

# **Spillover Effects of Climatological Disasters: Evidence from Drought and Bank Balance Sheets**

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## **Abstract**

Recently, regulators and financial institutions heavily discuss to develop stress tests to understand impact of climate risk on bank balance sheets. In this paper, we concentrate on the impact of drought on balance sheets of banks, which are at the core of economic activity. Our findings demonstrate that drought has a significant impact on banks' Z-score, ROA, the efficiency ratio and the nonperforming loan to total asset ratio extending over a long period of time. Overall, a one-standard-deviation increase in weighted PDSI averaged by 60 months, indicating increased long-term drought worsens Z-score, ROA, and the efficiency ratio by 0.035, 0.046, and 0.80, respectively. More importantly, our detailed analysis on nonperforming loans shows that agricultural production loans and farm loans are not significantly affected by drought possibly due to hedging. However, residential and consumer loans to economic participants that are not directly exposed to observable damage from drought are negatively affected by long-term drought. This finding indicates long-term spillover effects of climatological disasters.

*Keywords:* Climate, Disaster, Drought, Bank performance, Bank balance sheets, Nonperforming loans

## 1. Introduction

With the consequences of climate change being visible on a daily basis, impact of climate shocks on economies constitutes serious risks and financial institutions are not ambivalent about them. Recently, financial companies and regulators work towards the assessment of climate risks and transparent disclosure policies. For instance, the Task Force on Climate-related Financial Disclosures (TCFD) established up by the G20's Financial Stability Board (FSB) in 2015 issues a report with the recommendations regarding climate-related risk disclosures. Following the TCFD's framework and under the coordination of the United Nations Environment Programme-Finance Initiative, 16 major global banks develop a report issued in July 2018 on assessing climate-driven credit risk.

In a similar vein, financial regulators are also concerned about the evaluation of climate risk in the financial system. In April 2019, the Network for Greening the Financial System (NGFS), a coalition of 34 central banks releases their first report on climate-related financial risks and calls out central banks and bank supervisors to integrate climate-related risks into financial stability monitoring and micro-supervision. Several targeted initiatives are followed upon the TCFD's recommendations for climate risk disclosure policies.

Due to continuous increase in temperatures, drought has also started to become an important phenomenon. Relatedly, the United Nations' Natural Capital Financial Alliance, collaborating with several banks from Brazil, China, Mexico, and the United States, develop a stress testing tool *specifically for drought risk*. In the stress test, the impact of drought scenarios on companies borrowing from banks is assessed and associated loss and default risk of such companies are aggregated at banks' loan portfolios.

Although there are such efforts on the measurement of climate risks in general and droughts in particular on bank balance sheets, there is no systematic empirical study analyzing the impact of climate risk on banks. Moreover, while studying banks on their own is important as banks play a crucial role in the financial system, banks' balance sheets are particularly interesting as they reveal information regarding the impact of climate shocks on local economies.

Climate shocks or risks are local in nature. Thus, understanding the geography of the shocks and the economic entities exposed to those shocks is crucial. We utilize the geography of bank branches and their deposits to create a measure to quantify bank exposure to local climate shocks. Potentially, bank exposure to climate shocks also reflect the local economic' exposure to such

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 under-diversified geographically and they originate loans locally. (Petersen and Rajan, 2002 and Agarwal and Hauswald, 2010). Since such under-diversified banks mainly deal with local firms, these firms are more likely to be the firms that suffer from climate shocks. Especially, small firms tend to operate in fewer regions and are more exposed to regional shocks, compared to large firms. Importantly, small firms also mainly rely on bank loans for external funding (Berger and Udell, 1998 and Petersen and Rajan, 1994). All in all, we expect that bank balance sheets well reflect the impact of climate shocks to local economies and offer us a setup to analyze the impact of such climate shocks to local economies.

Hong, Li and Xu (2019) are among the first to evaluate the economic and financial impact of drought on food companies. The authors find that drought has a negative impact on the profitability of food companies using the Palmer Drought Severity Index (PDSI). Constructing 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, they document that such a portfolio generates an annualized return of 7%. This indicates that investors are not aware of the impact of persistent drought on the performance of food companies as this negative impact is not priced.

In another study of climate shocks on firms, Addoum, Ng, and Ortiz-Bobea (2019) evaluate the impact of extreme temperatures on the local establishments of US public firms. In general, authors do not document any significant impact. The authors explain this non-result by stating that public firms are big and diversified enough to offset the negative impacts of extreme temperatures, as they only study public firms.

In this study, we investigate the impact of drought on the performance of banks. Investigating the impact of drought on bank's balance sheets is important from various aspects. Firstly, as any firm or household borrows from banks, banks are at the core of the economic activity and all entities of the economy are connected through banks. This gives us the opportunity to evaluate the impact of drought on various market participants through bank balance sheets but not only looking into one industry such as the food industry as in Hong, Li and Xu (2019). To further investigate the issue, we also document cross-sectional variation in the NPLs by looking into various types of loans. This way, our findings can shed light on spillover effects on market participants that are not directly exposed to physical damage of climatological disasters such as drought.

Secondly, 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. Thirdly, we deal with public and private banks, which can contribute to the debate by not only looking at large corporations as opposed to Addoum, Ng, and Ortiz-Bobea (2019). Additionally, bank balance sheets also reflect the impact on small companies.

Fourth, most studies in the literature concentrate on floods and hurricanes as the damage by such disasters are observable. On the other hand, we concentrate on drought, where the effects can be difficult to observe in the short term and extends over a longer period of time. Our paper can contribute to the debate in the existing literature on the impact of climate proxied by flood (Atreya and Ferreira, 2015; Murfin and Spiegel, 2018; Keenan, Hill, and Gumber, 2018, and Bernstein, Gustafson, and Lewis, 2018; Eichholtz, Steiner, and Yönder, 2020).

Bank of America Merrill Lynch estimates the economic cost of the drought in 2015 to be US\$2.7 billion. Banks can be affected by drought through both industrial or household effects. At the industry side, extreme temperatures increasing the likelihood of extreme drought have been studied. Extreme temperature negatively impacts labor supply (Graff-Zivin and Neidell, 2012, 2014), agricultural industry including food companies (Hong, Li and Xu, 2019), and light manufacturing and service industries (Jones and Olken, 2010; Dell, Jones, and Olken, 2012). Additionally, firms in utilities industry are affected directly from water shortages and other industries are affected indirectly through increasing costs such as electricity prices.<sup>1</sup>

Industries that are not directly affected by drought or water shortage can still be affected by reductions in output from directly affected industries. 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. For instance, workers losing jobs or suffering income loss can fail to pay their mortgages. This is especially likely for

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<sup>1</sup> Drought impacts utility firms in two ways. Electricity production relies on hydropower which is dependent on reservoir water levels and are negative 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 citing fire liabilities. For more details, please see <https://www.nytimes.com/2019/01/29/business/pge-bankruptcy.html?>

workers in firms in agriculture and food industries. Even if an agricultural firm is insured against certain climate shocks and thus receive some relief with insurance payments, some business activity will still be lost: workers will not pick up berries and not receive salaries, catering firm 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 very likely.

