Understanding Drought Shocks: Bank Financial Stability and Loan Performance

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Abstract

Recently, regulators and financial institutions have been discussing the development of stress tests to understand the impact of climate on banks. We define a two-year drought shock at bank level using the coordinates of bank branches and test the impact of drought shocks on bank stability and loan performance. Applying a difference-in-differences strategy, we find that drought shocks significantly worsen Z-Score, ROA volatility, loan performance, and equity volatility of affected banks compared to unaffected banks. Our findings are robust to placebo shocks. We also document that affected banks are more likely to close branches in affected regions.

Keywords: Climate risk, drought, bank stability, bank financial performance

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1 Introduction

With the consequences of climate change being visible on a daily basis, the impact of climate shocks on economies constitute a serious risk and financial institutions are not ambivalent about them. Recently, financial companies and regulators have been working toward the assessment of climate risks and transparent disclosure policies. For instance, the Task Force on Climate Related Financial Disclosures (TCFD), established in 2015 by the G20's Financial Stability Board (FSB), issues a report with recommendations regarding climate-related risk disclosures.

Following the TCFD's framework and under the coordination of the United Nations (UN) Environment Programme-Finance Initiative, 16 major global banks developed a report issued in July 2018 on assessing climate-driven credit risk. In a similar vein, in April 2019, the Network for Greening the Financial System (NGFS), a coalition of 34 central banks, released its first report on climate-related financial risks. The report calls for central banks and bank supervisors to integrate climate-related risks into financial stability monitoring and micro-supervision.

The frequency and intensity of droughts have already increased due to climate change and are predicted to rise, especially for already dry areas.[1] Hence, assessing drought risk is arguably more important than ever. The Natural Capital Financial Alliance by the UN, collaborating with several banks from Brazil, China, Mexico, and the United States (US), develop a stress testing tool specifically for drought risk. In this stress test, the impact of

[1] For the trends in drought and more general impacts of climate change on land, please see the Intergovernmental Panel on Climate Change (IPCC) Special Report on Climate Change and Land. For the projections on drought intensity and frequency, please see the IPCC Special Report on Global Warming of 1.5°C.

drought scenarios on companies borrowing from banks is assessed and associated loss and default risk are aggregated at banks' loan portfolios.

Despite these initiatives to measure climate risks and droughts on bank balance sheets, there is no systematic empirical study analyzing the impact of drought risk on banks. While it is important to study banks as they play a crucial role in the financial system, their balance sheets are also interesting as they can reveal the impact of climate shocks on local economies.

Climate shocks are local in nature. Potentially, banks' exposure to climate shocks through their branches reflects local economic exposure to climate shocks. The median distance between the firm and the lending bank's branch is less than five miles as most US banks are still geographically under-diversified and they originate loans locally (Agarwal and Hauswald, 2010; Petersen and Rajan, 2002). The under-diversified banks mainly deal with local firms and these firms are more likely to suffer from climate shocks than larger public firms. In particular, small firms tend to operate in fewer regions and are more exposed to regional shocks compared to large firms. Importantly, small firms mainly rely on bank loans for external funding (Berger and Udell, 1998; Petersen and Rajan, 1994). We expect that bank balance sheets will reflect the impact of climate shocks on local economies and enable us to analyze the impact of climate shocks such as drought.

Hong et al. (2019) are the first to evaluate the economic and financial impact of drought, specifically on food companies. Using the Palmer Drought Severity Index (PDSI), the authors find that drought has a negative impact on the profitability of food companies. The authors compile a portfolio of food companies going short on the stocks of companies located in countries that are experiencing drought and long on the stocks of those in countries not experiencing drought. They report that such a portfolio generates an annualized return of 7%.

In this study, we investigate the impact of drought on the performance of banks. This is important for various reasons. Most firms and households borrow, at some level, from banks. For instance, utility firms are directly affected from drought via water shortages while other industries might be hurt indirectly through increasing costs such as electricity prices.[2]

Industries that are not directly affected by drought or water shortage can still be affected by reductions in output from industries that are directly affected. Directly-affected industries may not provide the necessary inputs for other industries or they might transmit their problems to other industries by demanding less of their goods. That is, drought-related problems can disrupt the whole supply-chain and create further problems.

Banks' exposure to climate risks can also be through households. Workers, who have suffered income loss, might fail to pay their mortgages. This is especially likely for workers in the agricultural and food industries. Even if an agricultural firm is insured against certain climate shocks, some business activity will still be lost: workers will not pick up berries and receive salaries, catering firms or restaurants will not serve food for workers, new farm equipment will not be bought, etc. Thus, spillover to other industries through households is also likely.

Based on these circumstances, the information available on bank balance sheets is more general and goes beyond a particular industry such as the food industry studied in Hong et al. (2019). Overall, our study can be considered as the first study reflecting drought impacts in a comprehensive way in the finance literature. Dealing with banks also gives us the opportunity to evaluate the impact of drought on different market participants through bank balance

[2]Drought impacts utility firms in two ways. Electricity production relies on hydropower which is dependent on reservoir water levels and are negatively affected by drought. Drought also increases the overall operating costs of utility firms by increasing the cost of electricity transfer. For instance, the power lines of Pacific Gas and Electric sparked California wildfires, which in turn cost up to $30 billion in fire liabilities. Subsequently, PG&E, California's largest utility firm, had to file for bankruptcy protection. For more details, please see https://www.nytimes.com/2019/01/29/business/pge-bankruptcy.html

sheets. With that in mind, we document cross-sectional variation in nonperforming loans (NPLs) by looking into various types of loans. This way, our findings shed light on spillover effects on market participants including households that are not directly exposed to droughts.

The evidence in the banking literature on how banks are affected by climate shocks is quite limited. The focus is on natural disasters, in general, and hurricanes and storms, in particular (Bos et al., 2018; Klomp, 2014; Schüwer et al., 2018). Our paper is the first to relate drought to bank balance sheets in the banking literature and among the first evaluating the impact of climate on bank balance sheets. Since banks deal with local and smaller firms our study can also contribute to the debate by looking beyond large corporations. In a related study, Addoum et al. (2020) evaluate the impact of extreme temperatures on the local establishments of US public firms and the authors do not document any significant impact. Their explanation of this non-result is that public firms in their sample are large and diversified enough to absorb the negative impacts of local temperature shocks.[3]

Studies on climate shocks mostly concentrate on floods and hurricanes, as the damage caused by these natural disasters are usually immediate and relatively easy to observe. However, in the case of drought, effects are difficult to notice in the short term and the resulting economic cost accumulates over a long period of time. Accordingly, there is only one drought event in the 2000s that is a declared federal disaster.[4] Our paper contributes to the literature on the impacts of climate shocks, in which the climate events being studied are mainly floods or hurricanes (Atreya and Ferreira, 2015; Bernstein et al., 2019; Eichholtz et al., 2020; Keenan et al., 2018; Murfin and Spiegel, 2020).

[3]There are studies documenting the negative impacts of extreme temperatures, on labor supply (Graff-Zivin and Neidell, 2012, 2014), and on light manufacturing and service industries (Dell et al., 2009; Jones and Olken, 2010).

[4]For more details, please visit https://www.fema.gov/openfema-dataset-disaster-declarations-summaries-v2.

The main challenge in analyzing drought shocks is that, by nature, drought extends over several months or even years. To capture drought shocks with definite economic impact, we identify two-year drought shocks at bank-level.[5] Following Hong et al. (2019), to measure drought, we collect PDSI data issued by the US National Oceanic and Atmospheric Administration (NOAA). Using the geographic location of bank branches, we assign the PDSI score of the climatological division that a branch is located in to that branch. Then, we aggregate the branch-level PDSI scores at the bank level by weighting each branch's PDSI score by the amount of deposits. NOAA classifies a drought event as severe or extreme when PDSI is below -3. Similarly, we identify banks as drought-hit (or treated) when their weighted PDSI score is below -3. Our identified shocks indicate that the West Coast and central regions experience drought more often than the banks in other regions.

To assess the impact of drought on banks, we determine control banks for each treated bank that are not hit by the drought-shock. Then, we quantify the effect of drought on bank stability and loan performance utilizing a difference-in-differences (diff-in-diff) estimation. Importantly, we use propensity score weighting based on bank size (or geographic concentration) in our regressions to assign more importance to control banks that have similar size as treated banks.

We find that drought-hit banks experience a loss of asset quality and an increase in riskiness. Z-Score, a measure of bank financial stability, significantly declines for drought-hit banks by 0.38 relative to banks in the control group, indicating a deterioration in bank stability. Treated banks' return-on-asset (ROA) volatility and equity return volatility increase by 0.35 and 0.11, respectively, both suggesting heightened riskiness. Drought also undermines

[5] In unreported analysis, we also evaluate one-year drought shocks. The impact of drought is weaker, indicating that the effect of drought shocks becomes more significant in a longer period as drought extends over a longer period of time.

banks' loan performance as the ratio of non-performing loans (in total loans) increases by 0.40%. All of these estimates of drought impact on banks are economically sizeable.

