of the banking sector.

6 Conclusion

This paper provides evidence that flash droughts constitute a meaningful and previously underappreciated source of financial instability. Exploiting high-resolution climate data and granular bank-level information for the United States, we show that rapid-onset droughts generate sizable and persistent declines in bank stability. These effects are economically significant, unfold over several years, and are comparable in magnitude to other well-documented climate and macroeconomic shocks, despite flash droughts being less visible and often escaping standard monitoring frameworks.

Our results highlight that the destabilizing impact of flash droughts operates primarily through profitability and credit-risk channels. Banks exposed to flash droughts experience sustained declines in returns and operating efficiency, followed by a gradual deterioration in loan performance. By contrast, we find no evidence of a liquidity channel, suggesting that funding conditions remain largely insulated from these localized climate shocks in the U.S. banking system. The dynamic sequencing of these effects—income losses preceding credit deterioration and balance-sheet adjustment—mirrors the transmission mechanisms identified for other climate phenomena, reinforcing the view that physical climate risks propagate to financial institutions through real-economy channels.

We also document strong seasonal asymmetries. Flash droughts occurring in spring and summer, when water stress most directly affects production, incomes, and asset values, have markedly larger and more persistent effects on bank stability than those occurring in colder months. This finding underscores that the economic relevance of climate shocks depends not only on their intensity but also on their timing, and that rapid-onset events can be particularly disruptive when they coincide with periods of heightened economic sensitivity.

Taken together, our findings suggest that flash droughts represent a distinct dimension of physical climate risk that is not well captured by existing approaches focused on slow-moving drought indicators or extreme disasters. As climate change is expected to increase the frequency and intensity of rapid soil-moisture declines, understanding their financial implications becomes increasingly important. From a policy perspective, our results point to the need for incorporating rapid-onset climate risks into financial surveillance and stress-testing frameworks, and for improving early-warning systems that account for the speed and economic salience of flash droughts. More broadly, they highlight how localized and short-lived climate shocks can generate persistent financial consequences, even in advanced and well-capitalized banking systems.

References

Abecasis, M. and Walker, R. (2023). Smaller US businesses and towns are likely to be hit hardest by bank turmoil. Tech. rep., Goldman Sachs Global Investment Research.

Brei, M., Kowalewski, O., Spiewanowski, P. and Strobl, E. (2025). As dry as a bone: how do banks cope with droughts? *FEB-RN Research Paper* .

Brei, M., Mohan, P., Barahona, A. P. and Strobl, E. (2024). Transmission of natural disasters to the banking sector: Evidence from thirty years of tropical storms in the caribbean. *Journal of International Money and Finance* 141: 103008.

Burke, M., Hsiang, S. M. and Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature* 527: 235–239.

Cameron, A. C. and Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources* 50: 317–372.

Case, J. L. and Zavodsky, B. T. (2018). Evolution of 2016 drought in the southeastern united states from a land surface modeling perspective. *Results in physics* 8: 654–656.

Christian, J. I., Basara, J. B., Otkin, J. A., Hunt, E. D., Wakefield, R. A., Flanagan, P. X. and Xiao, X. (2019). A methodology for flash drought identification: Application of flash drought frequency across the united states. *Journal of Hydrometeorology* 20: 833–846.

Coronese, M., Crippa, F., Lamperti, F., Chiaromonte, F. and Roventini, A. (2025). Raided by the storm: How three decades of thunderstorms shaped us incomes and wages. *Journal of Environmental Economics and Management* 130: 103074.

Cortés, K. R. and Strahan, P. E. (2017). Tracing out capital flows: How financially integrated banks respond to natural disasters. *Journal of Financial Economics* 125: 182–199.

Dafermos, Y., Nikolaidi, M. and Galanis, G. (2018). Climate change, financial stability and monetary policy. *Ecological Economics* 152: 219–234.

Damette, O., Fajeau, M. and Mathonnat, C. (2026). Climate shocks and banking sector stability: Evidence from el niño southern oscillation. *Ecological Economics* 239: 108782.

Degryse, H. and Ongena, S. (2005). Distance, lending relationships, and competition. *The Journal of Finance* 60: 231–266.

Dell, M., Jones, B. F. and Olken, B. A. (2014). What do we learn from the weather? the new climate-economy literature. *Journal of Economic literature* 52: 740–798.

Deryugina, T. and Hsiang, S. (2017). The marginal product of climate. Tech. rep., National Bureau of Economic Research.

Diffenbaugh, N. S., Singh, D., Mankin, J. S., Horton, D. E., Swain, D. L., Touma, D., Charland, A., Liu, Y., Haugen, M., Tsiang, M. et al. (2017). Quantifying the influence of global warming on unprecedented extreme climate events. *Proceedings of the National Academy of Sciences* 114: 4881–4886.

Fajeau, M., Generoso, R., Mathonnat, C. and Damette, O. (2025). Climate shocks and us bank stability. *Available at SSRN 5853543* .

Ford, T. W. and Labosier, C. F. (2017). Meteorological conditions associated with the onset of flash drought in the eastern united states. *Agricultural and forest meteorology* 247: 414–423.

Garmaise, M. J. and Moskowitz, T. J. (2009). Catastrophic risk and credit markets. *Journal of Finance* 64: 657–707, doi:10.1111/j.1540-6261.2009.01446.x.

Hannan, T. H. and Hanweck, G. A. (1988). Bank insolvency risk and the market for large certificates of deposit. *Journal of money, credit and banking* 20: 203–211.

Herbst, E. P. and Johannsen, B. K. (2024). Bias in local projections. *Journal of Econometrics* 240: 105655.

Hoell, A., Parker, B.-A., Downey, M., Umphlett, N., Jencso, K., Adnan Akyuz, F., Peck, D., Hadwen, T., Fuchs, B., Kluck, D. et al. (2021). A flash of insight: Learning lessons from the 2017 northern great plains drought. *Bulletin of the American Meteorological Society* 102: 721–729.

Hoerling, M., Eischeid, J., Kumar, A., Leung, R., Mariotti, A., Mo, K., Schubert, S. and Seager, R. (2014). Causes and predictability of the 2012 great plains drought. *Bulletin of the American Meteorological Society* 95: 269–282.

Hsiang, S., Kopp, R., Jina, A., Rising, J., Delgado, M., Mohan, S., Rasmussen, D. J., Muir-Wood, R., Wilson, P., Oppenheimer, M. et al. (2017). Estimating economic damage from climate change in the united states. *Science* 356: 1362–1369.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American economic review* 95: 161–182.

Jordà, Ò. (2023). Local projections for applied economics. *Annual Review of Economics* 15: 607–631.

Jordà, Ò. and Taylor, A. M. (2025). Local projections. *Journal of Economic Literature* 63: 59–110.

Kahn, M. E., Mohaddes, K., Ng, R. N., Pesaran, M. H., Raissi, M. and Yang, J.-C. (2021). Long-term macroeconomic effects of climate change: A cross-country analysis. *Energy Economics* 104: 105624.

Klomp, J. (2014). Financial fragility and natural disasters: An empirical analysis. *Journal of Financial stability* 13: 180–192.

Koetter, M., Noth, F. and Rehbein, O. (2020). Borrowers under water! rare disasters, regional banks, and recovery lending. *Journal of Financial Intermediation* 43: 100811.

Kotz, M., Wenz, L. and Levermann, A. (2024). Economic implications of climate change under different scenarios. *Global Environmental Change* 74: 102428.

Laeven, L. and Levine, R. (2009). Bank governance, regulation and risk taking. *Journal of financial economics* 93: 259–275.