We first quantify the effect of drought on the level of bank's financial distress using its Z-score as a proxy, bank's return on assets, and the efficiency ratio. Then, we further address the issue by looking into the performance of different types of loans. This enables us to document cross-sectional variation across different participants of the economy.

Consumer loans can be affected through the impact on the labor market in the industries that are affected directly by drought. Similarly, the performance of commercial loans is also affected especially for such affected firms and connected firms to those that are directly affected by drought.

At the center of this cycle lies the banking industry, which is a main source of credit in economy. All these effects on different market participants can add up to a significant impact on banking industry and banks' financial performance and their ability to collect debt payments. More specifically, a natural disaster such as a drought might decrease bank's performance and increase the percentage of NPLs credited to companies and residents in areas that are prone to such a disaster. In this respect, we generalize the study of Hong, Li and Xu (2019) by evaluating the impact of drought in a broader context using bank balance sheets than just looking into one sector such as food industry.

Additionally, in the banking literature, there has not been sufficient evidence on how banks are affected by climate in the long term. The focus is on natural disasters, in general, and hurricanes and storms, in particular (Klomp, 2014; Bos, Li, and Sanders, 2018). To our knowledge, this is the first study that thoroughly analyzes the impact of drought on the performance of banks. We also contribute to the debate arising from the non-results of Addoum, Ng, and Ortiz-Bobea (2019) on large public firms as in our case, the impact of climate on small private companies are reflected into bank balance sheets and we also evaluate more regional private banks.

Banks are geographically dispersed, and our data on the US banks provide us with the exact coordinates of each branch. Using branches as a geographic tool, we identify the climatological location of each branch using GIS approaches. We then calculate a weighted average drought score for each bank every year to proxy a bank's exposure to drought. In addition, banks issue loans in

different categories including real estate, consumer, commercial, and agricultural production. This diversity of bank loans creates multiple channels to analyze the impact of drought risk on economy and particularly on banks and facilitates a more comprehensive evaluation compared to the existing banking literature. Our paper contributes the current debate by precisely identifying the loan categories that are affected from drought. Our findings shed light on whether there are long-term spillover effects from directly affected companies, which are exposed to observable damage to other market participants.

Our findings indicate that long-term drought (from 12 months to 60 months) significantly decreases Z-score, ROA, and the efficiency ratio. A one-standard-deviation decrease in the weighted average PDSI by 60-months, indicating higher drought, decreases Z-score by 0.035, ROA by 0.046, and increases the efficiency ratio by 0.80. Importantly, the impact of drought monotonically becomes more prominent if we measure drought using 12-month average to 60-month average indicating that the impact of drought becomes more evident in the longer-term.

We next analyze nonperforming loans (NPLs). NPL data help us evaluate cross-sectional variation in the impact of drought on bank balance sheets as we have a more comprehensive data on NPLs. We first show that drought affects NPLs. A one-standard-deviation decrease in the weighted average PDSI increases the share of NPLs in total loans by 0.9% relative to mean of the NPL ratio if we measure by 60-month average of drought. We also evaluate the stages of delinquency. Our findings demonstrate that exposure to drought increases the ratio of NPLs that are past due between 30 to 90 days by 1.7%, and non-accrual loans by 1.5% relative to mean of the NPL ratio.

Among different types of loans, we find stronger impact of drought on real estate loans and consumer loans. While we find a weaker link for commercial loans, we do not find any impact on agricultural loans. This may potentially indicate that agricultural companies insure themselves against the impact of drought while there are still spillover effects especially on real estate loans and consumer loans. We also decompose real estate loans and our findings demonstrate that residential loans are strongly affected by drought indicating spillover effects. We do not find any significant impact of drought on farm loans. This again reflects a potential hedging by farmers.

Overall, our analyses consistently show that bank balance sheets are affected by long-term drought. In Section 2, we discuss our data and model. Then, we document our empirical findings in Sections 3, 4, and 5. In the final section, we conclude.

## 2. Data and Model

Among natural disasters amplified by climate change, we focus on drought and its impact on bank performance. We are motivated by Hong, Li, and Xu (2019), who investigate the impact of drought measured by PDSI on food companies' financial performance. PDSI is a comprehensive monthly index created by Palmer in 1965 and modified later by other researchers. 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.

We obtain PDSI data from the US National Oceanic and Atmospheric Association (NOAA). The data are reported monthly for each climate division in the contiguous US. The contiguous US consists of the 48 adjoining US states (plus Washington DC) and excludes the non-contiguous states of Hawaii and Alaska, and all off-shore insular areas. Climatologists divide contiguous US into 344 climate divisions. For each climate division, monthly station temperature and precipitation values are computed from daily observations. Divisions within each state are defined based on average state of climate. Except Rhode Island (one division), each state is divided into two to 10 divisions based on within-state climate variation. The data are provided by the National Center for Environmental Information (NCEI) of the US National Oceanic and Atmospheric Administration (NOAA) with the aim of interpreting and applying scientific understanding of climate change dynamics at state and country level. To evaluate the impact of long and short-term droughts, we average PDSI measures on the last 12, 24, 36, 48 and 60 months.

SNL Financial provides information on banks' branches such as location, deposit size of each branch. Using information on the location of each branch, specifically their coordinates, we first determine in which climatological division a bank's branch is so that we can assign a PDSI score for each branch. Then, for each quarter, weighting by the deposit size of each branch, we create a weighted PDSI for each bank for each year in our sample as presented in the formula below:

$$(1) \textit{Weighted PDSI}_{it}^n = \frac{\sum_{t-N}^{t-1} \sum_j (\textit{Deposits}_{ijt} * \textit{PDSI}_{ijt})}{\textit{Deposits}_{it}} / N$$

where  $i$  stands for Bank  $i$ ,  $j$  stands for Branch  $j$ ,  $t$  stands for quarter  $t$ , and  $n$  stands for the period ( $N$  quarters= $M$  months) that we average weighted PDSI.

Our weighted PDSI measure reflects the exposure of each bank to drought in a given quarter. Panel A of Table 1 summarizes the characteristics of PDSI weighted by branch deposits. PDSI at 12 months has the highest mean (0.11) and standard deviation (1.89). The standard deviation decreases as we average for longer period. PDSI at 60 months has a mean of 0.08 and a standard deviation of 1.13.