In terms of standard deviation, exposure to a drought shock reduces Z-Score of a treated bank by 0.62 standard deviations relative to a control bank. In a comparable study by Schüwer et al. (2018) dealing with Hurricane Katrina, authors find that the Z-Score of banks exposed to the hurricane declined by around 0.12 standard deviations relative to a control group. Although the impact of drought on bank balance sheets is not immediate, our findings indicate that droughts can have a greater impact than hurricanes or floods.

On the other hand, a treated bank exposed to a drought shock has an NPL ratio that is 0.60 standard deviations higher relative to a control bank. A 1% increase in unemployment rate increases NPL ratio by 0.61 standard deviations. So, the impact of a drought shock is comparable to a 1% decline in employment rate, indicating a strong economic significance of drought shocks.

All findings are in line with our expectations that drought shocks negatively impact bank stability and financial performance. Our diff-in-diff analyses satisfy the pre-trend conditions considering two quarters preceding the drought shock. Placebo analyses confirm that our main findings are driven by a two-year drought shock defined as a switch in the drought conditions from normal to severe or extreme drought and our results are robust to the exclusion of hurricane-exposed states.

We then analyze whether treated banks that are exposed to drought shocks close any branches located in affected climatological divisions. Our findings reflect that treated banks are more likely to close branches in divisions that are exposed to drought shocks versus branches in unaffected areas. This is consistent with the idea that treated banks close branches in affected regions to cut exposure to drought shocks. Some banks can avoid two-year drought shocks by closing affected branches during the shock. On the other hand, our analysis on branch closures is on the banks affected by a two-year drought shock and reveal that although treated banks close branches, they are still financially affected at the bank level.

Finally, we evaluate the categories of NPLs. We document that the NPL ratio significantly increases for agricultural and residential mortgages, commercial loans, and commercial mortgages for banks that are exposed to drought shocks. We do not find a significant result for consumer loans. Our NPL analyses on loan categories demonstrate that different participants of the economy are negatively affected by drought shocks. As opposed to Addoum et al. (2020), who find no significant results for large corporations, our findings might also indicate that large loans such as commercial mortgages and commercial loans used by larger firms are also affected by drought shocks. As banks are exposed to different industries and agents, our findings generalize the findings of Hong et al. (2019) and reflect the exposure of other economic agents outside the food industry to drought shocks.

Overall, our analyses consistently show that bank balance sheets are affected by drought shocks. In Section 2, we define drought shocks and develop our indentification strategy and methodology. Section 3 summarizes and explains our data. We document our empirical findings in Section 4. In the final section, we conclude.

2 Drought Identification and Methodology

2.1 Climate Shocks

Economies can face the impact of climate change through natural disasters (Easterling et al., 2000). The most common climatological disasters are hydro-meteorological disasters including hurricanes, floods, and drought. The economic damage from floods and hurricanes is physically observable and the damage these disasters cause is immediate. While droughts last for months or years, the Federal Emergency Management Agency (FEMA) data on hurricanes reflect that the average duration for hurricanes is approximately two days and the maximum duration corresponds to 21 days.

As hurricanes and floods are relatively short in duration and result in immediate damage, academic literature mainly concentrates on these types of disasters in order to assess climate impacts. In a broader study, Boustan et al. (2020) analyze the impact of natural disasters including hurricanes and floods on migration rates, housing prices, and poverty levels by constructing a panel data from 1920 to 2010. They find that US counties that are most affected by severe disasters experience an increase of 1.5% in net out-migration rates. This effect is half as disruptive as the effect of a large negative employment shock.

The risk of drought has also been increased by climate change (Dai, 2013). Climatologists have found that increasing temperature trends exacerbate the risks of droughts (Trenberth et al., 2014). However, droughts are not only caused by increases in the temperature. Evapotranspiration and precipitation are also important factors driving droughts. Dai and Zhao (2017a) evaluate the historical trends in drought and, in a complementary project, the authors simulate drought trends for the 21st century (Dai and Zhao, 2017b). They find that droughts have become more frequent primarily due to precipitation changes after 1980 and are likely to increase in the 21st century. According to the authors, increases in Pacific sea temperature affect precipitation and relatedly land dryness in North America.

The literature on the economic consequences of drought shocks is limited.[6] While temperature is only one of the factors driving drought, in a recent study Addoum et al. (2020)

[6] Bank of America Merrill Lynch estimates the economic loss in agriculture sector of the California drought, only in 2015, to be US $2.7 billion. For details, please see https://www.longfinance.net/media/documents/BAML_2015_Global_Water_primer_-_California_dreamin_of_water.pdf.

do not find any significant impact of extreme temperatures on firm profitability. On the other hand, Hong et al. (2019) are the first to evaluate the long-term economic and financial impact of drought on food companies. The authors find that drought has a negative impact on the profitability of food companies. They construct a portfolio of food companies going short on the stocks of companies in countries in drought and long on the stocks of those in countries not in drought. The authors document that such a portfolio generates an annualized return of 7%.

2.2 Defining Drought Shocks

While the impact of hurricanes and floods is realized in a short period of time and is physically observable, drought events last longer and are not visible to the naked eye. Moreover, there is neither a clear definition of a drought shock nor a clear-cut duration of a drought. A measure is needed to precisely assess the beginning, end, and spatial limits of a drought. This also makes it hard to quantify the economic consequences of drought events. Overall, the long-term nature of drought makes it a non-standard hazard.

To measure drought, we use the PDSI developed in Palmer (1965), which is currently maintained and reported by NOAA. It considers not only the temperature and moisture in the soil but also more complicated factors such as evapotranspiration and recharge rates. Overall, PDSI measures drought intensity and is first used in the economics literature by Hong et al. (2019).

Due to its complex nature, drought has memory, unlike temperature. Drought can simply be defined as “a prolonged period of drynessâĂŹâĂŹ or “prolonged and abnormal moisture deficienc”. The prolonged nature is important as farmers would not call a “dry spell” a drought until matters become rather significant. A dry spell of several months can have negative impact on stream-flow, groundwater, and the water level in lakes and reservoirs as well as soil moisture. To hit critical levels, the dry period should be long enough.[7] Hence, the preceding conditions as well as the characteristic of soil in an area, such as water-absorption and water-holding capacity, matter for drought conditions to emerge.

Due to all these conditions, creating a simple measure of drought is not possible. To capture this complex nature of drought, PalmerâĂŹs measure builds upon a hydrological water balance method that incorporates the moisture received (precipitation), the potential moisture lost (due to temperature), as well as water-absorption and water-holding capacity of the soil. Because of the dynamic nature of drought, PalmerâĂŹs measure requires the data on the factors mentioned above from the past 9 to 12 months.

The PDSI data are reported monthly for each climate division in the contiguous US by NOAA.[8] Climatologists divide the contiguous US into 344 climate divisions. Divisions within each state are defined based on the average state of the climate. Except Rhode Island (one division), each state is divided into 2 to 10 divisions based on intrastate climate variation. For each climate division, monthly temperature and precipitation values are computed from daily observations. The data are provided by the National Center for Environmental Information (NCEI) of NOAA with the aim of interpreting and applying scientific understanding of climate change dynamics at the state and country level. As the PDSI score declines, drought intensity increases.

NOAA classifies PDSI values between 2 and -2 as normal conditions. Values less than -2 are considered drought in different degrees. A value between -2 and -3 is moderate drought, between -3 and -4 is severe drought and a value lower than -4 represents extreme drought.

[7] A period of dry weather might be even desirable in some cases, such as if the preceding periods were abnormally wet.

[8] NOAA reports a modified version of the original index created by Palmer (1965).

In Figure 1, we compare the most recent decade with the previous decade in our sample and create a heat map representing the number of quarters when PDSI is lower than -3 in a climate division, aggregated at state level. PDSI value less than -3 is critical in our analysis as it indicates severe or extreme drought conditions. In the subperiod from 2011 to 2017, the frequency of severe or extreme droughts increases in most states relative to the subperiod from 2004 to 2010.[9] Banks might diversify drought risk by operating across different states, however, diversifying the drought risk is likely to get harder as more states are exposed to more frequent drought events.

Interestingly, the number of drought shocks have declined in the East Coast. The states in the southern Midwest experience more frequent drought shocks in the last decade. Considering that the East Coast is exposed to hurricanes, thereby combining both hurricanes and drought shocks, most US states became increasingly exposed to climate shocks in the last decade.

[Figure 1 about here.]