Lesk, C., Rowhani, P. and Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. *Nature* 529: 84–87.

Li, D., Plagborg-Møller, M. and Wolf, C. K. (2024). Local projections vs. vars: Lessons from thousands of dgps. *Journal of Econometrics* 244: 105722.

Montiel Olea, J. L. and Plagborg-Møller, M. (2021). Local projection inference is simpler and more robust than you think. *Econometrica* 89: 1789–1823.

Nguyen, H.-L. Q. (2019). Are credit markets still local? evidence from bank branch closings. *American Economic Journal: Applied Economics* 11: 1–32.

Noth, F. and Schüwer, U. (2023). Natural disasters and bank stability: Evidence from the US financial system. *Journal of Environmental Economics and Management* 119: 102792.

Oberfield, E., Rossi-Hansberg, E., Trachter, N. and Wenning, D. T. (2024). Banks in Space. *National Bureau of Economic Research* .

Olea, J. L. M., Plagborg-Møller, M., Qian, E. and Wolf, C. K. (2025). Local projections or vars? a primer for macroeconomists. *National Bureau of Economic Research* .

Osman, M., Zaitchik, B., Otkin, J. and Anderson, M. (2024). A global flash drought inventory based on soil moisture volatility. *Scientific Data* 11: 965.

Otkin, J. A., Svoboda, M., Hunt, E. D., Ford, T. W., Anderson, M. C., Hain, C. and Basara, J. B. (2018). Flash droughts: A review and assessment of the challenges imposed by rapid-onset droughts in the united states. *Bulletin of the American Meteorological Society* 99: 911–919.

Petersen, M. and Rajan, R. (2002). Does distance still matter? the information revolution in small business lending. *The Journal of Finance* 57: 2533–2570.

Plagborg-Møller, M. and Wolf, C. K. (2021). Local projections and vars estimate the same impulse responses. *Econometrica* 89: 955–980.

Rajan, R. and Ramcharan, R. (2023). Finance and Climate Resilience: Evidence from the long 1950s US Drought. Tech. Rep. w31356, National Bureau of Economic Research.

Rehbein, O. and Ongena, S. (2022). Flooded through the back door: The role of bank capital in local shock spillovers. *Journal of Financial and Quantitative Analysis* 57: 2627–2658.

Schüwer, U., Lambert, C. and Noth, F. (2019). How do banks react to catastrophic events? evidence from hurricane katrina. *Review of Finance* 23: 75–116, doi:10.1093/rof/rfy010.

Vicente-Serrano, S. M., Beguería, S. and López-Moreno, J. I. (2010). A multiscalar drought index sensitive to global warming: the standardized precipitation evapotranspiration index. *Journal of climate* 23: 1696–1718.

Yuan, X., Wang, Y., Ji, P., Wu, P., Sheffield, J. and Otkin, J. A. (2023). A global transition to flash droughts under climate change. *Science* 380: 187–191.

Appendices

A1 Flash Drought Data

Definition. Flash droughts are fundamentally distinguished from conventional droughts by their exceptionally rapid intensification kinetics. This phenomenon results from the critical convergence of a precipitation deficit and a positive anomaly in evaporative demand. They are defined by an abrupt transition from a normal water status to a severe soil moisture deficit within a span of only a few weeks (typically 2 to 4 weeks) and may persist (by around one half) for several months or evolve into a classic seasonal hydrological drought if unfavorable conditions continue (Otkin et al., 2018; Christian et al., 2019). The current scientific consensus (Walker et al., 2023) relies on two necessary criteria to qualify an event: (i) a rapid intensification rate, and (ii) the subsequent attainment of a confirmed drought state, generating tangible impacts on agrosystems and ecosystems.

Global Trends. A growing body of theoretical and empirical work indicates that anthropogenic warming is shifting the hydroclimate toward a regime in which droughts are more likely to develop rapidly rather than slowly. From a physical standpoint, this transition is consistent with the theory of soil moisture–climate interactions. Seneviratne et al. (2010) synthesize modelling and observational evidence showing that, in so-called transitional climate regimes where evapotranspiration is limited by soil moisture, drying of the root zone reduces latent heat flux and increases sensible heating, thereby amplifying near-surface temperature anomalies and favouring concurrent hot and dry extremes. In a warmer climate, the expansion and poleward shift of these transitional regimes, combined with a systematic increase in atmospheric moisture demand (higher vapour pressure deficit; Byrne and O'Gorman, 2016) and stronger land–atmosphere feedbacks (Zhou et al., 2019), imply that a given precipitation deficit will translate into a faster soil-moisture drawdown and a higher probability that heat extremes co-occur with soil drought. This land–atmosphere feedback framework provides the theoretical underpinning for the observed and attributed transition from slow-evolving to flash droughts.

On the empirical side, using three global soil-moisture reanalyses over 1951–2014, Yuan et al. (2023) document a global transition from slow-evolving to rapid-onset droughts. They show that both the ratio of flash droughts to total subseasonal droughts and the associated onset speed have increased significantly, with regional increases in flash-drought dominance over more than 74% of the IPCC SREX land regions. Detection–attribution analysis based on CMIP6 simulations indicates that these trends are driven by anthropogenic climate change, via amplified anomalies of evapotranspiration and reduced precipitation surplus that accelerate soil-moisture depletion during precipitation deficits, thereby shortening drought onset times.

Case studies. The continental United States has emerged as a documented hotspot for these intensification trends. The devastating events of 2011 in the Southern Plains and 2012 in the Central Great Plains serve as paradigmatic examples of this hazard. The 2012 flash drought, in particular, is often cited for its brutality: it evolved from near-normal conditions in May to severe drought across the Corn Belt by July—a "surprise" intensification that caused over $30 billion in agricultural losses (Hoerling et al., 2014; Otkin et al., 2016). The 2017 Northern High Plains flash drought demonstrated the failure of early-warning systems: it emerged rapidly in May following a wet spring, devastating wheat yields and livestock forage in the Dakotas and Montana before mitigation could be enacted (Hoell et al., 2021). Furthermore, the 2016 Southeast U.S. flash drought illustrated the critical hydrological-to-fire risk transition. Case and

Zavodsky (2018) documented how the rapid evolution of this drought, driven by record-high temperatures and moisture deficits, created explosive fire conditions that contributed to the historic wildfires in Gatlinburg, Tennessee. These precedents illustrate how rising temperatures and atmospheric demand can rapidly deplete soil moisture reserves, overwhelming the adaptive capacity of both agricultural systems and wildfire management strategies.

Soil Moisture Volatility Index, SMVI. To capture this rapid-onset behaviour, Osman et al. (2021) propose the Soil Moisture Volatility Index (SMVI), an event-based metric inspired by approaches to financial market volatility that seek to robustly identify rapid but meaningful price movements. Transposed to the hydrological context, the SMVI is designed to isolate episodes of sharp decline in root-zone soil moisture (RZSM).

Formally, the method compares a short-memory running mean of RZSM (one pentad, i.e. 5 days) to a longer-memory running mean (four pentads, i.e. 20 days). A flash drought onset is declared when two conditions are met: (i) the one-pentad mean remains below the four-pentad mean for at least four consecutive pentads (about 20 days), indicating a sustained and unusually rapid drying relative to the recent background state; and (ii) at the end of this intensification period, RZSM falls below a climatological drought threshold, typically the 20th percentile of the day-of-year distribution, chosen to be consistent with "moderate drought" (D1) conditions in the U.S. Drought Monitor. For each identified event, Osman et al. (2024) further define its end as the pentad when these SMVI criteria are no longer satisfied and quantify its severity as the cumulative soil-moisture deficit (in m^3/m^3) accumulated over this onset period.