We also obtain financial data such as Z-score components, ROA, efficiency ratio, NPL and fundamentals from SNL Financial. SNL Financial provides the main type of loans and their subcategories for branches of major banks in the US from 1998 to 2017, quarterly. SNL Financial mainly covers categories such as real estate loans including farm loans, loans secured by family residential properties, and construction and land development loans, consumer loans, commercial loans, and agricultural production loans. Panel B of Table 1 summarizes the characteristics of our dependent variables. The mean Z-score, ROA, and efficiency ratio is 1.93, 0.78 and 0.67, respectively. The overall NPL ratio is 3%. The banks in our sample are in the grey-zone of Z-score, are profitable, and have high overhead cost.

In the finance literature, NPLs are defined as loans whose payments are past due more than 3 months and that in the worst-case scenario turn into a non-accrual loan and then a write-off by bank. In addition to this narrow definition, we consider loans that are past due between 1 to 3 months. This category, especially, is important for our analysis. In terms of different stages of delinquency, we have the following categories for NPLs: Loans that are past-due more than 30 days and less than 90 days and bank accrues interest on them, loans that are past-due more than 90 days and like with the first category, bank still accrues interest on them, and non-accrual loans that are past-due more than three months and bank no longer accrues interest on them. The ratio for loans that are past due between 30 to 90 days is 1%, for loans that are past due more than 90 days is close to zero, and for non-accrual loans is 1%.

– Insert Table 1 here –

We relate our weighted PSDI score to Z-score, ROA, efficiency ratio, and the NPL ratio in a given quarter. We also analyze the impact of our weighted PDSI measure separately on four different categories of NPLs: Real estate loans including loans secured by farm lands, loans secured by family residential properties, and construction loans; consumer loans; commercial



loans, and agricultural production loans. This will help us have a better understanding of the source of any potential impact of drought on the banking sector and document cross-sectional variation. We concentrate on the US market as there are more available data on banks' loan performance (especially NPL) and the drought index within the US.

We obtain our final sample by merging PDSI data with bank financial data, branch data, and the control variables. We limit our sample to banks with available Bank Holding Company (BHC) identification number. Each BHC may have different branches in different climate divisions. Our final merged sample includes 42,335 quarter observations of NPLs under 713 distinct BHCs. We estimate the following model using ordinary least squares in order to demonstrate the impact of drought risk exposure on Z-score, ROA, and efficiency ratio:

*(2) Bank Performance = f(Weighted PDSI, Bank Characteristics, and State Controls)*

In various regressions, we use Z-score, ROA, and the efficiency ratio as the dependent variable. We regress each of these variables on the weighted PDSI measures (WPDSI) from 12 months to 60 months as independent variable and the control variables. We expect that as PDSI decreases indicating increase in drought, the dependent variables should worsen.

The Z-score is used to estimate the likelihood of financial distress and distance from bankruptcy. For non-manufacturing firms, including banks, it is a weighted average of 4 business ratios as follows:  $6.56 T_1 + 3.26 T_2 + 6.72 T_3 + 1.05 T_4$ , where  $T_1$  is working capital divided by total assets;  $T_2$  is retained earnings divided by total assets;  $T_3$  is earnings before interest and tax divided by total assets, and  $T_4$  is the book value of equity divided by total liabilities. We expect that as PDSI decreases (more drought), the Z-score decreases, and firm experiences increased likelihood of financial distress. We expect that as drought intensity increases, the profitability of banks proxied by ROA decreases.

Finally, the efficiency ratio is calculated as noninterest expense divided by the sum of net interest income and noninterest income (Houston, James, and Ringaert, 2001). The lower the ratio, the higher is the bank's efficiency and cost-saving. This ratio is a direct measure of a bank's ability to turn resources into revenue. An increase in the efficiency ratio indicates either increasing costs or decreasing revenues. So, we expect that as PDSI goes down, the efficiency ratio increases

indicating a decrease in the efficiency and cost-saving ability of banks. We further evaluate the impact of drought risk exposure on NPL ratios, and estimate the following model:

$$(3) \text{ NPL Ratio} = f(\text{Weighted PDSI}, \text{Lagged NPL Ratio}, \text{Bank Characteristics}, \text{and State Controls})$$

NPL is generally persistent implying that it takes time for the credit shock to materialize on bank loan performance (Klein, 2013). To address this issue, we add the first lag of the dependent NPL ratio as a control variable on the right-hand side. We estimate NPL ratio for different loan categories. This helps us evaluate the cross-sectional variation across different loan types and have better understanding on the channels how bank balance sheets can be affected from drought.

We regress NPL ratio on weighted PDSI measures (WPDSI) from 12 months to 60 months. We expect that if there is more drought risk exposure geographically, the NPL to total loans ratio increases. We also use NPL ratio for the categories mentioned above as dependent variables. Naturally, agricultural and farm loans are expected to be more affected by drought than residential real estate, commercial and consumer loans because they are directly affected by drought if they are not hedged. On the other hand, the spillover effects on the residential real estate, consumer and industrial loans might also affect our findings on these loans as consumers and firms that are not directly exposed to physical damage from drought but not hedged against climate risk.

As our drought risk exposure measure can be expected to be correlated with economic and geographic determinants, we use a large set of controls at bank and state level. The bank-level control variables are equity capital to total assets, loan loss provision to total assets, non-interest expense to total assets, total loans and leases to total assets, return on average assets to total assets, and the natural logarithm of total assets. The state-level control variables are GDP growth, inflation-adjusted percent change in personal income, percentage change in Housing Price Index, homeownership rate, and unemployment rate. Panel C of Table 1 summarizes the characteristics of all control variables in our model. We cluster standard errors at bank level and control for year-quarter fixed effects.

### **3. Drought and Bank Financial Performance**

In this section, we evaluate the impact of drought on bank financial performance proxied by Z-score, ROA, efficiency ratio, NPL ratio to total loans. Table 2 presents the results for the regression

of Z-score on drought intensity. In all columns, the coefficients of weighted PDSI are positive and increase monotonically as we measure drought averaging by 12 months to 60 months. This implies that drought has a significantly negative impact on Z-score and more importantly, as we average drought for a longer period, the negative impact becomes statistically and economically more evident. When we measure weighted PDSI by 60 months, one-standard-deviation decrease in weighted PDSI decreases Z-score by 0.035.

– Insert Table 2 here –

Table 3 presents the results for the estimation of ROA on weighted PDSI measures. In all regressions, we find that increase in drought lowers the profitability of banks. The negative impact of drought on ROA also becomes monotonically increasing as we measure drought by a longer period. In the longest period in our sample, a one-standard-deviation decrease in weighted PDSI measured by 60 months indicating increased drought results in a decline in ROA by 0.046.