To define drought shocks at the bank level, we focus on each bank's geographic exposure to drought. S&P Global Market Intelligence provides annual information on bank branches, such as location and total deposits of each branch. Using the geographical coordinates of each branch, we first map each bank branch to a climatological division so that we can assign a PDSI score for each branch. Then, weighting by the deposit size of each branch, we create a weighted PDSI (or WPDSI) score for each bank for every quarter in our sample as presented in the formula below.

[9] We start in 2004 to keep the number of years in both subperiods equal.

$$WPDSI_{i,t} = \frac{\sum_j Deposits_{i,j,t} * PDSI_{i,j,t}}{Deposits_{i,t}} \quad (1)$$

where i denotes bank i, j denotes branch j, and t denotes quarter t.

Our bank-level drought measure reflects the exposure of each bank to drought in a given quarter. PDSI can indicate a severe or extreme drought event at a specific location, yet whether these drought events can constitute a shock to the economy is not clear. Although temperatures or drought levels vary by time, there is a standard temperature structure in every region. In warmer regions, the economy can be expected to be structured to certain temperatures affecting production choices and lifestyles. Since such locations can be more resistant to drought in the short term, severe drought events can be more harmful or have economic consequences if the drought event extends for a longer time period.[10] While each observation is quarterly in our PDSI data, it represents approximately one-year of drought conditions for the preceding four quarters by the construction of PDSI.

In our study, we define drought shocks for a longer period (two years). We implement a condition that the weighted PDSI should be less than -3. This represents at least severe drought for the previous quarter and for the preceding four additional quarters, i.e. one-quarter and five-quarter lagged weighted PDSI should be less than -3. As each weighted PDSI value represents a one-year average, we are able to guarantee that there is at least severe drought (or extreme drought in the worst case) for two preceding years.[11] Additionally, we require that a *Treated Bank* is exposed to a shock following a one-year normal condition, i.e. weighted

[10] Hong et al. (2019) uses a three-year average of PDSI score to reflect the potential impact of drought shocks extending over a longer period of time.

[11] In unreported analyses, our findings indicate that one-year severe or extreme drought does not have economic effects on bank balance sheets.

PDSI is above -2 for two quarters.[12] For the remainder of the analysis, we assume that a *Treated Bank* is exposed to a two-year long drought shock and define a drought shock dummy as shown in Equation (2).

$$Treated\ Bank_{i,t} = \begin{cases} 1, & \text{if } WPDSI_{i,t-1} \leq -3, WPDSI_{i,t-5} \leq -3, \\ & -2 < WPDSI_{i,t-9} < 2, -2 < WPDSI_{i,t-10} < 2 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where i denotes bank i and t denotes quarter t.

We also define a *Control Bank* group. If a bank is under normal conditions, the weighted PDSI is between -2 and 2 for the two-year shock period. We also put the same condition for the year before the shock period, as in the treated group. We match each of treated banks with the control banks that are under normal conditions. Overall, our control banks remain in normal conditions before and during the corresponding drought shock. Equation (3) represents the *Control Banks*.

$$Control\ Bank_{i,t} = \begin{cases} 1, & \text{if } -2 < WPDSI_{i,t-1} < 2, -2 < WPDSI_{i,t-5} < 2, \\ & -2 < WPDSI_{i,t-9} < 2, -2 < WPDSI_{i,t-10} < 2 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

[12] A value of PDSI represents a drought level around 9 to 12 months due to the data for the factors used to calculate PDSI such as temperature and precipitation. To guarantee that a bank is not exposed to severe drought for a year, we implement a condition on weighted PDSI that it is above -2 for the previous two quarters.

where i stands for Bank i and t stands for quarter t.

[Figure 2 about here.]

Figure 2 displays the change in weighted PDSI for treated banks and control banks during shock periods. Time=0 represents the last quarter before the shock starts. Time=8 represents the end of the drought shock. As seen in Figure 2, both groups start at a weighted PDSI above -2, i.e. normal moist conditions, which is by our construction of the selection of treated and control banks. For the treated group, the mean of weighted PDSI decreases to below -4, which is extreme drought. The mean of weighted PDSI remains around zero for the control group. Overall, our treated banks are exposed to a drought shock following normal conditions while the control banks remain in normal conditions. Although we do not put any conditions in the quarters following the shock, the weighted PDSI for treated banks seem to increase to moderate levels after the shock supporting our two-year shock definition. In general, after two years of drought, the conditions improve to moderate levels.

In total, we identify 217 bank-level drought shocks after cleaning for missing bank financials.[13] We have 889 unique publicly traded banks and 181 of them have been exposed to at least one drought shock in our sample, corresponding to 20% of all banks that we cover. As more states are exposed to more frequent drought shocks in the recent decade (shown in Figure 1), it will become even more difficult for banks to diversify away drought shocks. While the mean bank size for all banks in our sample increases by 38% during the post-crisis period relative to the pre-crisis period, the mean bank size increases by 1,117% for banks that are exposed to a drought shock.

Additionally, while the mean of Herfindahl-Hirschman Index for all banks in our sample decreases by 7% during the post-crisis period relative to the pre-crisis, it decreases by 9% for

[13] In the rare cases of drought shocks lasting longer than two years, we count such shocks as only one shock.

banks that are exposed to a drought shock. So, larger banks that are more likely to diversify away drought shocks seem to be increasingly affected as well. These figures indicate that our analysis is important for banks and regulators to understand drought shocks as banks will be more likely to be exposed to such shocks in the future.

[Figure 3 about here.]

Figure 3 reflects the frequency of bank-level drought shocks over years. A year is counted as a shock year if it is fully or partially affected by a two-year drought shock. Overall, the frequency of drought shocks is significantly higher in the second half of the sample compared to the first half.[14]

2.3 Estimation Methodology

To evaluate whether drought shocks affect bank stability and loan performance, we follow a diff-in-diff strategy. As explained in the previous sections, we define a drought shock at bank level for a two-year period. Specifically, we identify banks having a two-year severe or extreme drought following a normal year as in (2). For each shock period, we identify control banks as defined in (3) and match them with banks exposed to drought shocks. We then follow a diff-in-diff approach. In the diff-in-diff model, we use two quarters. We take the last quarter (Time=0 in Figure 2) before the shock period starts and the quarter in which the shock ends (Time=8 in Figure 2). We compare the financial stability of affected banks to their peers

[14] In the figure, 2016 and 2017 might be underrepresented as we do not include drought shocks that can extend into 2018 and 2019.

in the final quarter of the drought shock relative to the quarter just before the drought shock starts. To quantify the drought impact on banks we run the following regression:

$$y_{i,t} = \beta_0 + \beta_1 \textit{Treated Bank}_i + \beta_2 \textit{Treated Bank}_i \times \textit{Post-Shock}_i + \beta_3 \textit{Post-Shock}_i + \beta_4 x_{i,t} + \gamma_t + \delta_i + u_i \tag{4}$$

where y_i is the financial stability and performance indicator for bank i. Our dependent variables are Z-Score, ROA volatility, equity volatility, and NPL ratio. $\textit{Post-Shock}_i$ is a dummy variable indicating the post-drought shock quarter. $x_{i,t}$ is a matrix of covariates: bank characteristics and macro controls. γ_t are year-quarter fixed effects for the pre- and post-crisis quarters and δ_i are state- and bank-fixed effects.

Our sample in these regressions consists of treated banks and corresponding control banks for each treated bank. The coefficient of interest is β_2. This coefficient captures the impact of drought on the treated banks relative to a control group of banks that are not exposed to drought shocks. Note that year-quarter fixed effects wipe out the impacts of time-varying factors and all there is left is the cross-sectional variation between banks.

The drought shock itself is exogenous as it is a climatological event. Overall, in our diff-in-diff model, the impact of drought shock is identified by comparing the pre- and post-shock financials of a bank that is exposed to a two-year drought shock relative to a control group.

Z-Score measures distance to default so the impact of drought indicates whether banks are more likely to experience financial distress when they are exposed to a drought shock. In ROA and equity volatility regressions, we test how drought shocks affect the stability of operating and stock returns. We study the ratio of non-performing loans to understand how asset quality of banks changes due to a drought shock.

3 Bank-Level Data

We collect data on bank characteristics from S&P Global Market Intelligence for the sample period of 2000 to 2017.[15] These bank-level variables are quarterly, with the exception of bank-branch location information, which is updated annually. We also use equity returns (daily returns including dividends) on bank stocks, which we obtain from the Center for Research in Security Prices (CRSP). We first identify public banks with financial and branch-level information and merge them with the PDSI data.[16] Our initial sample consists of 889 publicly traded banks, of which 847 are commercial banks and 42 are saving banks. Among these banks we identify 217 bank-level shocks for 181 unique banks. We exclude the years of global financial crisis (2008 and 2009)[17].