This construction is physically and statistically appealing. The comparison between short- and longer-memory running means acts as a volatility filter, targeting genuinely rapid transitions while damping high-frequency noise in the raw series. The percentile constraint ensures that only events culminating in actual drought conditions are retained, rather than transient dry spells that remain within the range of normal variability. Osman et al. (2021) also emphasise that the SMVI is explicitly sensitive to interruptions in drought onset: rainfall events can reset the index and terminate a developing episode. As a result, the method preferentially identifies drying episodes that are both rapid and largely uninterrupted, which is precisely the regime of greatest relevance for agricultural and ecological impact assessment.

Relative to widely used drought indicators such as the Standardized Precipitation Index (SPI), the Standardized Precipitation–Evapotranspiration Index (SPEI), or the Evaporative Demand Drought Index (EDDI), the SMVI offers several distinctive advantages for diagnosing flash droughts.

First, the SMVI is intrinsically event-based and formulated at the daily resolution. In contrast, SPI and SPEI are most commonly implemented and disseminated on monthly accumulation windows (e.g. 1-, 3-, or 6-month scales). This monthly framing is well suited to characterising seasonal or multi-year droughts but tends to smooth out abrupt changes occurring on weekly or sub-monthly timescales, unless high-frequency versions and explicit rate-of-change criteria are used. By focusing on the relative evolution of short- versus longer-memory soil moisture anomalies, the SMVI is directly sensitive to the subseasonal intensification that defines flash droughts.

Second, the SMVI is a state indicator anchored in the terrestrial system, whereas SPI and SPEI primarily characterise atmospheric forcing (precipitation totals or the balance between precipitation and potential evapotranspiration), and EDDI quantifies the atmosphere's "drying power" (evaporative demand). Root-zone soil moisture reflects the integrated response of the land surface to these forcings, including the interplay between precipitation input, actual evapotranspiration, and runoff or drainage. By operating on RZSM, the SMVI therefore diagnoses the evolution of the variable that is most directly relevant for

vegetation water stress.

Third, because it is built on soil moisture rather than on an explicitly modelled water balance, the SMVI leverages the implicit integration performed by land-surface models, reanalyses, or observation-based soil-moisture products. From the analyst's perspective, this avoids the need to specify and calibrate a potentially uncertain water-balance model to derive indices such as SPEI, while still capturing the net effect of precipitation deficits and enhanced atmospheric demand on soil-water availability. This makes the SMVI particularly well suited for constructing consistent inventories of flash-drought events (onset timing, and, in subsequent work, duration and severity) that can be directly linked to observed agricultural and ecological impacts.

Methodology. Following Osman et al. (2024), we track soil moisture across the contiguous United States using daily root-zone soil moisture (RZSM) data. In practice, we reconstruct the SMVI on two complementary products that differ by soil-layer depth. First, we use the 0–10 cm layer from the North American Land Data Assimilation System (NLDAS-2), which closely reflects near-surface soil water availability and is strongly coupled to short-term atmospheric fluxes. We also compute SMVI series using the 0–40 cm RZSM from the SMERGE 2.0 dataset, which integrates soil moisture over a deeper column and provides a more conservative proxy for plant-available water. Comparing flash-drought inventories derived from these two layers allows us to assess the sensitivity of our results to the vertical scale at which soil moisture is measured and to distinguish surface-driven volatility from deeper root-zone stress.

We identify flash droughts events based on a set of criteria derived from Osman et al. (2024):

1. *Rapid decrease in soil moisture*: A decrease in the 5-day running average of RZSM falling below the 20-day running average. This criterion captures rapid changes in soil moisture relative to the recent climatology, serving as a key indicator of flash drought onset.

2. *Exceedance of drought threshold*: The occurrence of this decline reaching below the 20th percentile of RZSM based on the long-term record for the corresponding day, signifying an abnormal moisture deficit. The selection of the 20th percentile threshold aligns with recommendations from the U.S. Drought Monitor (USDM), which identifies this level as indicative of "Moderate Drought – D1" conditions.

3. *Minimum duration*: The persistence of these conditions for a minimum of four consecutive pentads (20 days), confirming that the initial drying lasts long enough to have meaningful impacts on vegetation and soil moisture reserves.

4. *Aggregation of close events*: If two or more flash drought events are identified in the same grid cell with onset dates that are three pentads or less apart, they are considered as one combined event. The event starts on the onset date of the first drought and concludes on the recovery date of the last event. This approach is based on the practical understanding that a brief wetting period may not be sufficient to alleviate the initial drought conditions if rapidly followed by another drying event.

Once, drought onsets are recovered, we calculate the severity of the drought event for all identified events during the period 1979-2019 as the cumulative soil-moisture deficit in $m^3 \cdot m^{-3}$:

$$S_i(t) = \sum_{t=t_o}^{t=t_f} \mathrm{RZSM}_{20th}(t) - \mathrm{RZSM}_{5d}(t) \tag{6}$$

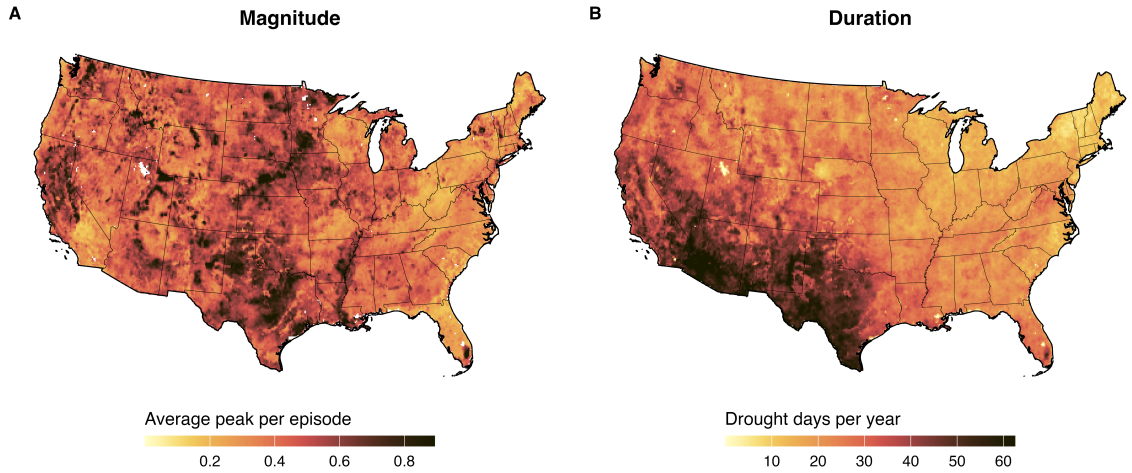


Figure A1: Spatial Distribution of Flash Drought Episode Magnitude and Duration

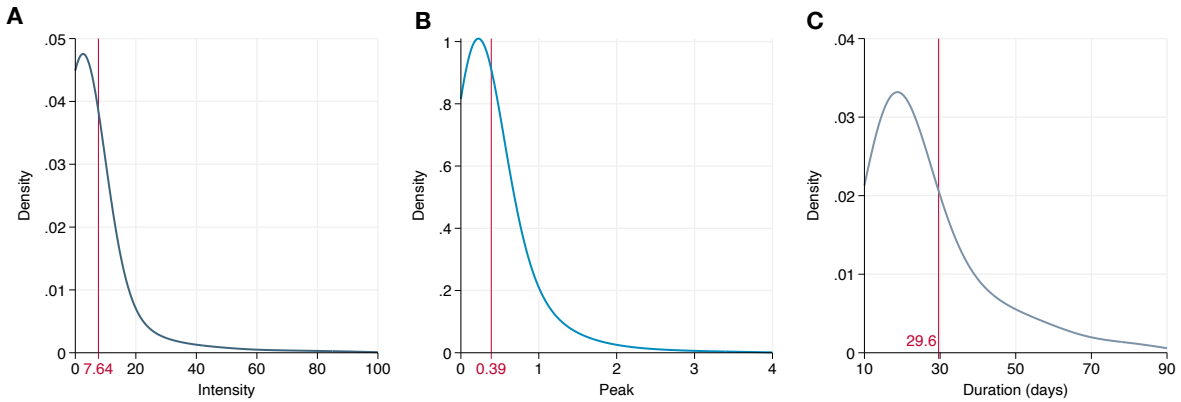


Figure A2: Kernel density estimates of drought characteristics.