– Insert Table 3 here –

We also evaluate the impact of drought on efficiency ratio as shown in Table 4. The results confirm our expectations that drought decrease efficiency ratio. In line with Z-score and ROA, we observe that coefficients of weighted PDSI across regressions are monotonically decreasing. Economically, a one-standard-deviation decrease in weighted PDSI decreases bank efficiency ratio by 0.008, resulting in less efficiency.

– Insert Table 4 here –

Lastly, we investigate the effect of drought on the NPL ratio to total loans. Table 5 presents the results. The results are similar to Z-score, ROA, and efficiency ratio regressions. A decline in weighted PDSI measured for 60 months by one standard deviation increases NPL ratio by 0.9% relative to sample mean of NPL. Overall, our findings demonstrate that drought has a negative impact on bank financial performance. The long-term impact of drought is more prominent,

especially if we measure drought for 60 months. Our results reflect that although the impact of drought is slow by its nature, there is a strong negative impact of drought in the long run.

– Insert Table 5 here –

## **4. Cross-Sectional Variation across Loan Types**

### *4.1. Stages of delinquency*

In this subsection, we first evaluate how the impact of drought differs across different stages of delinquency. Table 6 reports the regressions for loans that are past-due more than 30 days and less than 90 days (Panel A); loans that are past-due more than 90 days and that bank still accrues interest on them (Panel B); and non-accrual loans that are past-due more than 90 days and that bank no longer accrues interest on them (Panel C). We name them as first-stage, second-stage and third-stage NPLs, respectively. Dependent variables are the ratio of each of these different stages of loans divided by total loans each quarter.

Our findings demonstrate that NPLs that are in the first and third stages are significantly affected by drought. Similar to our findings in the previous section, as we measure drought by a longer term, the economic significance of our results monotonically increases. When weighted drought measured by 60 months, a one-standard-deviation increase in weighted PDSI decreases, first-stage NPL ratio by 1.7% and the ratio for non-accrual loans by 1.5%, relative to mean. Results for the second-stage NPLs are not significant. This can potentially indicate that drought affects borrowers negatively in the first stage. Some of these borrowers may be able to recover and repay their loans before or during the second stage while for others, NPL may eventually turn into a non-accrual loan. In the worst-case scenario, this can result with a write-off by the bank.

– Insert Table 6 here –

### *4.2. Variation across loan types*

We also decompose NPLs across different loan types. We aim to evaluate whether the impact of drought spills over to other market participants besides farm and agriculture. Table 7 shows the results for different loan categories including real estate, consumer, commercial, and agricultural loans. Our findings demonstrate that there is no significant impact of drought on agricultural

production loans. The insignificant impact is potentially due to hedging opportunities as agricultural production is directly exposed to drought so food and agricultural companies can hedge against fluctuations in the agricultural product prices.

On the other hand, we find significant effect of drought on real estate, consumer loans, and commercial loans especially when we average weighted PDSI by 60 months. As weighted PDSI by 60 months decreases by one standard deviation, the NPL ratio for real estate and consumer loans increases by 0.7% and 1.6% respectively, relative to mean.

These findings demonstrate that there are spillover effects to the other parts of the economy, which are not directly exposed to drought and accordingly not hedged. To our knowledge, our results may also be the first in the literature to indicate that there are economic effects of natural disasters such as flood, earthquake, hurricane, and drought on economic participants that are not physically exposed to such disasters.

– Insert Table 7 here –

#### *4.3. Variation across real estate loans*

Our analysis has shown that real estate loans bear the most economically significant impact from long-term drought across different loan types. In this subsection, we decompose real estate loans by further analyzing its sub-categories: farm loans, family residential loans, and loans for construction and land development. Our findings in Table 8 show that only residential family loans are significantly affected by the negative impact of drought. A one-standard-deviation decrease in weighted PDSI by 60 months, NPL ratio increases by 0.8%.<sup>2</sup> Farm loans, similar to loans for agricultural production, are not affected by drought potentially due to hedging. Construction and land development loans are also not affected by drought. This may be due to that construction loans have a shorter-term maturity relative to the long-term nature of drought. On the other hand, real estate loans have longer maturity, which can be more affected by drought.

– Insert Table 8 here –

### **5. Robustness Tests**

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<sup>2</sup> Unreported regressions also demonstrate monotonicity averaging weighted PDSI across different time intervals.

As we discuss before, in order to address the issue of persistency in NPLs, we control for the first lag of each NPL ratio. Another approach would be to control for the lag that is exactly one quarter before the starting quarter of the averaging of weighted PDSI so the period covering weighted PDSI measure does not overlap with the lagged NPL ratio. Panel A of Table 9 presents the results for this approach. Compared to Table 1, results become even more significant.

As an additional robustness check, we use bank fixed effects in our regressions to capture the impact of any unobservable firm characteristics. Panel B of Table 9 shows the results. Our results are also robust to the inclusion of bank fixed effects.

– Insert Table 9 here –

## **6. Concluding Remarks**

There is an increasing debate on the long-term impact of climatological disasters. Most studies evaluate the impact of flood or hurricanes (Atreya and Ferreira, 2015; Murfin and Spiegel, 2018; Keenan, Hill, and Gumber, 2018, and Bernstein, Gustafson, and Lewis, 2018; Eichholtz, Steiner, and Yönder, 2020), which in general have a direct physical damage. On the other hand, the effect of drought extends over a longer period of time. In this project, we evaluate the impact of drought on bank balance sheets. We evaluate banks due to the fact that they are at the core of economic activity and different market participants are connected through banks.

Overall, we find that there is a significant negative impact of drought on Z-score, ROA, and bank efficiency. The economic impact becomes more prominent as we measure drought for a longer time period up to 60 months. These results show that long-term drought has a significant impact on bank balance sheets.

Then, we turn our attention to NPLs. Our data cover different types of NPL, which give us the opportunity to explore cross-sectional variation in the impact of drought across the types of loans. Our findings demonstrate that agricultural production and farm NPLs are not significantly affected by drought. Since drought has a direct observable effect on agricultural production and farms, such market participants can hedge against drought. On the other hand, we find strong evidence for the impact of long-term drought on residential loans and consumer loans. These findings indicate that there are long-term spillover effects to the market participants that are not exposed to direct physical damage from climatological disasters such as drought.

To our knowledge, this is the first study documenting such spillover effects extending over a longer period of time. Our findings also contribute to the banking literature by documenting effects of climate on bank balance sheets. Our results also reflect important implications to policy makers and contribute to the debate on the long-term economic and financial impact of climate.