Our main dependent variables are Z-Score, ROA volatility, equity volatility for bank stability, and NPL ratio for loan performance. As in Demirgüç-Kunt and Huizinga (2010), Z-Score is defined as the natural logarithm of return on assets plus equity capital ratio divided by the standard deviation of return on assets over the last 8 quarters. An increase in Z-Score indicates an improvement in bank stability. ROA volatility is calculated as the standard deviation of return on assets over the last 8 quarters, similar to Laeven and Levine (2009). Equity volatility is the volatility of the market-adjusted equity returns of the bank computed using daily data for each quarter, as in Campbell and Taksler (2003). NPL ratio

[15] S&P Market Intelligence merges the main sources for banking data such as Chicago FED and FDIC and provides a comprehensive bank financials database. They collect branch-level data from the Summary of Deposits.

[16] We focus on publicly traded banks as one of our main financial stability measures is stock volatility.

[17] Our results are robust to the inclusion of the crisis years.

is the summation of total non-accrual loans and total loans that are 90 or more days past due but are still accruing interest divided by the first lag of a bank's total loans.

S&P Global Market Intelligence also reports subcategories of NPL, such as agricultural and farm loans, consumer loans, loans secured by family residential properties, commercial and industrial loans, and commercial mortgages that includes commercial real estate loans and construction and land development loans.

[Table 1 about here.]

Table 1 summarizes the descriptive statistics of our dependent and control variables for treated and control banks. Out of 217 bank-level shocks that we identify, we exclude 21 shocks due to no control banks that can be matched with treated banks and 74 shocks that correspond to the crisis years.[18] In the end, in 122 shocks, we have at least one control bank that we can match with treated banks and have no missing financials. There are 98 shocks for which we can calculate equity volatility. The mean of Z-Score, ROA volatility, equity volatility, and NPL ratio are 3.48, 0.71, 1.18, and 1.68 for the treated banks, respectively. For the control group, the mean of Z-Score, ROA volatility, equity volatility, and NPL ratio are 3.90, 0.42, 1.25, and 1.59, respectively. Treated banks have lower Z-Score, higher ROA volatility, and more NPLs. Conversely, treated banks have lower equity volatility than the control banks.

We use a large set of control variables. Along with bank characteristics, we use variables to control for macroeconomic factors. The data for macroeconomic variables are collected from the Federal Reserve Economic Data (FRED). In creating macro-controls for each bank, the procedure used in obtaining weighted PDSI is also used here: For each bank, state-level macro variables are weighted by the deposit size of that bank in each state. These macro-controls

[18] The shocks that are dropped due to the crisis years include the shocks that start before the crisis and end during the crisis or the shocks that start during the crisis and end after the crisis. On the other hand, our results are robust to the inclusion of the shocks that correspond to the crisis years.

are GDP growth rate, housing price index return, homeownership rate, and unemployment rate. The bank-level control variables are ratios of equity capital to total assets, total loans and leases to total assets, and the natural logarithm of total assets. All control variables and stock returns are winsorzied at 5% and 95% levels.[19] Overall, treated banks are smaller in size and have similar loan to assets and equity capital ratios. When compared to control banks, treated banks experience higher GDP-growth and housing price increase in the areas they are active, and they are exposed to slightly higher unemployment rates in states they operate.

4 Results

4.1 Impact of Drought on Bank Stability and Performance

We start our analysis by testing the impact of drought on bank stability and financial performance. Table 2 presents the results. Our variable of interest is the interaction term between the treated bank and post-shock dummies. The table reports weighted least square regressions, where standard errors are weighted by propensity score weights. All regressions include year-quarter, state, and bank fixed effects.

[Table 2 about here.]

The main coefficient of interest is the coefficient of the interaction term, which is displayed in the second row of the table. In the first column, we observe that treated banks unconditionally have a Z-Score 24 percentage points above the control groups'. However, this edge erodes with the shock: the coefficient of the interaction is -0.38 and statistically significant at 1%. This indicates a decline in Z-Score by 0.38 relative to a control bank when a

[19] Our results are robust to winsorization at 1% and 99%, and 2.5% and 97.5% levels. After winsorizing stock returns, we calculate equity volatility on winsorized stock returns.

treated bank is exposed to a two-year drought shock. Other risk measures increase as well: the ROA volatility and equity volatility of treated banks increase relative to control group by 0.35 and 0.11, respectively. These estimates indicate that a bank's financial stability significantly worsens if it is exposed to drought shocks. We also find that drought shocks significantly increase NPL ratio by 0.40% at 1% significance level. Macroeconomic control variables are generally significant across regressions and seem to matter more for NPL ratios. In general, the empirical findings displayed in Table 2 exhibit the negative impacts of droughts on banks.

Economically speaking, exposure to a drought shock decreases Z-Score of a treated bank by 0.62 standard deviations compared to a control bank, whereas a 1% increase in unemployment rate decreases Z-Score by 0.13 standard deviations. As a result, the economic impact of a drought shock is significantly higher than a 1% decline in employment rate.

The selection of the control banks is critical to our analysis. As we explain in Equation (3), control banks consist of the banks that are always under normal conditions during periods when some other banks are in at least severe drought. This way, we aim to guarantee that a control bank is not exposed to severe drought before and during the shock period. A potential concern is that small and focused banks could usually be exposed to a drought shock. For this purpose, we apply a weighted-least-squares model with propensity score weighting. To satisfy the balancing property, the propensity scores are separately determined using size and the Herfindahl-Hirschman Index (HHI) calculated based on branch deposits across states. While the results are similar independent of the propensity score weights, we present results with propensity score weights based on bank size.[20] Additionally, all regressions control for bank- and state-level characteristics, including the size of the bank.

[20]Estimation results without the propensity score matching are in the appendix Table A1.

Although our shock is exogenous in nature, it is always a possibility that the impact of a different and concurrent shock is also picked up by our estimates. For that reason, we exclude the period of the 2008-2009 financial crisis from our sample.[21] There are also major hurricanes hitting the East Coast during our sample period and they are more than likely to affect the banks negatively in the region (see Schüwer et al. (2018)). To confirm that our results are not driven by hurricanes, we rerun our main analysis in a subsample with significantly less hurricane exposure.[22] Our results are robust to this subsample and results are available in Table A2 of the Appendix.

[Table 3 about here.]

In the diff-in-diff analysis, one of the most important tests that is difficult to satisfy is the pre-trend analysis. For this purpose, we include the 1-quarter and 2-quarter lagged observations and time dummies for these periods for the pre-shock period and interact them with the treated bank dummy. Table 3 presents the results for main dependent variables.[23] The regression includes observations for four quarters: the 1st and 2nd lags of the pre-shock period, pre-shock quarter and the post-shock quarter.

While the interaction between the treated bank and the post-shock dummy remains significant in all regressions, the coefficients of interaction terms between the treated bank and pre-shock quarter dummies are not statistically significant. These findings indicate that

[21] Our results are robust if we include the drought shocks that occur in 2008 and 2009.

[22] We drop banks operating in states that experienced at least fifty hurricanes and five major hurricanes historically. These states are Florida, Texas, Louisiana, and North Carolina. Our identified drought shocks are location- and time-specific. For another shock to drive our results, both the location and timing have to coincide, which is difficult for hurricanes to satisfy. Since we study 8 quarters after the start of a drought, only the hurricanes which had immediate impact during the these 8 quarters would be picked up by estimates. In that sense, by dropping all the banks from hurricane exposed states, we take a more conservative approach than necessary.

[23] In unreported regressions, all subcategories of NPL also satisfy the pre-trend test.

the observed divergence for the post-shock quarter does not exist in the quarters preceding the shock period.

4.2 Placebo Analysis

In our analytical setup, our shock definition is important. To test whether our findings are not randomly driven based on our shock definition, we run a placebo test. The aim of this exercise is to show that what matters is the level of PDSI, not the change in its level. Accordingly, our main analysis relies on the assumption that the level of PDSI matters rather than the change in PDSI. We run Equation (4), modifying our definition of shock as a placebo test keeping the control group definition similar. We define a first placebo shock as a decline in weighted PDSI within the normal-condition range, that is weighted PDSI decreasing to between -2 and 0 from between 0 and 3.[24] We make a placebo assumption that any variation within the normal range, that is between -2 and 2, should not have any economic impact. Equation (5) presents the definition of placebo banks. If we do not find β_2 to be statistically significant, placebo analyses indicate that our main findings are not driven by any change in PDSI but the level of PDSI corresponding to severe or extreme drought.

$$Placebo\ Bank^{normal}_{i,t} = \begin{cases} 1, & \text{if } -2 < WPDSI_{i,t-1} < 0, -2 < WPDSI_{i,t-5} < 0, \\ & 0 \leq WPDSI_{i,t-9} < 3, 0 \leq WPDSI_{i,t-10} < 3 \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

[24] In this specification, the upper bound for normal conditions is 3 instead of 2 due to sample size limitations. For the control group in the placebo tests, the upper bound is also set at 3.

$$
Placebo\ Bank_{i,t}^{moderate} = \begin{cases} 1, & \text{if } -3 < WPDSI_{i,t-1} \leq -1, -3 < WPDSI_{i,t-5} \leq -1, \\ & 0 \leq WPDSI_{i,t-9} < 3, 0 \leq WPDSI_{i,t-10} < 3 \\ 0, & \text{otherwise} \end{cases} \tag{6}
$$

where i stands for bank i and t stands for quarter t.