Note: Panel A shows the distribution of drought intensity, Panel B the distribution of peak severity, and Panel C the distribution of drought duration. Each panel reports the empirical density for non-zero observations and includes a vertical line marking the sample mean.

$\text{RZSM}_{20th}(t)$ is the 20th percentile climatology of the root zone soil moisture for each pentad t, and $\text{RZSM}_{5d}(t)$ is the 5-day moving average of root zone soil moisture at pentad t.

A2 Bank Data

A2.1 General Outlay of Banking Data

The architecture of banks typically involves a hierarchical structure with different levels of operations and administrative functions. Here's a general overview:

Headquarter and main office The headquarters is the central hub of a bank's operations and administration. It houses top-level executives, management, and key decision-makers. Strategic planning, policy formulation, and major administrative functions are carried out at the headquarters. The main office is a large branch that serve as significant operational center within a specific city or town. It handle a broad range of banking services, including customer accounts, loans, and investments. The main office may have specialized units for services like wealth management, corporate banking, and commercial lending.

Branches Branches are the most common customer-facing entities of a bank, providing various financial services to the public. They are distributed across different locations, often within cities and towns, to make banking services accessible to a wider population. Branches handle day-to-day transactions, account management, and customer service. According to the Federal Deposit Insurance Corporation, a site must have a branch charter if deposits are received, or checks paid or money lent.

The bank data used throughout this paper rests on two primary sources : Call Reports and Summary of Deposits. Note that each bank has a unique identification number that works as a regulatory identification (RSSD ID) from the National Information Center (NIC). This identification number is used to trace the banks over the two datasets.

A2.2 Call Reports

Coverage $bank \times quarterly$.
Source *Federal Financial Institutions Examination Council (FFIEC), Wharton Research Data Services (WRDS), and the Federal Reserve Bank of Chicago.*

The *Consolidated Reports of Condition and Income* (Call Reports) in the United States are regulatory financial reports that banks are required to submit to federal banking authorities. These reports are a critical part of the supervisory and examination process conducted by regulatory agencies, primarily the Federal Deposit Insurance Corporation (FDIC), the Federal Reserve System, and the Office of the Comptroller of the Currency (OCC). Every bank is required to file a Call Report as of the close of business on the last day of each calendar quarter.

Call Report data provide detailed quarterly information on balance sheet items and income statements at the bank level from 1992 to 2023. The data can be extended further back to 1976 through the earlier *Report of Conditions and Income*, though variable definitions prior to the 1990s are often inconsistent. Moreover, our empirical design requires merging with the *Summary of Deposits* (SOD), which only became available in 1994. Importantly, Call Reports are consolidated at the bank level, offering a comprehensive view of the entire banking organization, including the main office and all associated branches.

Each data item in the Call Reports is identified by a unique MDRM (Micro Data Reference Manual) code,

which combines a four-letter mnemonic indicating the data series with a numeric variable identifier. For example, RCON2170 and RCFD2170 both refer to total assets, but the former captures domestic offices only, while the latter includes both domestic and foreign operations.

The specific Call Report form a bank files depends on its organizational structure and size. Currently, there are three versions. The *FFIEC 031* form is used by institutions with both domestic and foreign offices. It includes additional schedules—such as *Schedule RC-H* (Selected Balance Sheet Items for Domestic Offices) and *Schedule RC-I* (Assets and Liabilities of International Banking Facilities)—to capture the geographic breakdown of balance sheet positions. In contrast, the *FFIEC 041* form is used by banks operating solely within the United States and excludes these international reporting components. The *FFIEC 041* form was introduced in March 2001, replacing the earlier *FFIEC 032*, *033*, and *034* forms, which had previously been used by domestic banks segmented by asset size. This consolidation improved data comparability and streamlined the reporting process. Finally, the *FFIEC 051* form was introduced in 2016 to reduce the regulatory burden for smaller institutions—those with domestic offices only and less than $5 billion in assets—by eliminating or reducing the frequency of less relevant items, while preserving core regulatory data.

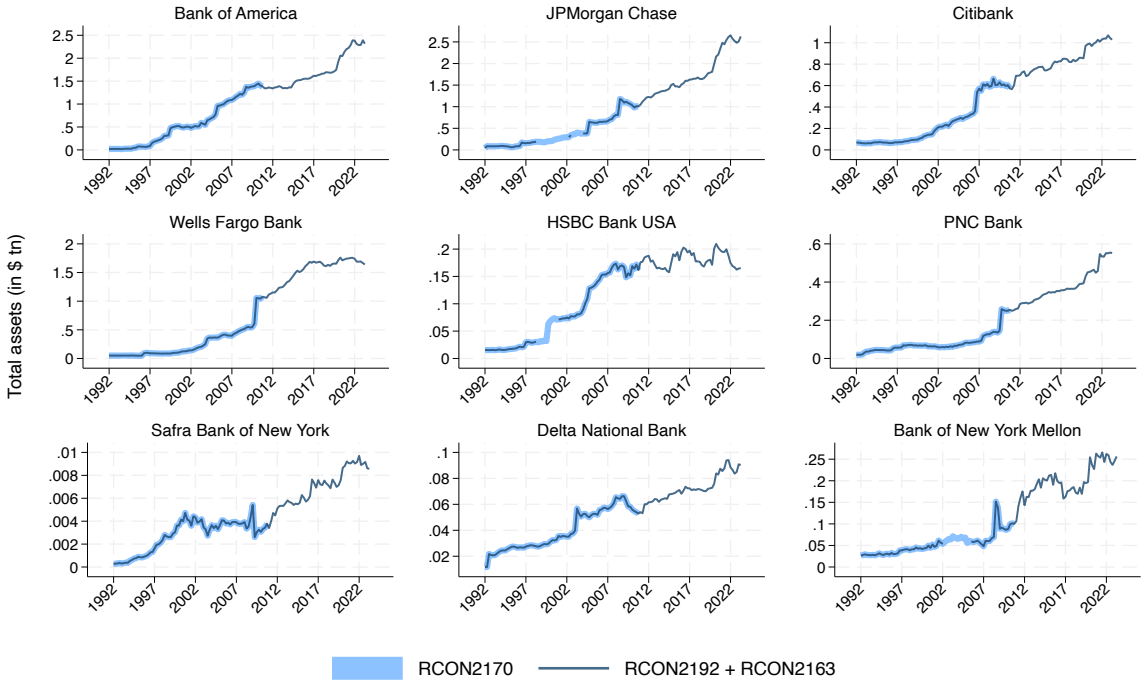


Figure A3: Asset extension from large banks' filing FFIEC form 031

Note: For large banks filing the FFIEC 031 form—used by institutions with both domestic and foreign offices—the domestic assets series (RCON2170) is no longer reported directly as of 2011. We reconstruct it using Schedule RC-H – Selected Balance Sheet Items for Domestic Offices, where RCON2170 equals the sum of RCON2192 (total assets excluding net due from foreign operations) and RCON2163 (net due from own foreign offices, Edge and Agreement subsidiaries, and IBFs). We verify the consistency of the reconstructed series with pre-2011 data to ensure comparability across reporting forms and over time.