## References

- Agarwal, S. and Hauswald, R. 2010. "Distance and Private Information in Lending". *The Review of Financial Studies*, 23: 2757-2788.
- Atreya, A. and Ferreira S. 2015. "Seeing is Believing? Evidence from Property Prices in Inundated Areas". *Risk Analysis*, 35: 828–848.
- Berger, A. N. and Udell, G. F. 1998. "The Economics of Small Business Finance: The Roles of Private Equity and Debt Markets in the Financial Growth Cycle". *Journal of Banking and Finance* 22: 613-673.
- Bernstein, A., Gustafson M., and Lewis R. 2018. "Disaster on the Horizon: The Price Effect of Sea Level Rise". *Journal of Financial Economics*, Forthcoming.
- Bos, J., Li, R., and Sanders, M. 2018. "Hazardous Lending: The Impact of Natural Disasters on Banks' Asset Portfolio". *Working Paper*, Graduate School of Business and Economics, Maastricht University.
- Dell, M., Jones, B. F. and Olken, B. A. 2009. "Temperature and Income: Reconciling New Cross-sectional and Panel Estimates". *American Economic Review*, 99: 198– 204.
- Eichholtz, P., Steiner, E., and Yönder, E. 2020. "No Shelter from the Storm: Hurricanes and Commercial Real Estate Values", *Working Paper*.
- Graff-Zivin, J. and Neidell, M. 2012. "The Impact of Pollution on Worker Productivity". *American Economic Review*, 102: 3652–3673.
- Graff-Zivin, J. and Neidell, M. 2014. "Temperature and the Allocation of Time: Implications for Climate Change". *Journal of Labor Economics*, 32: 1–26.
- Hong, H., Li, F. W., and Xu, J. 2019. "Climate Risks and Market Efficiency". *Journal of Econometrics*, Forthcoming.
- Houston, J. F., James, C. M., and Ryngaert, M. D. 2001. "Where Do Merger Gains Come From?" *Journal of Financial Economics*, 60: 285-331.
- Jones, B. F. and Olken, B. A. 2010. "Climate Shocks and Exports". *American Economic Review*, 100: 454–459.
- Keenan, J. M., Hill T., and Gumber A. 2018. "Climate Gentrification: From Theory to Empiricism in Miami-Dade County, Florida". *Environmental Research Letters*, 13: 054001.
- Klein, N. 2013. "Non-performing Loans in CECEE: Determinants and Macroeconomic Performance". *Working Paper*, International Monetary Fund.



Klomp, J. 2014. "Financial Fragility and Natural Disasters: An Empirical Analysis". *Journal of Financial Stability*, 13: 180 -192.

Murfin, J. and Spiegel M. 2018. "Is the Risk of Sea Level Capitalized in Residential Real Estate?" *Review of Financial Studies* Climate Finance Call, Conditionally Accepted.

Petersen, M. A. and Rajan, R. G. 1994. "The Benefits of Lending Relationships: Evidence from Small Business Data". *Journal of Finance*, 49: 3-37.

Petersen, M. A. and Rajan, R. G. 2002. "Does Distance Still Matter? The Information Revolution in Small Business Lending". *Journal of Finance*, 57: 2533-2570.

**Table 1. Summary Statistics**

<b>Panel A. PDSI</b>	<b>Mean</b>	<b>S.D.</b>	<b>0.25</b>	<b>Median</b>	<b>0.75</b>	<b>N</b>
Weighted PDSI (M=12 months)	0.11	1.89	-0.92	0.14	1.34	36352
Weighted PDSI (M=24 months)	0.09	1.63	-0.76	0.18	1.04	36352
Weighted PDSI (M=36 months)	0.06	1.43	-0.72	0.14	0.91	36352
Weighted PDSI (M=48 months)	0.06	1.26	-0.67	0.13	0.83	36352
Weighted PDSI (M=60 months)	0.08	1.13	-0.64	0.14	0.81	36352
<b>Panel B. Dependent Variables</b>	<b>Mean</b>	<b>S.D.</b>	<b>0.25</b>	<b>Median</b>	<b>0.75</b>	<b>N</b>
Z-score	1.93	0.88	1.33	1.82	2.39	33341
ROA	0.78	1.55	0.58	0.89	1.15	28735
Efficiency Ratio	0.67	0.17	0.58	0.65	0.74	28597
NPL Ratio	0.03	0.03	0.01	0.02	0.03	36352
NPL Ratio (30 to 90 days)	0.01	0.01	0	0.01	0.01	36352
NPL Ratio (> 90 days)	0	0.01	0	0	0	36352
Non-accrual Loans Ratio	0.01	0.02	0	0.01	0.02	36352
NPL Ratio (Real Estate)	0.03	0.03	0.01	0.02	0.04	36248
NPL Ratio (Consumer)	0.02	0.03	0.01	0.01	0.02	36043
NPL Ratio (Commercial)	0.03	0.04	0.01	0.01	0.03	36266
NPL Ratio (Agricultural Production)	0.01	0.05	0	0	0.01	21708
NPL Ratio (Family Residential)	0.03	0.03	0.01	0.02	0.03	36120
NPL Ratio (Farm)	0.03	0.11	0	0	0.02	29615
NPL Ratio (Construction)	0.06	0.11	0	0.01	0.06	35823
<b>Panel C. Control Variables</b>	<b>Mean</b>	<b>S.D.</b>	<b>0.25</b>	<b>Median</b>	<b>0.75</b>	<b>N</b>
<i>Bank-level</i>						
Equity Capital / Total Assets	10.18	3.87	8.5	9.76	11.25	33335
Loan Loss Provision / Total Assets	0	0	0	0	0	36330
Non-interest Expenses / Total Assets	3.3	2.26	2.58	2.98	3.49	36324
Total Loans / Total Assets	65.3	12.83	58.67	66.93	74.2	36271
Logarithm of Total Assets	13.93	1.73	12.78	13.5	14.65	31428
<i>State-level</i>						
Weighted State GDP growth	3.94	7.37	0.94	2.76	6.28	36352
Weighted % Change in State Personal Income	2.27	4.26	0.53	1.56	3.55	36352
Weighted % Change in State Housing Price Index	516.89	382.12	210.45	402.64	681.02	36352
Weighted State Home Ownership Rate	152.54	134.67	66.8	128.6	214.2	36352
Weighted State Unemployment Rate	16.55	13.1	7.3	12.2	21.46	36352

The table summarizes the statistics and defines all variables used in our models. Our quarterly sample covers 1998 to 2017. All weighted variables are weighted by deposit size. Panel A describes PDSI (drought) measures. Weighted PDSI (12 months) is the average drought intensity over the last 12 months. Accordingly, PDSI (24 months), PDSI (36 months), PDSI (48 months) and PDSI (60 months) are the average drought measures over the last 24, 36, 48 and 60 months, respectively. Panel B summarizes all dependent variables. For non-manufacturing firms, including banks, the (Altman) z-score is a weighted average of 4 business ratios as follows:  $6.56 T_1 + 3.26 T_2 + 6.72 T_3 + 1.05 T_4$ , where  $T_1$  is working capital divided by total assets;  $T_2$  is retained earnings divided by total assets;  $T_3$  is earnings before interest and tax divided by total assets, and  $T_4$  is the book value of equity divided by total liabilities. ROA is the return on average assets. The efficiency ratio is calculated as noninterest expense divided by the sum of net interest income and noninterest income. NPL ratio is the proportion of non-performing loans to total loans and for each category of loans. NPL Ratio (30 to 90 days) is loans that are past-due more than 30 days and less than 90 days divided by total loans. NPL Ratio (> 90 days) is loans that are past-due more than 90 days and that bank still accrues interest on them, divided by total loans. Non-accrual Loans Ratio is loans that are past-due more than 90 days and that bank no longer accrues interest on them, divided by total loans. Panel C presents control variables that are at bank and state level and are described in the table.

