As dry as a bone: how do banks cope with droughts?*

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Abstract

Understanding the potential impacts of climate change on economic outcomes requires comprehensive knowledge of how economic agents adapt to shifting climatic conditions. In this study, we delve into the adaptation strategies employed by US banks in response to droughts from 2000 to 2019. Our investigation reveals that local banks exhibit significant strategic adjustments in their lending portfolios during these periods. Specifically, we observe a contraction in lending to small businesses and the agricultural sector, counterbalanced by an expansion of loans directed towards households. These circumstances correspond with an accumulation of liquidity reserves in local banks, potentially driven by a precautionary rationale, and a striking lack of a parallel surge in non-performing loans. Notably, surplus liquidity is often funneled towards other banks. The scope and magnitude of these responses are markedly more pronounced in local banks compared to larger, multi-state entities. Furthermore, we demonstrate that the deployment of government financial assistance in drought-impacted areas modifies the lending and deposit behavior of banks, thereby alleviating the negative impacts. Consequently, our study offers critical insights into the dynamic role of local banks in climate adaptation, and highlights the profound influence of policy interventions in navigating the financial challenges that arise from drought conditions.

Keywords: climate change, drought, banks, lending, deposit, agriculture, government help
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1. Introduction

In recent years, large-scale intensive droughts have been observed on all continents, affecting more people than any other natural disaster.[1] In North America, droughts stand out as complex, recurring, and among the costliest of natural disasters. Over the past two decades, the US has witnessed escalating impacts from droughts, attributed to their increasing frequency or severity (Wilhite and Hayes, 1998; Easterling et al., 2000).

The rising economic and social tolls have intensified the focus on droughts in agroeconomics. Kuwayama et al. (2019); Cui (2020); Lobell et al. (2014) analyzed the impact of drought on crop and maize yields in the US. However, unlike the analyses of the impact of floods (refer to Koetter et al. (2020) for Germany), hurricanes (Schüwer et al. (2019); Massa and Zhang (2021) for the US, and Brei et al. (2019) for the Caribbean Islands), as well as all natural disasters jointly (Barth, Miller, Sun and Zhang (2022); Barth, Hu, Sickles, Sun and Yu (2022)), the impact of droughts on US commercial banks remains largely unexplored. Our study aims to close this gap, with a particular emphasis on lending to the agricultural sector.

Agriculture, a sector directly dependent on temperature and precipitation, is especially vulnerable to climate change (Howden et al., 2007). In the 1930s, the Dust Bowl drought caused some 200,000 farm bankruptcies in the U.S. Southern Great Plains, and yields of wheat and corn were reduced by as much as 50% (Rosenzweig et al., 2001). In 2012, the drought broke the record and became the spatially most extensive drought in the last century, and is believed to be one of the costliest in U.S. history. In response, the federal government, primarily through the United States Department of Agriculture (USDA), provided a variety of assistance measures to help farmers and ranchers deal with the effects of the drought since 2012.

The financial aid may be important even as existing research indicates that farmers are adapting to the changing climate. Aragón et al. (2021) finds that extreme heat expands the area planted with a diverse crop mix and amplifies the use of domestic labor on the farm. Additionally, Jagnani et al. (2021) demonstrate that farmers escalate pesticide use and increase the weeding effort in response to higher temperatures promoting weed growth. However, the rise in input use partially

[1] For a comprehensive understanding of the concepts, definitions, and types of drought, refer to Wilhite and Glantz (1985); Wilhite and Buchanan-Smith (2005); Wilhite (2012).

compensates for the decline in agricultural productivity. Kuwayama et al. (2019) documents a decrease in production in the U.S. as a result of drought. However, no effect on the value of cash receipts and production expenses was found, which they attribute to the inflation of agricultural commodity prices caused by local scarcity. The surge in food prices could be one of the factors contributing to the adverse impacts of droughts on the food industry (Hong et al., 2019).

Rajan and Ramcharan (2023), using data on drought from the 1950s, shows that the adaptation of farmers to climate shock depends on the availability of credit during the drought period. They demonstrate that towns with access to bank credit reported lower net immigration and lesser population decline compared to towns without such financial access. In a similar vein, Noy (2009) reports that countries with more developed bank credit markets appear to be more robust and better able to endure natural disasters, while they find no evidence that stock markets are important in insulating economies from the macroeconomic impact of natural disasters.