These changes in form structure and variable definitions over time require careful harmonization to ensure consistency in financial time series. For example, large banks filing the *FFIEC 031* form—used by institutions with both domestic and foreign offices—ceased reporting the domestic assets series (RCON2170) directly as of 2011. However, this variable can be reconstructed using information from *Schedule RC-*

H – Selected Balance Sheet Items for Domestic Offices, where RCON2170 is computed as the sum of RCON2192 (*Total assets excluding net due from foreign offices, Edge and Agreement subsidiaries, and IBFs*) and RCON2163 (*Net due from own foreign offices, Edge and Agreement subsidiaries, and IBFs*). In contrast, smaller banks using the *FFIEC 041* and *051* forms—which apply to banks with only domestic offices—continue to report RCON2170 directly. We validate the reconstructed series for consistency with historical data prior to 2011 to ensure that the definition and perimeter of domestic assets remain comparable across forms and over time (see Figure A3).

Additionally, some financial variables in the Call Reports are reported on a year-to-date basis, accumulating over the course of the year rather than reflecting standalone quarterly values. If left unadjusted, such reporting practices would introduce significant seasonal distortions. We therefore identified and transformed these variables to recover consistent quarterly observations. These harmonization efforts were essential for producing robust time-series data and form the basis for our empirical analysis. The complete structuring of variables and adjustments is documented in Table A3.

We restrict our analysis to commercial banks chartered in the contiguous United States (CONUS). While the broader financial sector includes a variety of institutions, commercial banks operate under a standardized regulatory framework with uniform capital and liquidity requirements, making them more directly comparable. They also play a central role in business lending and mortgage financing, making them particularly exposed to the economic disruptions induced by climate anomalies. Their lending portfolios—spanning corporate, real estate, and consumer loans—are directly affected by changes in borrower creditworthiness, collateral values, and regional economic conditions, all of which are shaped by climate variability. By focusing on commercial banks, we ensure a homogeneous sample that captures institutions operating under similar constraints and financial reporting structures. Other financial entities, such as credit unions or industrial banks, exhibit distinct business models and balance sheet structures that could introduce confounding effects unrelated to the mechanisms we investigate. Moreover, the geographical footprint of commercial banks makes them particularly relevant for assessing localized climate exposures, as they remain key providers of credit in climate-sensitive regions.

We include all commercial banks in our analysis, even if they fail during the period. Retaining only surviving banks would introduce survival bias, distorting the estimated effects of climate shocks. Additionally, many failed banks are absorbed through mergers, altering the structure of the sector. To account for these dynamics, we trace mergers over time using the *Uniform Bank Performance Report* (UBPR) definition, which identifies significant mergers as those involving a 25% or greater increase in assets. By incorporating failed and merged banks, we capture the full evolution of the banking sector and provide a more comprehensive assessment of climate-related risks.

A2.3 Summary of Deposits

Coverage *branch* × *yearly*.
Source *Federal Deposit Insurance Corporation (FDIC).*

Accurately geolocating bank branches is essential for linking financial data to localized economic and environmental factors, yet substantial gaps exist in the geographic information provided by the FDIC dataset. While data on branch deposits are readily available, latitude and longitude coordinates are missing for a significant proportion of branches. In the 1990s, up to 50% of branches are unaccounted for in raw data, leaving large portions of deposits effectively unaccounted for in regional analyses. This is-

sue persisted into the early 2010s, complicating efforts to precisely link banking activity with climate exposure.

To address these limitations, we implemented a three-layer geocoding methodology. First, we used the OpenStreetMap (OSM) API to retrieve full address coordinates. For unmatched cases, we refined results using the U.S. Census API. Finally, residual records were geocoded at the ZIP code level using OSM. This approach significantly enhances the spatial accuracy of the FDIC dataset, as illustrated in Figure A4, enabling more precise measurement of localized banking activity and its exposure to climate anomalies.

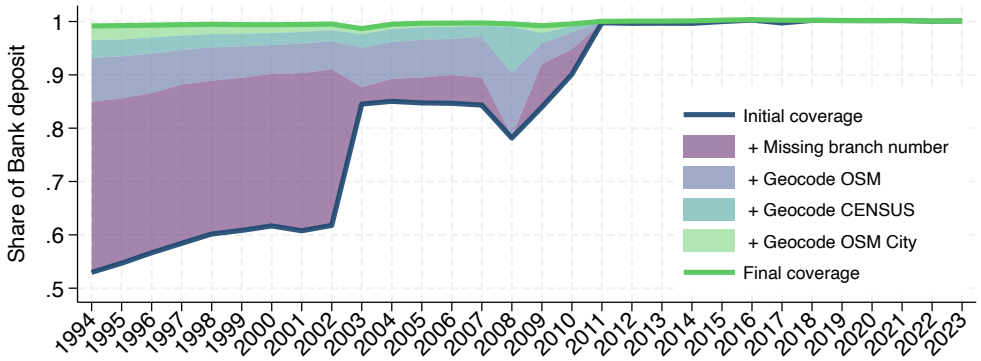


Figure A4: Improved coverage of branch location with geocoding

Note: This figure illustrates the enhanced geolocation coverage achieved through our three-layer geocoding methodology. Missing branch number or branch coordinates, affecting up to 50% of deposits in the 1990s, were systematically resolved using OpenStreetMap and U.S. Census APIs, with residual cases geocoded at the ZIP code level using OSM API. This improvement ensures a more accurate linkage between banking activity and climate exposure.

Beyond technical geolocation challenges, correctly assigning climate exposure to banks requires recognizing the dispersion of their operational activities. Unlike firms operating within a single geographic area, banks strategically locate branches to optimize market reach, customer base, and regulatory advantages. Headquarters locations often reflect tax or administrative considerations rather than operational concentration. For instance, Bank of America was headquartered in New York City until recently before relocating to Las Vegas, a move unrelated to its nationwide lending footprint. This distinction underscores the necessity of measuring climate exposure based on actual branch presence rather than relying solely on headquarters locations.

Consequently, regional climate shocks affect banks only to the extent that they have business operations in the impacted area. While macro-level studies often assume homogeneous sector-wide exposure, individual bank-level analyses must account for the geographic dispersion of banking activities. A commonly employed methodology in banking research is to weight climate shocks by a bank's local business exposure, typically using mortgage origination or local deposit shares (e.g. Cortés and Strahan, 2017; Koetter et al., 2020; Rehbein and Ongena, 2022). However, mortgage origination may not be entirely exogenous to climate exposure, as lending decisions adjust dynamically to evolving risk conditions.

By leveraging an improved geocoding framework and deposit-weighted exposure measures, our approach provides a more precise mapping of bank-level climate risk. The geolocation enhancements documented in Figure A4 ensure that we accurately capture the full scope of regional banking activity, strengthening the reliability of our analysis of climate-induced financial disruptions.

Figure 3 displays the resulting spatial distribution of bank branches and headquarters across the United

States in 2023, based on FDIC Summary of Deposits data. Covering nearly the entire commercial banking sector, the figure reflects the population footprint, with a clear concentration of activity along the eastern part of the contiguous United States.