**Table 2. Impact of Drought on Z-score**

	<b>Z-score</b>				
	(1) M=12	(2) M=24	(3) M=36	(4) M=48	(5) M=60
Weighted PDSI (M months)	0.01266** (2.303)	0.01815** (2.465)	0.02309** (2.429)	0.02981** (2.561)	0.03461** (2.550)
Equity Capital / Total Assets	0.03921*** (4.207)	0.03930*** (4.217)	0.03932*** (4.223)	0.03941*** (4.234)	0.03947** (4.241)
Loan Loss Provision / Total Assets	5.93062 (1.287)	6.15721 (1.332)	6.40771 (1.382)	6.60734 (1.426)	6.80024 (1.467)
Non-interest Expenses / Total Assets	-0.04503* (-1.732)	-0.04511* (-1.737)	-0.04514* (-1.740)	-0.04508* (-1.738)	-0.04509* (-1.737)
Total Loans / Total Assets	-0.05474*** (-27.334)	-0.05473*** (-27.358)	-0.05473*** (-27.391)	-0.05471*** (-27.370)	-0.05468*** (-27.343)
ROA	0.05504*** (3.848)	0.05481*** (3.854)	0.05475*** (3.866)	0.05444*** (3.864)	0.05429*** (3.863)
Logarithm of Total Assets	-0.09689*** (-5.357)	-0.09703*** (-5.375)	-0.09748*** (-5.399)	-0.09806*** (-5.430)	-0.09850*** (-5.451)
State GDP growth	0.00011 (0.048)	0.00012 (0.049)	0.00008 (0.033)	0.00016 (0.066)	0.00020 (0.084)
% Change in State Personal Income	-0.00042 (-0.433)	-0.00031 (-0.319)	-0.00023 (-0.233)	-0.00024 (-0.248)	-0.00024 (-0.244)
% Change in State Housing Price Index	-0.00014 (-1.271)	-0.00012 (-1.157)	-0.00012 (-1.080)	-0.00011 (-0.976)	-0.00010 (-0.941)
State Home Ownership Rate	0.00053 (1.111)	0.00048 (1.000)	0.00044 (0.927)	0.00039 (0.808)	0.00036 (0.753)
State Unemployment Rate	-0.00120 (-0.467)	-0.00100 (-0.387)	-0.00083 (-0.318)	-0.00051 (-0.193)	-0.00030 (-0.113)
Constant	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	22,698	22,698	22,698	22,698	22,698
Adjusted R-squared	0.704	0.704	0.705	0.705	0.705

The table presents the regression results of banks' Z-score on drought measures. Z-score is a weighted average of 4 business ratios as follows:  $6.56 T_1 + 3.26 T_2 + 6.72 T_3 + 1.05 T_4$ , where  $T_1$  is working capital divided by total assets;  $T_2$  is retained earnings divided by total assets;  $T_3$  is earnings before interest and tax divided by total assets, and  $T_4$  is the book value of equity divided by total liabilities. Weighted PDSI (12 months) is the average PDSI on last 12 months weighted by branch deposit size. Accordingly, PDSI (24 months), PDSI (36 months), PDSI (48 months) and PDSI (60 months) are the average PDSI on last 24, 36, 48, and 60 months, respectively. We control for bank characteristics, state-level variables, and year-quarter fixed effects. *Heteroskedasticity-robust* standard errors are clustered at the bank level. Statistical significance at the 10%, 5%, and 1% levels are denoted by \*, \*\* and \*\*\*, respectively. Robust t-statistics are in parentheses.

**Table 3. Impact of Drought on ROA**

	ROA				
	(1) M=12	(2) M=24	(3) M=36	(4) M=48	(5) M=60
Weighted PDSI (M months)	0.01765* (1.954)	0.02499** (2.205)	0.02825** (2.030)	0.03825** (2.281)	0.04580** (2.333)
Equity Capital / Total Assets	0.12242*** (3.517)	0.12250*** (3.523)	0.12247*** (3.524)	0.12255*** (3.529)	0.12262*** (3.532)
Loan Loss Provision / Total Assets	-241.42867*** (-22.954)	-241.04895*** (-22.916)	-240.81592*** (-22.876)	-240.40802*** (-22.812)	-240.05869*** (-22.756)
Non-interest Expenses / Total Assets	-0.01476 (-0.242)	-0.01486 (-0.244)	-0.01484 (-0.244)	-0.01479 (-0.243)	-0.01480 (-0.244)
Total Loans / Total Assets	0.00199 (1.021)	0.00201 (1.029)	0.00199 (1.019)	0.00203 (1.044)	0.00206 (1.065)
Logarithm of Total Assets	0.10830*** (6.059)	0.10807*** (6.066)	0.10754*** (6.066)	0.10670*** (6.063)	0.10605*** (6.064)
State GDP growth	0.00553*** (3.030)	0.00552*** (3.033)	0.00541*** (2.967)	0.00553*** (3.030)	0.00560*** (3.070)
% Change in State Personal Income	-0.00068 (-0.298)	-0.00053 (-0.234)	-0.00047 (-0.208)	-0.00047 (-0.208)	-0.00045 (-0.198)
% Change in State Housing Price Index	-0.00019 (-1.212)	-0.00017 (-1.115)	-0.00017 (-1.088)	-0.00015 (-0.992)	-0.00015 (-0.955)
State Home Ownership Rate	0.00035 (0.640)	0.00029 (0.515)	0.00028 (0.489)	0.00019 (0.343)	0.00015 (0.263)
State Unemployment Rate	-0.00165 (-0.535)	-0.00139 (-0.444)	-0.00132 (-0.414)	-0.00084 (-0.263)	-0.00051 (-0.158)
Constant	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	22,741	22,741	22,741	22,741	22,741
Adjusted R-squared	0.384	0.385	0.385	0.385	0.385

This table presents the results for regression of banks' ROA on drought measures. ROA is the return on average assets. Weighted PDSI (12 months) is the average PDSI on last 12 months weighted by branch deposit size. Accordingly, PDSI (24 months), PDSI (36 months), PDSI (48 months) and PDSI (60 months) are the average PDSI on last 24, 36, 48, and 60 months, respectively. We control for bank characteristics, state-level variables, and year-quarter fixed effects. *Heteroskedasticity-robust* standard errors are clustered at the bank level. Statistical significance at the 10%, 5% and 1% levels are denoted by \*, \*\*, and \*\*\*, respectively. Robust t-statistics are in parentheses.