Moreover, Rajan and Ramcharan (2023) shows that agricultural investment and long-term productivity increase more in drought-exposed areas with bank finance. Their results are in line with previous studies illustrating that climate change adaptation by farmers alters production and trade patterns (Costinot et al., 2016). Similarly, their findings support the earlier indication that a rise in temperature could lead to emigration from agricultural regions in the U.S (Feng et al., 2012).

Existing research underscores the pivotal role of bank credit access in the agricultural sector and local economies, a significance that may amplify during droughts. Scott et al. (2022) report a higher demand for agricultural loans when real farm income decreases. However, during periods of robust real farm income, the demand for bank loans is weak. Thus, they concluded that credit demand and farm income move counter-cyclically, and loan supply has a less pronounced impact on the growth rate of loans than demand does. This counter-cyclical relationship between farm income and loan demand aligns with previous findings of income and investment smoothing in the agricultural sector (Whitaker, 2009), and the inverse relationship between income and credit use (Prager et al., 2018). Consequently, we may expect that the demand for agricultural loans will rise during drought periods, in particular insurance markets for disaster risk are generally incomplete (Froot, 2001).

However, existing literature suggests that farmers often cannot borrow as much as they need

Turvey and Weersink (1997). Credit rationing may limit farmers' ability to accumulate capital and suppress aggregate farm output (Briggeman et al., 2009). Blancard et al. (2006) argue that difficulties in access to credit can be attributed to several factors, including the relatively small size of most farms, issues with collateral, and substantial lags between purchasing inputs and selling outputs. We also expect that farmers might encounter difficulties accessing external funding during drought periods as they are more opaque compared to public firms and generate less geographically diversified cash flows. Furthermore, Berg and Schrader (2012) document that after a natural disaster, asymmetric information becomes acute in credit markets as borrowers are unable to pledge damaged or destroyed collateral and employment becomes uncertain. Meanwhile, a survey of a representative sample of commercial agricultural lenders reveals that approximately 96% of agricultural loans made by commercial banks from 2001 to 2021 were secured with collateral (Federal Reserve Bank of Kansas City, 2021).

This situation potentially gives local banks an advantage over large banks. Local banks benefit from physical proximity to the local economy, enabling them to supplement 'hard' quantitative data, usually denoted as transaction lending, with relevant 'soft' information on potential borrowers. This soft information improves screening and monitoring quality, makes these processes less costly, and facilitates relationship lending (Petersen and Rajan, 1994). Thus, local banks might be particularly crucial during drought periods, as they are better equipped and more willing to provide (additional) credit to local enterprises (Degryse and Van Cayseele, 2000; Elsas, 2005). Notably, agricultural lending is even more localized than small business lending (Rajan and Ramcharan, 2023). Therefore, we hypothesize that large and small banks will exhibit different lending patterns during drought seasons.

Our study focus on the lending and deposit activities of banks in counties affected by drought, as defined by the U.S. Drought Monitor (USDM), during the 2000–2020 period. The USDM determines drought conditions based on various indicators including precipitation, temperature measures, soil moisture, streamflow, vegetation indices, reservoir and lake levels, groundwater levels, and snowpack. The USDM composite index, which indicates the counties in drought on a weekly basis, plays a significant role in shaping US drought policy at the local economies level. Moreover, Kuwayama et al. (2019) confirmed that it is correlated with observed agricultural outcomes.

We match the USDM index with three different bank-level datasets to analyze its impact on lending activity, particularly with regard to agricultural loans. It is crucial to note that our analysis of loans and deposits is confined to commercial banks. According to the USDA, commercial banks provided between 41.4% and 56.6% of all non-real estate loans between 2000 and 2020 (USDA Economic Research Service, 2021). As reported by Scott et al. (2022), non-real estate debt from commercial banks surged by 40.7%, escalating from $40.7 billion to $63.1 billion between 2000 and 2020.

Our analysis is not confined to the agricultural sector; we also examine bank lending to enterprises and individuals during drought periods. This approach stems from the argument put forth by Cortés and Strahan (2017) that disasters generally lead to increased demand for bank loans. In this context, our study sheds new evidence on lending behaviors following natural disasters, revealing that overall bank lending remains unaltered during drought periods. It is crucial to note that droughts, distinct from sudden events like hurricanes or floods, exert a prolonged impact on local economies, primarily affecting farmers and food production companies.