A2.4 U.S. Bank Data

The banking dataset used in this study provides a comprehensive account of financial activity in the U.S. banking system. It includes nearly 800,000 observations from more than 10,000 U.S. banks and 80,000 branches, covering 30 years of quarterly data from 1994Q1 to 2023Q2. The dataset's branch-level granularity is complemented by detailed geolocation efforts, offering a robust foundation for local banking analysis.

Banks are typically organized in a hierarchical structure, with distinct levels dedicated to strategic, administrative, and operational functions. At the top are the headquarters, which serve as the strategic core, where executives and senior management oversee planning, policy formulation, and governance activities. Headquarters often shape the geographic expansion of the bank, as proximity to them can enhance operational oversight and customer engagement—particularly in dense markets where managerial costs tend to be higher (Oberfield et al., 2024). Beneath the headquarters are the main offices, which operate as key regional hubs. These facilities offer a wide range of financial services, including account management, loan origination, and investment facilitation, and often include specialized units for wealth management, corporate banking, or commercial lending. At the base of the hierarchy are the branches, which act as the primary customer-facing units. Widely distributed across regions, branches are in charge of daily banking operations such as processing transactions, managing accounts, and delivering customer service. As emphasized by Oberfield et al. (2024), branch location decisions are shaped by both geographic and economic considerations, as banks aim to balance proximity to retail deposits with regional credit demand.

Our empirical setup exposes banks to climate variability that is spatially transmitted across regions. This feature of our investigation requires two complementary layers of data on the banking sector. First, we use consolidated bank-level information to examine the financial stability risks posed by ENSO-induced climate shocks. Second, we assess how geographically dispersed each bank's operations are across the U.S. territory. Accordingly, the bank data used in this paper are drawn from two primary sources. Each bank is identified by a unique regulatory identifier provided by the National Information Center (NIC), which allows for consistent tracking across both datasets.

Bank consolidated domestic activity. In the United States, *Call Reports* are regulatory financial statements that banks must submit at the headquarter level to federal banking authorities. These reports are a key component of the supervision and examination framework overseen by agencies such as the Federal Deposit Insurance Corporation (FDIC), the Federal Reserve System, and the Office of the Comptroller of the Currency (OCC). All banks are required to file a *Call Report* as of the close of business on the last day of each calendar quarter.

Accordingly, the *Call Reports* provide quarterly detailed information on banks' balance sheets and income statements from 1992 to 2023. Although historical data are available as far back as 1976 through the *Report of Conditions and Income*, inconsistencies in variable definitions before 1992 limit longitudinal comparability. Moreover, our empirical strategy requires merging these data with branch-level information, which is only available from 1994 onward. The *Call Reports* are consolidated at the bank level and

provide a comprehensive view of each banking organization, encompassing not only the main office but also all affiliated branches. The data are compiled from several sources over time, including the Federal Financial Institutions Examination Council (FFIEC), Wharton Research Data Services (WRDS), and the Federal Reserve Bank of Chicago.

The *Call Reports* have undergone periodic revisions, requiring careful reconciliation of variables across different reporting forms to maintain consistency over time. For example, large banks filing the FFIEC 031 form, which is designated for banks with both domestic and foreign offices, report domestic assets indirectly from 2011. Unlike smaller banks that use the FFIEC 041 form and report domestic assets directly, the FFIEC 031 form requires reconstruction of domestic assets using data from Schedule RC-H. This meticulous reconstruction ensures consistency in financial series despite changes in reporting structures, providing a reliable foundation for our analysis of climate-related risks.[2]

Bank branch local activity. To fully capture the financial transmission of geographically specific climate shocks, it is essential to extend our analysis to the branch level. While many banks operate as single-branch entities serving specific communities, others maintain extensive networks spanning multiple regions. These networks reflect strategic decisions to expand operations based on local economic opportunities. Understanding the geographic dispersion of banking activities is critical for assessing the impact of localized climate events on financial stability.

A region-specific climate event affects banks only to the extent that they have business operations in the affected area. Macro-analyses that encompass entire national banking sectors often overlook this issue (Klomp, 2014). However, for studies focusing on individual banks, the geographic distribution of branches becomes paramount. Localized shocks cannot be meaningfully aggregated across regions without accounting for the dispersion of banking operations.

Our dataset provides two crucial pieces of information to address these challenges. First, it includes precise branch addresses, from which we obtained accurate latitude and longitude coordinates (see Figure 3), enabling granular identification of where banks operate. Second, it provides detailed deposit amounts for each branch, offering a meaningful proxy for banks' local activity. Deposits present a broader and more comprehensive measure of banking activity than commonly used metrics like mortgage origination, which focus narrowly on a specific loan segment. By leveraging deposit data, our study provides a more inclusive assessment of local banking activity and its exposure to geographically specific shocks, offering insights beyond those captured in previous work (e.g., Cortés and Strahan, 2017; Koetter et al., 2020; Rehbein and Ongena, 2022).

Geocoding. Accurate geolocation of bank branches is essential for linking financial data to localized economic and environmental factors, yet significant gaps exist in the geographic information provided by the FDIC dataset. While data on branch deposits were readily available, precise latitude and longitude information was missing for a substantial proportion of branches. Up to 50% of branches lacked geolocation data in the 1990s, leaving these deposits effectively unaccounted for in regional analyses. These issues persisted into the early 2010s, complicating efforts to link localized banking activity with climate information accurately.

To address this limitation, we developed a systematic three-layer geocoding methodology. First, full address queries were run using the OpenStreetMap (OSM) API. For unmatched cases, we refined results using the U.S. Census API. Finally, residual records were geocoded at the ZIP code level using OSM.

[2]See Table A3 in the Appendix for more details.

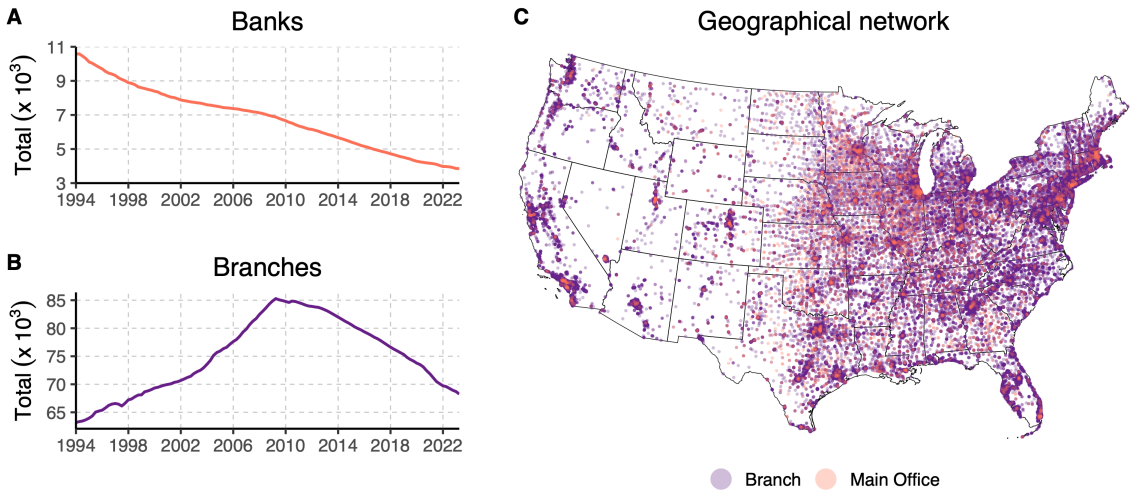


Figure A5: U.S. Banking sector from 1994 to 2023 (panel A & B) and its geographical network in 2023 (panel C).