**Table 4. Impact of Drought on Efficiency Ratio**

	Efficiency Ratio				
	(1) M=12	(2) M=24	(3) M=36	(4) M=48	(5) M=60
Weighted PDSI (M months)	-0.00263** (-2.106)	-0.00350** (-2.208)	-0.00488** (-2.509)	-0.00637*** (-2.724)	-0.00800*** (-2.932)
Equity Capital / Total Assets	-0.00627*** (-2.982)	-0.00629*** (-2.987)	-0.00630*** (-2.991)	-0.00632*** (-3.000)	-0.00634*** (-3.013)
Loan Loss Provision / Total Assets	-5.05663** (-2.085)	-5.09674** (-2.105)	-5.15708** (-2.135)	-5.20118** (-2.153)	-5.26218** (-2.178)
Non-interest Expenses / Total Assets	0.03190*** (4.349)	0.03191*** (4.348)	0.03192*** (4.348)	0.03191*** (4.351)	0.03192*** (4.357)
Total Loans / Total Assets	-0.00137*** (-4.543)	-0.00137*** (-4.542)	-0.00137*** (-4.548)	-0.00138*** (-4.569)	-0.00139*** (-4.593)
ROA	-0.06240*** (-6.265)	-0.06236*** (-6.265)	-0.06233*** (-6.265)	-0.06226*** (-6.256)	-0.06221*** (-6.251)
Logarithm of Total Assets	-0.01790*** (-5.955)	-0.01787*** (-5.950)	-0.01777*** (-5.932)	-0.01765*** (-5.904)	-0.01753*** (-5.872)
State GDP growth	-0.00020 (-0.700)	-0.00020 (-0.680)	-0.00020 (-0.677)	-0.00022 (-0.735)	-0.00023 (-0.796)
% Change in State Personal Income	0.00059** (2.200)	0.00057** (2.133)	0.00055** (2.066)	0.00055** (2.071)	0.00055** (2.047)
% Change in State Housing Price Index	-0.00004** (-2.113)	-0.00004** (-2.188)	-0.00004** (-2.273)	-0.00005** (-2.367)	-0.00005** (-2.439)
State Home Ownership Rate	0.00015* (1.928)	0.00016** (1.996)	0.00017** (2.087)	0.00018** (2.202)	0.00020** (2.307)
State Unemployment Rate	-0.00056 (-1.205)	-0.00059 (-1.255)	-0.00065 (-1.354)	-0.00072 (-1.487)	-0.00079 (-1.619)
Constant	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	22,660	22,660	22,660	22,660	22,660
Adjusted R-squared	0.377	0.377	0.377	0.378	0.378

The table presents the results for regression of banks' efficiency ratio on drought measures. The efficiency ratio is calculated as noninterest expense divided by the sum of net interest income and noninterest income. Weighted PDSI (12 months) is the average PDSI on last 12 months weighted by branch deposit size. Accordingly, PDSI (24 months), PDSI (36 months), PDSI (48 months) and PDSI (60 months) are the average PDSI on last 24, 36, 48, and 60 months, respectively. We control for bank characteristics, state-level variables, and year-quarter fixed effects. *Heteroskedasticity-robust* standard errors are clustered at the bank level. Statistical significance at the 10%, 5% and 1% levels are denoted by \*, \*\* and \*\*\*, respectively. Robust t-statistics are in parentheses.

**Table 5. Drought and NPL Ratio**

	NPL Ratio				
	(1) M=12	(2) M=24	(3) M=36	(4) M=48	(5) M=60
Weighted PDSI (M months)	-0.00011*** (-3.366)	-0.00016*** (-4.055)	-0.00017*** (-3.774)	-0.00022*** (-4.000)	-0.00026*** (-4.201)
NPL Ratio (lagged, t-1)	0.91520*** (108.493)	0.91505*** (108.399)	0.91490*** (108.126)	0.91463*** (107.846)	0.91439*** (107.516)
Equity Capital / Total Assets	-0.00004 (-1.573)	-0.00004 (-1.609)	-0.00004 (-1.607)	-0.00004 (-1.645)	-0.00004* (-1.678)
Loan Loss Provision / Total Assets	0.56062*** (7.714)	0.55923*** (7.685)	0.55816*** (7.663)	0.55733*** (7.661)	0.55628*** (7.649)
Non-interest Expenses / Total Assets	-0.00002 (-0.370)	-0.00002 (-0.370)	-0.00002 (-0.369)	-0.00002 (-0.365)	-0.00002 (-0.356)
Total Loans / Total Assets	-0.00001 (-1.106)	-0.00001 (-1.131)	-0.00001 (-1.118)	-0.00001 (-1.162)	-0.00001 (-1.200)
ROA	0.00014 (1.427)	0.00014 (1.443)	0.00014 (1.433)	0.00014 (1.446)	0.00014 (1.455)
Logarithm of Total Assets	-0.00001 (-0.213)	-0.00001 (-0.207)	-0.00001 (-0.162)	-0.00001 (-0.108)	-0.00000 (-0.061)
State GDP growth	-0.00004*** (-4.303)	-0.00004*** (-4.321)	-0.00004*** (-4.261)	-0.00004*** (-4.305)	-0.00004*** (-4.338)
% Change in State Personal Income	-0.00001 (-0.440)	-0.00001 (-0.484)	-0.00001 (-0.501)	-0.00001 (-0.494)	-0.00001 (-0.495)
% Change in State Housing Price Index	0.00000 (0.574)	0.00000 (0.335)	0.00000 (0.299)	0.00000 (0.103)	0.00000 (0.018)
State Home Ownership Rate	0.00000 (0.036)	0.00000 (0.305)	0.00000 (0.314)	0.00000 (0.571)	0.00000 (0.712)
State Unemployment Rate	-0.00001 (-1.089)	-0.00002 (-1.198)	-0.00002 (-1.217)	-0.00002 (-1.374)	-0.00002 (-1.490)
Constant	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	23,196	23,196	23,196	23,196	23,196
Adjusted R-squared	0.890	0.890	0.890	0.890	0.890

This table presents the impact of drought on NPL ratio of banks. Dependent variable is the ratio between total non-performing loans and total loans. Weighted PDSI (12 months) is the average PDSI on last 12 months weighted by branch deposit size. Accordingly, PDSI (24 months), PDSI (36 months), PDSI (48 months) and PDSI (60 months) are the average PDSI on last 24, 36, 48, and 60 months, respectively. We control for bank characteristics, state-level variables, and year-quarter fixed effects. *Heteroskedasticity-robust* standard errors are clustered at the bank level. Statistical significance at the 10%, 5%, and 1% levels are denoted by \*, \*\* and \*\*\*, respectively. Robust t-statistics are in parentheses.