We define a second quasi-placebo in which the weighted PDSI of the treated banks in the post-shock quarter should decrease by at least 1 unit compared to the pre-shock quarter. In this case, we allow weighted PDSI to go down to moderate drought level, as shown in Equation (6). This analysis is based on the assumption that a moderate drought shock should have weak to no economic impact.

[Figure 4 about here.]

Figure 4 compares the trends for both placebo groups. Panel A presents the weighted PDSI for the placebo banks within normal range with the corresponding controls. While the placebo shock can be observed in the weighted PDSI of treated banks, the weighted PDSI of control banks have more variation relative to our main shock group remaining in the normal range. The placebo group including moderate drought, presented in Panel B, represents a similar trend as the main shock group. Placebo shock hits and accordingly, there is a sharp decline in the weighted PDSI and recovery after the shock. The control group seems to be more stable, similar to the control group in the main drought shock analysis.

In the first placebo shock, we assume a decline in the weighted PDSI within the normal range of PDSI between -2 and 2 as shown in Equation (5). Our aim is to show that the placebo shock has no impact on the performance of banks exposed to placebo shocks relative to the control group. Table 4 presents our findings. In all regressions in Panel A, the interaction term is statistically insignificant.

[Table 4 about here.]

To define a placebo shock similar to our shock definition with at least 1-unit decline in the weighted PDSI, we relax our assumption that the weighted PDSI should remain within the normal range. Instead, we set a lower bound of the weighted PDSI at -3 but do not allow it to go below -3 as presented in Equation (6). The range of PDSI between -2 and -3 is assumed to be moderate drought. This level is still above our main shock definition, that is less than -3, which is at least severe drought or goes down to extreme drought. We present the results in Panel B of Table 4. Again, we do not find any significant coefficient of the interaction term in all regressions. Overall, our placebo tests indicate that our main findings are driven by the severe and extreme drought conditions and not by any change in PDSI.

4.3 Drought Shocks and Branch Closures

Our findings thus far indicate that droughts indeed affect banks and these effects are visible on balance sheets. A natural question is whether banks are also aware of these negative impacts and how they respond if they are aware. In this section, we study the response of drought-hit (treated) banks and test whether these banks cut their exposure to geographical areas with drought exposure. More specifically, we test whether treated banks are more likely to close a branch in climatological divisions that experienced a drought shock compared to other divisions they operate. These shock-receiving divisions are the divisions that effectively put a bank into the treated-bank category. Hence, in our treated group, although these banks close the branches even during the shock, they cannot escape from such shocks as they remain in treated group.

We also analyze the timing of banks' branch closures in drought-hit divisions. We test whether banks are quick to respond and close their branches during the drought shock or if branch closures take place only after the drought. Banks shutting down branches in drought-ravaged regions also matter for local economies as branch closures would impede access to capital and hurt the region further.

To study the likelihood of branch closures, we model the probability of a branch closure using a logistic regression. The dependent variable is a binary variable capturing whether at least one branch of bank i in division j is closed during quarter t; $Closure_{i,j,t}$. Our main variable of interest affecting branch closure is the drought variable, $Shock_j$, which is a binary variable taking a value of one when the climatological division j receives a drought shock (defined as in the main analysis, i.e. when PDSI is below -3), that is, the divisions treated banks' drought shock stemmed from. The variable $Shock_j$ takes the value of zero in divisions treated banks operate in but drought conditions are not realized. Thus, the coefficient of $Shock_j$ represents the difference in branch closure probabilities between divisions with and without drought shocks.

[Table 5 about here.]

The estimation results are presented in Table 5. The regressions include, in addition to $Shock_j$, the same bank-level control variables as in the main analysis. Similarly, state-, time-, and bank-fixed effects are included. In the first column of the table, the logistic regression is estimated for five years of quarterly data: two years during the drought shock and three years after the shock. In the second and third columns, the shock and its aftermath (post-shock) are analyzed separately to understand how quick the banks are in reacting to drought shocks, by closing a branch in the affected areas. In all three specifications, the coefficient of $Shock_j$ is positive and statistically significant. The findings indicate that banks are more likely to close branches in the divisions that are exposed to a drought shock relative to the divisions that are not exposed to drought shocks. The estimated coefficient of 1.91 in Column (1) implies that the odds of branch closure is higher in drought regions, by 1.91, relative to unaffected regions.

4.4 Categories of NPL and Effects on Market Participants

To further evaluate how different market participants are affected from drought shocks, we concentrate on the subcategories of NPL. Banks work with actors from various industries, meaning that how different loan categories perform can be informative about different segments of the economy. While some industries might be directly affected from drought due to problems such as water shortages, there are also industries that are linked to those affected industries that could create supply chain issues. Households can also be affected due to loss of jobs or failure to pay mortgages, which can show in mortgage delinquencies.

[Table 6 about here.]

Table 6 presents our findings on the categories of NPL. We find a statistically significant impacts on NPL ratios of agricultural and commercial loans as well as those of, residential and commercial mortgages. The biggest increase is in the NPL ratio of agricultural loans, which may not be surprising given the drought shock. The NPL ratio in agricultural loans increases by 1.14 percentage points while the consumer loans are unaffected. In subcategories of mortgages, consumer side seems to suffer less relative to commercial side: The increase in the NPL ratio of commercial mortgages is almost double of that of residential mortgages (0.37 vs 0.66 percentage points). Similar to commercial mortgages, the NPL ratio in commercial loans also goes up by 0.91 percentage points if a bank is exposed to a drought shock. Overall, our analysis on NPLs based on the categories of loans reflects that the negative impact of drought shocks is not only confined to agricultural industries, but a greater part of the economy suffers.

5 Concluding Remarks

Regulators and major banks in the banking industry are increasingly concerned about the impact of climate shocks on bank balance sheets. While these institutions seek ways such as stress testing to understand how banks are affected by climate events, there is no comprehensive study in the literature. Additionally, the literature mainly concentrates on hurricanes and floods. Hurricane and floods are short in duration and their damage is immediate and physically observable. On the other hand, the damage from drought or extreme temperature extends over a long period of time. Accordingly, there is no clear definition of drought shocks considering the duration or economic consequences.

Defining a two-year drought shock and applying a diff-in-diff strategy, we focus on the impact of drought shocks on bank stability and loan performance. Using the coordinates of bank branches and branch-level deposits, we create a weighted measure of exposure to drought shocks at bank level. Overall, our findings indicate that bank-level drought shocks distort bank stability and worsen a bank's financial performance. Compared to a control bank, drought shock to a treated bank significantly decreases Z-Score by 0.38 and increases ROA volatility, equity volatility, and NPL ratio, and by 0.35, 0.11, and 0.40%, respectively. Correspondingly, Z-Score decreases by 0.62 standard deviations and ROA volatility, equity volatility, and NPL ratio increase by 2.89, 0.39, and 0.60 standard deviations, respectively. Our findings are robust to placebo analyses and the exclusion of hurricane-exposed states.

We also find that there is a higher likelihood that a treated bank being exposed to a drought shock closes any branch located in an affected climatological division. We also evaluate the categories of NPL. We document that NPL ratios significantly increase for agricultural, residential mortgages, commercial loans, and commercial mortgages. On the other hand, we do a find any significant impact on consumer loans.

To our knowledge, our paper is pioneering in defining of drought shock and in documenting the impact of drought shocks on bank balance sheets. Our findings generalize the findings of Hong et al. (2019), which concentrates on one industry, as we deal with banks linking all market participants through credit channels. Our study is also complimentary to the work of Addoum et al. (2020), which finds no results for the impact of extreme temperatures on large corporations.

Overall, our paper has important implications for banks, regulators, and market participants and helps enhance our understanding of the impact of climate events in general and drought shocks in particular. The implications of our analysis will be increasingly intuitive for the near future as severe and extreme drought events across the US become more frequent.