Note: Spatial distribution of bank branches and headquarters based on FDIC Summary of Deposits data. Branch locations are geocoded using a three-step process incorporating OpenStreetMap, U.S. Census, and ZIP code-level approximations to address missing geographic coordinates. Headquarters locations are sourced from Call Reports and mapped according to official registry data.

To our knowledge, this is the first comprehensive effort to address geolocation gaps in the FDIC dataset. As illustrated in Figure A5, this process resulted in complete geolocation of branch-level deposits, substantially improving the dataset's reliability and enabling precise linkage of localized bank activity with local climate information.

Bank universe. Our analysis focuses on the domestic activities of financial institutions chartered as commercial banks within the contiguous United States (CONUS). Restricting the sample to a homogeneous class of banks allows for a more straightforward interpretation of transmission mechanisms and results. Commercial banks play a central role in the U.S. financial system, offering critical services such as credit intermediation, deposit-taking, and liquidity provision. In contrast, other institutions, such as savings banks and credit unions, operate under different regulatory frameworks and narrower mandates, making them less comparable to commercial banks.

We include all banks that operated during the sample period, regardless of whether they failed. Limiting the sample to surviving banks over a 30-year period would overlook the sector's structural evolution, including the trend toward consolidation and the increasing dominance of larger institutions. Moreover, excluding failed banks would misrepresent the composition of the banking sector, which includes a substantial proportion of small, single-branch banks, and introduce survival bias, distorting the dynamics of financial stability. Nevertheless, to address mergers, which often involve surviving banks absorbing smaller or failing institutions, we trace these events using the Uniform Bank Performance Report (UBPR) definition employed for supervisory purposes. A significant merger is defined as one resulting in a 25% or greater increase in assets. By incorporating this information, our analysis captures the evolving structure and continuity of banking operations over the sample period.

Stylized facts on banking sector concentration. Beyond the reduction in the number of banks, the evolution of the U.S. banking sector between 1994 and 2023 also underscores a pronounced increase in

Table A1: Statistics by bank size

1994Q1	Small banks (<1bn)	(1-10bn)	Large banks (10-25bn)	(≥ 25bn)	All banks
Number of banks	10,208 (96.6%)	315 (3.0%)	33 (0.3%)	16 (0.2%)	10,572 (100.0%)
Number of branches	31,958	18,594	6,531	5,874	62,957
Total assets ($bn)	982	1,059	527	720	3,291
Total deposits ($bn)	840	745	336	423	2,345
Average no. states (σ)	1.0 (0.1)	1.0 (0.2)	1.1 (0.3)	1.4 (0.8)	1.0 (0.1)
Average no. counties (σ)	1.4 (1.0)	10.0 (11.5)	25.7 (18.7)	29.9 (18.6)	1.8 (3.4)

2023Q1	Small banks (<1bn)	(1-10bn)	Large banks (10-25bn)	(≥ 25bn)	All banks
Number of banks	3,102 (80.4%)	633 (16.4%)	51 (1.3%)	70 (1.8%)	3,856 (100.0%)
Number of branches	13,449	14,437	3,941	36,505	68,332
Total assets ($bn)	949	1,722	789	14,008	17,469
Total deposits ($bn)	822	1,440	641	11,957	14,861
Average no. states (σ)	1.1 (0.5)	1.8 (1.4)	3.3 (2.3)	9.2 (9.6)	1.4 (1.9)
Average no. counties (σ)	2.4 (1.9)	8.8 (9.8)	22.7 (17.5)	49.7 (44.8)	4.6 (10.3)

Note: This table presents summary statistics on U.S. banks by size at the beginning (1994Q1) and end (2023Q1) of the sample period. Banks are classified based on total asset thresholds, with small banks holding less than $1 billion in assets and large banks segmented into size groups. Authors' calculations based on Call Reports and Summary of Deposits data from the Federal Deposit Insurance Corporation (FDIC). All variables are winsorized at the 0.1%-99.9% level to mitigate the influence of extreme values.

concentration, as illustrated in Figure 3 and Table A1. In the early 1990s, the landscape was characterized by a multitude of small, local banks. Three decades later, there is a substantial decline in the total number of banks, while large institutions now dominate the market, holding a growing share of both assets and deposits. Moreover, these large banks have extended their reach across a wider array of counties, reflecting a more geographically integrated credit and deposit market.

The right panel of Figure 3, which maps the spatial distribution of branches and main offices in 2023, highlights this geographic expansion: the network of branches now spans both urban centers and more peripheral regions. This trend towards concentration raises important questions regarding the system's resilience in the face of localized environmental shocks, such as extreme weather events, and the implications for financial stability and community-level climate adaptation. Recent evidence points to the fact that the spatial expansion of banks and the strategic reallocation of financial resources can significantly influence local economic outcomes and their vulnerability to environmental hazards (see, for example, Oberfield et al., 2024; Rajan and Ramcharan, 2023).

A3 Identification Strategy

We use Local Projections (LPs) as introduced by Jordà (2005), a flexible and robust econometric methodology for estimating the dynamic effects of flash drought shocks on bank stability. LPs involve a sequence of regressions of the endogenous variable, shifted forward in time, onto its lags and a set of control variables, directly estimating the dynamic response over multiple horizons. Compared to traditional Vector AutoRegressive (VAR) models, LPs impose fewer parametric restrictions, enabling the computation of Impulse Response Functions (IRFs) without assuming a fixed structure for the data-generating process.

LPs offer significant advantages for this analysis. Recent studies show that LP and VAR models yield comparable impulse response estimates, but LP inference is simpler and more robust to specification errors (Montiel Olea and Plagborg-Møller, 2021; Plagborg-Møller and Wolf, 2021; Jordà, 2023; Olea et al., 2025). Additionally, LPs are less prone to the "curse of dimensionality," which can affect VAR models when dealing with numerous variables or lags. These features make LPs particularly well-suited for analyzing the non-linear and time-varying impacts of flash droughts, which are characterized by rapid onset, strong spatial heterogeneity, and differential exposure across regions and banking institutions.

This approach enables us to quantify both short- and medium-term effects, capturing immediate responses and the persistence of climate-induced banking instability. By incorporating fixed effects and exploiting geolocated branch-level data, LPs allow us to link localized flash-drought-induced climate anomalies to bank-level outcomes, ensuring the analysis reflects heterogeneity across banks and regions.

Define y_{it}^{k} as the various ($k = 1, \dots, K$) bank stability metrics (e.g., Z-score) for bank $i = 1, \dots, N$ at time t. The h-period ahead cumulative change in bank stability, $\Delta_h y_{it+h}^{k} \equiv y_{it+h}^{k} - y_{it}^{k}$, is the long-difference or percentage point change in the metric over h steps ($h = 0, \dots, H$).[3]

Let r_{it} represent the intensity of the flash drought shock affecting bank i at time t, constructed from high-frequency climatic indicators capturing rapid soil moisture depletion and abnormal evapotranspiration dynamics. A set of bank-level and regional controls are consolidated into the vector X_{it}. This design measures how deviations in r_{it} from its baseline level $\bar{r}_{it}$ influence bank stability. The cumulative response (CR) of bank stability as the flash drought shock deviates by δ from a baseline level $\bar{r}_{it}$ is estimated as:

$$CR\left(\Delta_h y_{it+h}^{k}, \delta\right) = \mathbb{E}\left(\Delta_h y_{it+h}^{k} \mid r_{it} = \bar{r}_{it} + \delta; X_{it}\right) - \mathbb{E}\left(\Delta_h y_{it+h}^{k} \mid r_{it} = \bar{r}_{it}; X_{it}\right). \tag{7}$$