**Table 6. Drought and Stages of Delinquency**

	NPL Ratio (30 to 90 days)				
	(1) M=12	(2) M=24	(3) M=36	(4) M=48	(5) M=60
<b>Panel A</b>					
Weighted PDSI (M months)	-0.00005* (-1.803)	-0.00007* (-1.927)	-0.00009** (-2.056)	-0.00013** (-2.327)	-0.00017** (-2.474)
Constant	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	23,196	23,196	23,196	23,196	23,196
Adjusted R-squared	0.556	0.556	0.556	0.556	0.556
<b>Panel B</b>					
Weighted PDSI (M months)	-0.00001 (-0.905)	-0.00001 (-1.198)	-0.00002 (-1.470)	-0.00002 (-1.159)	-0.00002 (-1.023)
Constant	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	23,196	23,196	23,196	23,196	23,196
Adjusted R-squared	0.838	0.838	0.838	0.838	0.838
<b>Panel C</b>					
Weighted PDSI (M months)	-0.00007** (-2.520)	-0.00009*** (-3.196)	-0.00009*** (-2.951)	-0.00013*** (-3.561)	-0.00015*** (-3.958)
Constant	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	23,196	23,196	23,196	23,196	23,196
Adjusted R-squared	0.910	0.910	0.910	0.910	0.910

This table reports the result of regression for loans that are past-due more than 30 days and less than 90 days (Panel A); loans that are past-due more than 90 days and that bank still accrues interest on them (Panel B); and non-accrual loans that are past-due more than 90 days and that bank no longer accrues interest on them (Panel C). We call them first-stage, second-stage and third-stage NPLs, respectively. Dependent variables are the ratio of each of these loans divided by total loans of a bank in each quarter. Weighted PDSI (12 months) is the average PDSI on last 12 months weighted by branch deposit size. Accordingly, PDSI (24 months), PDSI (36 months), PDSI (48 months) and PDSI (60 months) are the average PDSI on last 24, 36, 48, and 60 months, respectively. We control for bank characteristics, state-level variables, and year-quarter fixed effects. *Heteroskedasticity-robust* standard errors are clustered at the bank level. Statistical significance at the 10%, 5%, and 1% levels are denoted by \*, \*\* and \*\*\*, respectively. Robust t-statistics are in parentheses.



**Table 7. Types of Loans**

	<b>Agricultural Production</b>	<b>Real Estate</b>	<b>Consumer</b>	<b>Commercial</b>
Weighted PDSI (60 months)	-0.00020 (-0.443)	-0.00021*** (-2.761)	-0.00032** (-2.013)	-0.00028* (-1.647)
Constant	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	14,115	18,219	23,098	23,165
Adjusted R-squared	0.372	0.894	0.504	0.674

This table presents the results for regression of different loan categories on drought measures. Loans include agricultural production, real estate, consumer, and commercial. The dependent variables are the ratio of each of these loans divided by total loans of a bank in each quarter. Weighted PDSI (60 months) is the average PDSI on last 60 months weighted by branch deposit size. We control for bank characteristics and state-level variables, and year-quarter fixed effects. *Heteroskedasticity-robust* standard errors are clustered at the bank level. Statistical significance at the 10%, 5% and 1% levels are denoted by \*, \*\*, and \*\*\*, respectively. Robust t-statistics are in parentheses.

**Table 8. Decomposing Real Estate Loans**

	<b>Real Estate</b>	<b>Farm</b>	<b>Residential Family Properties</b>	<b>Construction and Land Development</b>
Weighted PDSI (60 months)	-0.00021*** (-2.761)	-0.00086 (-1.317)	-0.00023*** (-2.771)	-0.00046 (-1.230)
Constant	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	18,219	18,219	18,219	18,219
Adjusted R-squared	0.894	0.578	0.844	0.797

This table presents the results for different sub-categories of real estate loans. The dependent variables are the NPL ratio for loans secured by residential family properties, loans secured by farm land, and construction & land development loans. Weighted PDSI (60 months) is the average PDSI on last 60 months weighted by branch deposit size. We control for bank characteristics, state-level variables, and year-quarter fixed effects. *Heteroskedasticity-robust* standard errors are clustered at the bank level. Statistical significance at the 10%, 5% and 1% levels are denoted by \*, \*\*, and \*\*\*, respectively. Robust t-statistics are in parentheses.

**Table 9. Robustness Checks**

<b>Panel A</b>	<b>NPL Ratio</b>				
	(1)	(2)	(3)	(4)	(5)
Weighted PDSI (M=12 months)	-0.00030** (-2.292)				
Weighted PDSI (M=24 months)		-0.00069*** (-2.918)			
Weighted PDSI (M=36 months)			-0.00121*** (-3.505)		
Weighted PDSI (M=48 months)				-0.00184*** (-3.915)	
Weighted PDSI (M=60 months)					-0.00279*** (-4.585)
NPL Ratio (lagged, t-N/3-1)	0.72323*** (32.252)	0.55695*** (17.679)	0.45017*** (11.074)	0.39932*** (8.375)	0.40660*** (7.614)
Constant	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	22,438	21,192	19,199	17,150	15,286
Adjusted R-squared	0.686	0.532	0.446	0.400	0.374
<b>Panel B</b>	<b>Z-score</b>	<b>ROA</b>	<b>Efficiency Ratio</b>	<b>NPL Ratio</b>	
Weighted PDSI (60 months)	0.01602*** (5.141)	0.01896* (1.947)	-0.00713*** (-5.723)	-0.00148*** (-8.786)	
Constant	Yes	Yes	Yes	Yes	
Bank Controls	Yes	Yes	Yes	Yes	
Year-quarter FE	Yes	Yes	Yes	Yes	
Bank FE	Yes	Yes	Yes	Yes	
Observations	22,695	22,737	22,657	22,695	
Adjusted R-squared	0.894	0.581	0.596	0.672	

The table presents the results for robustness tests. In Panel A, instead of the first lag of each NPL ratio, we control for the lag that is exactly one period before the starting quarter of the drought. Panel B includes bank fixed effects *Heteroskedasticity-robust* standard errors are clustered at the bank level. Statistical significance at the 10%, 5% and 1% levels are denoted by \*, \*\*, and \*\*\*, respectively. Robust t-statistics are in parentheses.