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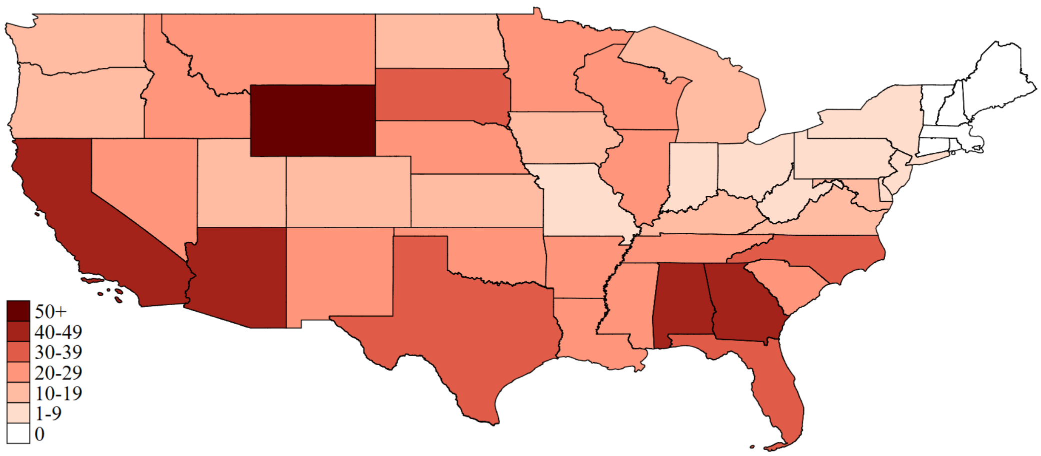
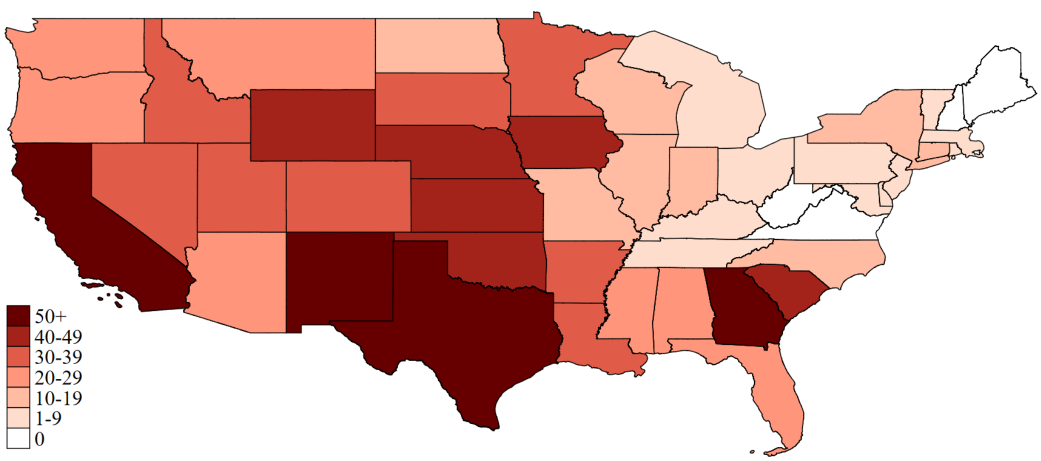
Severe and Extreme Droughts by State



(a) 2004–2010 Subperiod



(b) 2011–2017 Subperiod

Figure 1. The figure shows the frequency of severe and extreme droughts by state. Panel A presents the period between 2004 and 2010. Panel B presents the period between 2011 and 2017.

Drought Shock and Weighted PDSI of Treated and Control Banks

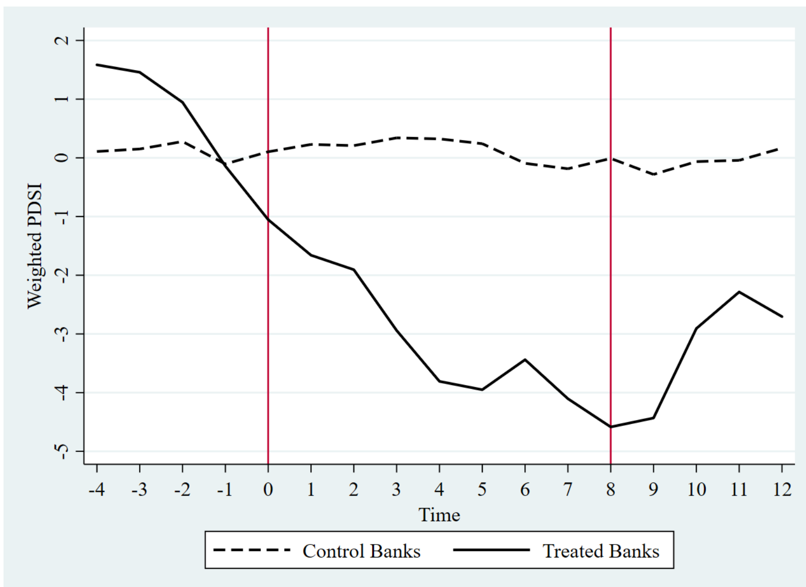


Figure 2. The figure shows the Weighted PDSI of treated and control banks determined as in Equations (2) and (3) for a two-year drought shock. Time=0 represents the starting quarter of the shock and Time=8 represents the end quarter of the shock.

Frequency of Bank-Level Drought Shocks by Year

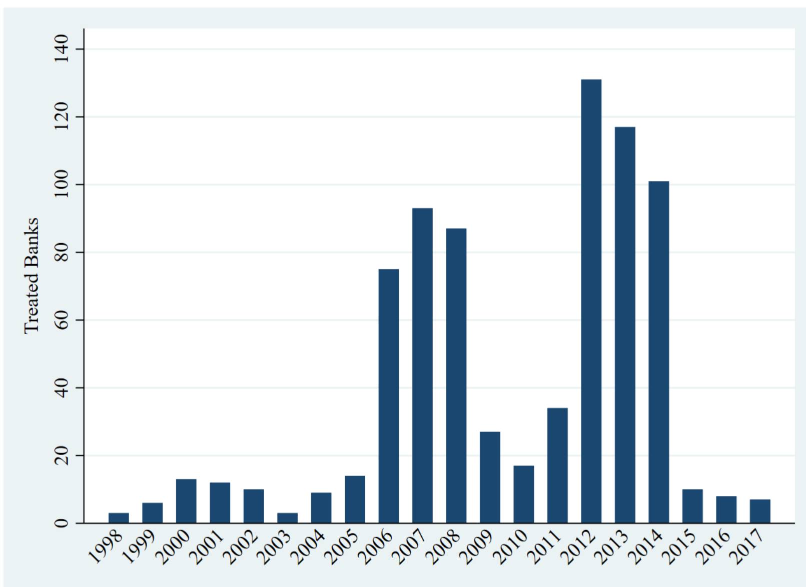
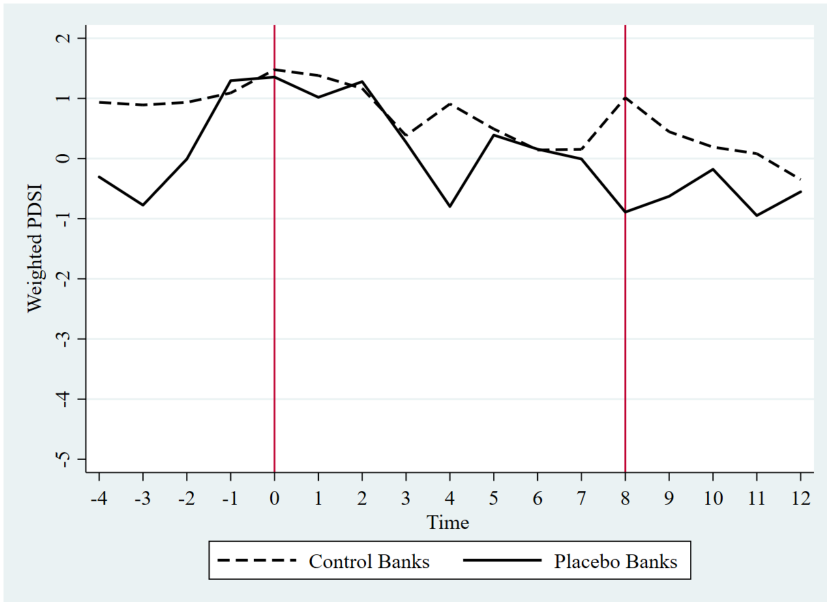
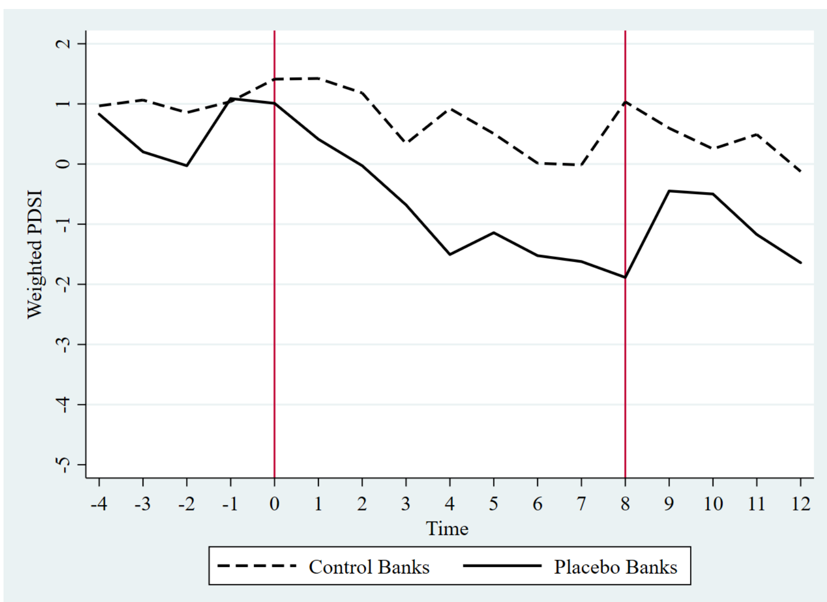


Figure 3. The figure shows the frequency of bank-level drought shocks by year measured by weighted PDSI.