Assuming linearity, this cumulative response is the sum of impulse responses (IR) over the horizon h: $CR\left(\Delta_h y_{it+h}^{k}, \delta\right) = \sum_{\iota=1}^{h} IR\left(\Delta y_{it+\iota}^{k}, \delta\right)$. To avoid relying on linearity, Jordà (2023) suggests estimating the cumulative response directly using fixed-effects panel regressions, which leads to the following generic specification that will serve as the basis for different exercises:

$$\Delta_h y_{it+h} = \lambda_h y_{it-1} + \omega_h d_{it} + \Gamma_h X_{it} + \phi_i + q_t + u_{h,it}, \tag{8}$$

where y_{it} denotes a bank-level outcome for bank i at time t, $\Delta_h y_{it+h}$ is the h-period-ahead change, and d_{it} is the bank-level flash drought exposure measure constructed from branch-level exposure. The vector X_{it} includes a parsimonious set of bank and regional controls. Bank fixed effects ϕ_i absorb time-invariant

[3]Using long-difference specifications in LPs offers important advantages in terms of bias reduction. Specifically, the small-sample bias of order $O(T^{-1})$ identified by Herbst and Johannsen (2024) is largely suppressed when long-differences are used instead of levels. This is particularly important in dynamic settings with high persistence, where traditional estimators suffer from significant bias that compounds over time. Long-differencing mitigates this issue by breaking the correlation between regressors and residuals, thus yielding more reliable impulse response estimates even in relatively short samples.

heterogeneity across institutions, and time fixed effects q_t capture common shocks. Standard errors are clustered at the bank level to account for serial correlation in bank outcomes.

Finally, we address seasonality in bank accounting by incorporating quarter fixed effects and transforming dependent variables using a four-quarter uncentered moving average. Beyond mitigating seasonal fluctuations, this smoothing procedure helps address the inherent noisiness of LP estimates, which do not impose cross-horizon smoothness restrictions—as VARs typically do. While LPs tend to exhibit lower bias, this comes at the cost of higher variance, reflecting the standard bias–efficiency trade-off (Li et al., 2024). As suggested by Jordà and Taylor (2025), smoothness can be restored using rolling-window averages, which act as nonparametric kernel estimators of the conditional mean and help recover the underlying response profile from small-sample variation.

A4 Variable overview

Table A2: Summary Statistics

	Mean	25^{th}	50^{th}	75^{th}	σ	Min	Max	Obs.
Activity concentration								
Number of bank branches	10.96	1	3	6	109.8	1	6581	802,054
Number of States of bank op.	1.126	1	1	1	0.978	1	49	802,054
Number of counties of bank op.	2.769	1	1	2	6.901	1	209	802,054
Financial variables								
Bank's distance to default (Z-score)	176.3	72.30	135.9	232.6	154.0	-0.039	1326	783,458
Non performing loan ratio (NPL)	0.008	0.001	0.004	0.010	0.013	0.000	0.148	801,806
Foreclosure ratio (FOR)	0.003	0.000	0.000	0.002	0.008	0.000	0.111	801,809
Return on assets (ROA)	0.002	0.002	0.003	0.004	0.004	-0.041	0.055	800,028
Cost-to-income ratio (CIR)	0.700	0.568	0.657	0.763	0.319	0.000	5.881	800,187
Total equity ratio (EQ)	0.111	0.084	0.099	0.120	0.065	0.017	0.927	801,810
Deposit ratio	0.836	0.814	0.859	0.890	0.099	0.002	0.967	801,810
Gross loan ratio	0.612	0.519	0.634	0.729	0.163	0.000	0.964	801,810
Real estate loan ratio	0.394	0.270	0.395	0.519	0.174	0.000	0.866	801,810
Total assets, log	11.77	10.85	11.62	12.48	1.401	0.000	21.67	801,810

Note: This table presents summary statistics for the main variables used in the analysis. Bank-level financial data are drawn from the Consolidated Reports of Condition and Income (Call Reports) covering the period 1994–2023. All variables are winsorized at the 0.1% and 99.9% levels to reduce the influence of outliers. For descriptive purposes, ENSO magnitude (r_t) is presented as a continuous variable, with negative values corresponding to *La Niña* events.

Table A3: Main Variables, Descriptions, and Sources

Variable Name	Description and Source
branch_nbr	Number of branches operated by a bank. Derived from Summary of Deposits (FDIC).
states_nbr	Number of U.S. states where a bank operates branches. Based on Summary of Deposits (FDIC).
county_nbr	Number of counties where a bank operates branches, reflecting regional diversification. Derived from Summary of Deposits (FDIC) data.
npl	Non-performing loan ratio: captures the quality of a bank's loan portfolio, defined as the sum of loans 90+ days past due and non-accrual loans, divided by total assets. Loans 90+ days past due includes loans overdue by more than 90 days but still accruing interest. For domestic-only banks (Form 041), this is derived from RCON1407 for periods prior to 2011. From 2011 onwards, RCON1407 is no longer available and is reconstructed as the sum of the following subcomponents: RCONF174, RCONF175, RCON3494, RCON5399, RCONC237, RCONC239, RCON3500, RCONF180, RCONF181, RCONB835, RCON1607, RCONB576, RCONK214, RCONK217, RCON5390, RCON5460, and RCON1227. For consolidated banks (Form 031), the equivalent adjustments are made using the same series. Non-accrual loans represent loans that have stopped accruing interest due to repayment concerns. For Form 041, this is RCON1403 prior to 2011. After 2011, RCON1403 is no longer directly available and is reconstructed as the sum of similar subcomponents. Similar adjustments apply for consolidated banks (Form 031). Source: FFIEC, WRDS, Chicago Fed.
fr	Foreclosure ratio: real estate owned (RCON2150) divided by total assets (RCON2170). Represents foreclosed properties as a share of assets. Source: FFIEC, WRDS, Chicago Fed.
roa	Return on assets: net income (RIAD4340, transformed from year-to-date to quarterly) divided by total assets (RCON2170). Source: FFIEC, WRDS, Chicago Fed.
cir	Cost-to-income ratio: operating expenses (RIAD4093) divided by the sum of net-interest revenue (RIAD4107 - RIAD4074) and other operating income (RIAD4079). Source: FFIEC, WRDS, Chicago Fed.
eq	Total equity-to-assets ratio: total equity (RCON3210) divided by total assets (RCON2170). Source: FFIEC, WRDS, Chicago Fed.
zscore	Z-score: sum of equity-to-assets ratio and ROA, normalized by ROA's rolling 8-quarter standard deviation. Equity and assets data come from RCON3210 and RCON2170, respectively. Historical data ensure full computation starting in 1994. Source: FFIEC, WRDS, Chicago Fed.
rela	Ratio of real estate loans to total assets. Derived from RCON1410 for periods prior to 2011. After 2011, RCON1410 is obtained as the sum of RCONF158, RCONF159, RCON1420, RCON1797, RCON5367, RCON5368, RCON1460, RCONF160, and RCONF161. Source: FFIEC, WRDS, Chicago Fed.
loana	Gross loan ratio: gross loans (RCON1400) divided by total assets (RCON2170). Source: FFIEC, WRDS, Chicago Fed.
size	Bank size, measured as the natural logarithm of total assets (RCON2170). For large banks reporting with Form 031, total assets are reconstructed as the sum of RCON2192 (domestic assets) and RCON2163 (net due from foreign offices). Source: FFIEC, WRDS, Chicago Fed.
merger	Significant mergers, defined as events resulting in a 25% or greater increase in total assets (RCON2170) over one year. Source: FFIEC, WRDS, Chicago Fed.