Placebo Shocks



(a) Placebo Shock within Normal Range



(b) Placebo Shock to Moderate Drought

Figure 4. The figure shows the weighted PDSI of placebo and control banks. Panel A shows placebo banks determined as in Equation (5) and Panel B shows placebo banks determined as in Equation (6) and their corresponding control groups. Time=0 represents the starting quarter of the placebo shock and Time=8 represents the end quarter of the placebo shock.

Descriptive Statistics

	Treated Banks			Control Banks			Treated-Control
	N	Mean	SD	N	Mean	SD	Mean Diff
Weighted PDSI	244	-2.82	2.06	2500	0.05	1.13	-2.87
Bank Stability and Performance							
Z-Score	244	3.48	1.10	2500	3.90	1.00	-0.42
ROA Volatility	244	0.71	1.09	2500	0.42	1.18	0.29
Equity Volatility	196	1.18	0.33	1748	1.25	0.44	-0.07
NPL	244	1.68	1.80	2500	1.59	2.82	0.09
Controls							
Equity Capital	244	10.97	2.68	2500	10.23	2.49	0.74
Loans	244	0.67	0.12	2500	0.66	0.12	0.01
Assets (in logs)	244	20.22	1.57	2500	20.84	1.64	-0.62
GDP Growth	244	2.71	1.35	2500	1.65	1.39	1.06
Housing Price Index	244	1.12	1.15	2500	0.75	1.21	0.37
Home Ownership	244	60.75	7.13	2500	67.82	5.11	-7.07
Unemployment	244	7.54	1.97	2500	6.23	1.59	1.31
Subcategories of NPL							
Agricultural	76	0.67	2.67	694	1.24	4.14	-0.57
Consumer	194	0.96	4.29	1840	0.59	1.80	0.37
Residential Mortgage	194	1.24	2.24	1840	1.79	2.45	-0.55
Commercial Mortgage	194	1.99	2.44	1840	2.30	2.86	-0.31
Commercial	194	1.52	2.78	1840	1.46	2.91	0.06

Table 1. The table presents the descriptive statistics. Z-Score is defined as the natural logarithm of return on assets plus equity capital ratio divided by the standard deviation of return on assets over the last 8 quarters. ROA volatility is the standard deviation of return on assets over the last 8 quarters. Equity volatility is the volatility of the market-adjusted equity returns of the bank, computed using daily data for each quarter. NPL ratio is the summation of total non-accrual loans and total loans that are past due 90 and more days but are still accruing interest, divided by the first lag of a bank's total loans. Bank-level characteristics are asset size, equity capital to assets and loans to assets. State-level characteristics include GDP growth, housing price index return, home ownership rate, and unemployment rate. NPL ratio and its subcategories, equity capital to assets, loans to assets, GDP growth, home ownership rate, and unemployment rate are reported in percentages.

Drought Shocks and Bank Stability and Performance

VARIABLES	(1) Z-Score	(2) ROA Volatility	(3) Equity Volatility	(4) NPL
Treated Bank	0.236*	-0.172	-0.127**	-0.627***
	(1.732)	(-1.165)	(-2.315)	(-2.954)
× Post-Shock	-0.377***	0.347**	0.113***	0.398***
	(-2.972)	(2.429)	(3.592)	(2.599)
Post-Shock	-0.011	0.095	-0.001	0.043
	(-0.160)	(1.183)	(-0.033)	(0.422)
Equity Capital	0.028	0.063**	0.011*	-0.008
	(1.290)	(2.028)	(1.774)	(-0.234)
Loans	0.870**	-1.371**	0.173	-1.297*
	(2.010)	(-2.213)	(1.082)	(-1.840)
Assets	-0.131	-0.136	-0.021	0.388***
	(-1.083)	(-0.831)	(-0.556)	(2.917)
GDP Growth	0.018	-0.011	-0.019**	-0.099***
	(0.734)	(-0.365)	(-2.547)	(-3.305)
Housing Price Index	0.018	-0.116**	0.007	-0.231***
	(0.408)	(-2.280)	(0.445)	(-2.853)
Home Ownership	0.000	0.023	-0.025***	-0.114***
	(0.021)	(1.266)	(-3.151)	(-3.899)
Unemployment	-0.080*	-0.014	0.041**	0.401***
	(-1.800)	(-0.329)	(2.545)	(4.085)
Constant	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Observations	2,742	2,742	1,942	2,742
Adj. R-squared	0.594	0.433	0.742	0.845

Table 2. The table presents the results for the impact of drought shocks on bank stability and financial performance. Treated banks are the banks that are exposed to two-year drought shocks and control banks are unaffected banks during the shock period. The regressions include the last quarter (Time=0 in Figure 2) just before the shock starts and the quarter that the shock ends (Time=8 in Figure 2). Variable descriptions are as in Table 1. The regressions include state, year-quarter, and bank fixed effects. Propensity score weighting standard errors are reported in parentheses. Significance is indicated as follows: * p<0.1; ** p<0.05; *** p<0.01.

Diff-in-Diff Pre-Trend Tests

VARIABLES	(1) Z-Score	(2) ROA Volatility	(3) Equity Volatility	(4) NPL
Treated Bank	0.176*	-0.143	-0.083**	-0.557***
	(1.951)	(-1.523)	(-2.014)	(-3.262)
× Post-Shock	-0.343***	0.307**	0.081**	0.515***
	(-2.855)	(2.478)	(2.316)	(3.302)
× Pre-Shock (1 lag)	-0.076	0.025	-0.052	0.046
	(-1.039)	(0.241)	(-1.527)	(0.377)
× Pre-Shock (2 lags)	-0.029	-0.025	0.024	0.038
	(-0.434)	(-0.322)	(0.721)	(0.330)
Post-Shock	-0.069	0.184***	-0.008	0.057
	(-1.277)	(2.637)	(-0.394)	(0.675)
Pre-Shock (1 lag)	-0.088*	0.109*	-0.001	-0.065
	(-1.907)	(1.830)	(-0.040)	(-0.799)
Pre-Shock (2 lags)	-0.011	0.006	-0.023	-0.036
	(-0.247)	(0.095)	(-0.981)	(-0.454)
Constant	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Observations	5,487	5,487	3,887	5,487
Adj. R-squared	0.668	0.489	0.725	0.817

Table 3. The table presents the results for the impact of drought shocks on bank stability and financial performance. Treated banks are the banks that are exposed to two-year drought shocks and control banks are unaffected banks during the shock period. The regressions include the one-lagged and two-lagged quarters, the last quarter (Time=-2, -1, and 0 in Figure 2) just before the shock starts and the quarter that the shock ends (Time=8 in Figure 2). Variable descriptions are as in Table 1. The regressions include state, year-quarter, and bank fixed effects. Propensity score weighting standard errors are reported in parentheses. Significance is indicated as follows: * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Placebo Shocks

VARIABLES	(1) Z-Score	(2) ROA Volatility	(3) Equity Volatility	(4) NPL
	Panel A. Placebo Shock within Normal Range			
Treated Bank	-0.338*	0.087	-0.026	0.129
	(-1.718)	(1.182)	(-0.352)	(0.600)
× Post-Shock	0.153	0.002	0.026	0.119
	(1.359)	(0.021)	(0.648)	(0.957)
Post-Shock	-0.493***	0.095	0.015	-0.170
	(-2.712)	(1.081)	(0.193)	(-0.709)
Constant	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Observations	776	776	656	776
Adj. R-squared	0.507	0.498	0.629	0.901
	Panel B. Placebo Shock including moderate Drought			
Treated Bank	-0.678*	-0.082	-0.035	0.078
	(-1.951)	(-0.159)	(-0.193)	(0.295)
× Post-Shock	0.097	-0.235	0.069	0.073
	(0.664)	(-1.277)	(1.574)	(0.503)
Post-Shock	-0.361	0.222	-0.063	0.092
	(-1.251)	(0.780)	(-0.361)	(0.366)
Constant	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Observations	398	398	346	398
Adj. R-squared	0.599	0.211	0.660	0.784

Table 4. The table presents the results for the impact of placebo shocks on bank stability and financial performance. Treated banks are defined as in Equations (5) and (6). Control banks are unaffected banks during the placebo shocks. The regressions include the last quarter (Time=0 in Figure 4) just before the shock starts and the quarter that the shock ends (Time=8 in Figure 4). Variable descriptions are as in Table 1. The regressions include state, year-quarter, and bank fixed effects. Propensity score weighting standard errors are reported in parentheses. Significance is indicated as follows: * p<0.1; ** p<0.05; *** p<0.01.

Drought Shocks and Branch Closures

VARIABLES	(1) All Sample	(2) During-Shock	(3) Post-Shock
Shock	1.911***	1.445**	2.434***
	(6.046)	(2.293)	(5.984)
Equity Capital	0.981	0.914	1.064
	(-0.384)	(-0.717)	(0.638)
Loans	0.367	0.127	0.005*
	(-0.650)	(-0.622)	(-1.939)
Assets	1.521	0.809	2.761
	(1.520)	(-0.236)	(1.513)
GDP Growth	0.926	0.613*	0.873
	(-0.973)	(-1.745)	(-0.955)
Housing Price Index	1.025	0.679	1.773**
	(0.225)	(-1.221)	(2.569)
Home Ownership	1.265**	1.075	1.289**
	(2.076)	(0.219)	(2.029)
Unemployment	0.978	0.720	1.003
	(-0.120)	(-0.410)	(0.010)
Constant	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Observations	10,838	3,386	6,149

Table 5. The table presents the logistic regression of branch closure probability. We test whether treated banks that are exposed to drought shocks are more likely to close any branch in an affected climatological division. Odds ratios are presented instead of coefficients. Heteroskedasticity-robust standard errors are reported in parentheses. Significance is indicated as follows: * p<0.1; ** p<0.05; *** p<0.01.

Drought Shocks and Subcategories of NPLs

VARIABLES	(1) Agricultural	(2) Consumer	(3) Residential Mortgage	(4) Commercial Mortgage	(5) Commercial
Treated Bank	-1.107	-0.085	-0.898**	-0.853*	-0.775
	(-1.554)	(-0.187)	(-2.263)	(-1.853)	(-1.196)
× Post-Shock	1.143**	0.378	0.373**	0.658***	0.913***
	(2.335)	(0.874)	(2.194)	(2.829)	(3.116)
Post-Shock	-0.026	0.106	0.031	-0.101	0.236
	(-0.030)	(0.466)	(0.258)	(-0.604)	(1.022)
Equity Capital	0.154	0.006	0.173	-0.086	0.090
	(0.741)	(0.131)	(1.366)	(-1.326)	(1.595)
Loans	10.728	-2.975	-1.537	-3.621***	-2.379
	(1.567)	(-0.806)	(-1.005)	(-2.591)	(-1.373)
Assets	-0.007	-0.044	0.259	0.779**	0.051
	(-0.004)	(-0.115)	(1.295)	(2.171)	(0.106)
GDP Growth	-0.089	-0.055	0.084	-0.173***	-0.192***
	(-0.824)	(-0.770)	(1.165)	(-2.909)	(-2.623)
Housing Price Index	0.141	-0.143	-0.245***	-0.362***	0.013
	(0.576)	(-1.153)	(-2.583)	(-2.783)	(0.104)
Home Ownership	-0.153	-0.102	-0.028	0.025	-0.021
	(-0.560)	(-1.436)	(-0.500)	(0.394)	(-0.238)
Unemployment	0.229	0.043	0.333***	0.438***	-0.267
	(0.760)	(0.274)	(3.432)	(3.227)	(-1.456)
Constant	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Observations	768	2,029	2,029	2,029	2,029
Adj. R-squared	0.329	0.574	0.641	0.648	0.384

Table 6. The table presents the results for the impact of drought shocks on the categories of NPL, that are NPLs of agricultural loans, consumer loans, residential mortgages, commercial mortgages, and commercial loans. Treated banks are the banks that are exposed to two-year drought shocks and control banks are unaffected banks during the shock period. The regressions include the last quarter (Time=0 in Figure 2) just before the shock starts and the quarter that the shock ends (Time=8 in Figure 2). Variable descriptions are as in Table 1. The regressions include state, year-quarter, and bank fixed effects. Propensity score weighting standard errors are reported in parentheses. Significance is indicated as follows: * p<0.1; ** p<0.05; *** p<0.01.

Appendix

Drought Shocks
(OLS Estimations)

VARIABLES	(1) Z-Score	(2) ROA Volatility	(3) Equity Volatility	(4) NPL
Treated Bank	0.029	-0.094	-0.163***	-0.720***
	(0.224)	(-0.540)	(-2.931)	(-3.649)
× Post-Shock	-0.262**	0.261*	0.068*	0.597***
	(-2.286)	(1.720)	(1.690)	(3.476)
Post-Shock	0.042	-0.001	0.005	0.029
	(0.653)	(-0.013)	(0.200)	(0.304)
Equity Capital	0.042***	0.062***	0.004	-0.038*
	(3.213)	(3.565)	(0.798)	(-1.941)
Loans	0.582*	-1.452***	0.046	-1.792***
	(1.911)	(-3.606)	(0.362)	(-3.924)
Assets	0.050	-0.327***	-0.017	0.149
	(0.753)	(-3.747)	(-0.604)	(1.503)
GDP Growth	0.026	-0.041*	-0.010	-0.102***
	(1.434)	(-1.733)	(-1.355)	(-3.795)
Housing Price Index	0.018	-0.036	0.016	-0.109**
	(0.569)	(-0.845)	(1.326)	(-2.232)
Home Ownership	-0.010	0.014	-0.019***	-0.075***
	(-0.634)	(0.684)	(-2.610)	(-3.122)
Unemployment	-0.117***	0.038	0.034**	0.426***
	(-3.081)	(0.752)	(2.299)	(7.464)
Constant	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Observations	2,742	2,742	1,942	2,742
Adj. R-squared	0.496	0.349	0.735	0.846

Table A1. The table presents the results of OLS estimation for the impact of drought shocks on bank stability and financial performance. Treated banks are the banks that are exposed to two-year drought shocks and control banks are unaffected banks during the shock period. The regressions include the last quarter (Time=0 in Figure 2) just before the shock starts and the quarter that the shock ends (Time=8 in Figure 2). Variable descriptions are as in Table 1. The regressions include state, year-quarter, and bank fixed effects. Heteroskedusticity-robust standard errors are reported in parentheses. Significance is indicated as follows: * p<0.1; ** p<0.05; *** p<0.01.

Drought Shocks in Non-Hurricane Regions

VARIABLES	(1) Z-Score	(2) ROA Volatility	(3) Equity Volatility	(4) NPL
Treated Bank	0.210	-0.128	-0.116**	-0.516**
	(1.489)	(-1.136))	(-2.049)	(-2.424
× Post-Shock	-0.334**	0.308**	0.122***	0.301**
	(-2.496)	(2.030)	(3.556)	(2.005)
Post-Shock	-0.012	0.121	0.001	0.022
	(-0.184)	(1.575)	(0.033)	(0.229)
Equity Capital	0.031	0.046*	0.011	0.015
	(1.459)	(1.858)	(1.577)	(0.473)
Loans	1.039**	-1.128** *	0.192	-1.700*
	(2.127)	(-2.420)	(0.996)	(-2.369)
Assets	-0.042	-0.174	-0.051	0.415***
	(-0.389)	(-1.015)	(-1.291)	(2.882)
GDP Growth	0.012	0.004	-0.013	-0.068**
	(0.453)	(0.105)	(-1.534)	(-2.329)
Housing Price Index	0.006	-0.137**	0.000	-0.269***
	(0.123)	(-2.527)	(0.024)	(-3.537)
Home Ownership	0.001	0.029	-0.023***	-0.116***
	(0.051)	(1.624)	(-2.600)	(-3.828)
Unemployment	-0.052	-0.060	0.040**	0.286***
	(-1.082)	(-1.279)	(2.202)	(3.402)
Constant	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Observations	2,336	2,336	1,648	2,336
Adj. R-squared	0.594	0.456	0.744	0.878

Table A2. The table presents the results for the impact of drought shocks on bank stability and financial performance using the sample excluding hurricane-exposed states. Treated banks are the banks that are exposed to two-year drought shocks and control banks are unaffected banks during the shock period. The regressions include the last quarter (Time=0 in Figure 2) just before the shock starts and the quarter that the shock ends (Time=8 in Figure 2). Variable descriptions are as in Table 1. The regressions include state, year-quarter, and bank fixed effects. Propensity score weighting standard errors are reported in parentheses. Significance is indicated as follows: * p<0.1; ** p<0.05; *** p<0.01.