As anticipated, there is a decline in bank lending related to agricultural production and farms during droughts. We also identify a reduction in the provision of loans to small businesses during droughts. It is plausible that the retreat from lending to small businesses stems from banks' precautionary stance, exacerbated by the amplified asymmetry of information on their performance following a natural disaster Berg and Schrader (2012); Stephane (2021). Validating this theory, we note that lending volumes for commercial and industrial ventures remain largely unaffected by drought conditions. Similarly, overarching real estate lending appears resistant to drought influences. Yet, upon closer examination, it becomes evident that specific categories of real estate-secured loans, especially those pegged to farmland, construction projects, or family residences, are sensitive to drought conditions.

A salient observation is the resilience in lending to farmers post-2012, which we posit is due to the government aid programs designed to help agricultural producers grappling with drought. From 2012 onward, there wasn't any discernible shift in the loan portfolio, especially a downturn in agricultural lending. This resilience likely stems from the confidence instilled by these government initiatives, ensuring banks continued their support to the agricultural sector amidst droughts. This observation supports the findings by Kuwayama et al. (2019), which underscore that the USDM offers insights on impacts to crop yields, which is also used in the resource allocation decisions within government drought disaster assistance programs.

To the best of our knowledge, our study is the first to investigate the effects of drought on the lending and deposit dynamics controlling for different types of commercial banks. This fills a significant gap in existing literature, broadening our understanding of drought's ramifications on local economies. While previous studies have focused on the production capabilities of local farms, food processing units, and agricultural companies (Hong et al., 2019; Rajan and Ramcharan, 2023), we delve into the often overlooked financial domain, specifically the operations of commercial banks, both large and small.

In 2021, the Financial Stability Oversight Council (FSOC) acknowledged the growing threat of climate change to U.S. financial stability in a landmark report.[2] Within the realm of climate risk, regulators distinguish between two main categories: physical and transition risks. The former arises from direct climatic events such as wildfires, storms, and floods, while the latter emerges from policy actions steering the economy away from fossil fuels. Our research adds to the discourse on banks' exposure to physical risks by shedding light on their behavioral changes, particularly in lending and deposit taking, under drought conditions.

The structure of the remaining paper is as follows. In Section 2, we describe our data and the basic framework. In Section 3, we present our results related to new loans, while Section 4 discusses the changes in banks' loan portfolio. In Section 5, we analyze the impact of drought on deposits and interest rates. Finally, Section 6 closes the argument.

2. Data

In this section, we describe the various databases we use, as well as the variables we obtain for subsequent analyses.

2.1. Drought data

2.1.1. U.S. Drought Monitor

Our spatial designation of drought-affected areas is based on the USDM, used for the disaster declaration process described. The USDM consists of weekly maps jointly produced by the National Drought Mitigation Center at the University of Nebraska-Lincoln, the National Oceanic

[2]https://home.treasury.gov/system/files/261/FSOC-Climate-Report.pdf

and Atmospheric Administration, and the U.S. Department of Agriculture. These maps classify U.S. regions into five different drought classifications: abnormally dry (D0), moderate (D1), severe (D2), extreme (D3), and exceptional (D4). The classification is based on five quantitative drought indicators, local condition and impact reports from expert observers, and anticipated drought impacts subjectively validated by the indicators used. The USDM has been shown to significantly capture the reduction in crop yields Kuwayama et al. (2019).

We identify drought-affected areas as those experiencing severe drought (D2) or above. D2 is also one of the threshold conditions for a county, or its neighboring counties, to be designated as drought disaster areas. We define our drought index at the locational (5km grid cell level) as the sum of the weeks within the growing season (May through October) that reach the D2 threshold, and zero otherwise.

To link branch-level information to our drought index, we used the geographic coordinates of the branch's address to determine its location within the USDM 5km grid cell schemata. This gives us an annual indicator of the number of weeks a branch was located in an area subject to at least D2 drought conditions. We assume that farming clients are likely to do business with branches closest to them. We generate bank-county level drought indices by weighting their current branch level drought indices within a county by the share of each branch's bank-county level total deposits in the previous year.

2.1.2. Disaster Declaration

The Secretary of Agriculture can authorize emergency loans for farmers who have suffered losses due to natural disasters in designated counties and counties adjacent to them. The U.S. Department of Agriculture (USDA) can designate a county if it has suffered severe physical property or production losses due to unusual and adverse weather conditions or natural phenomena. Severe physical property losses are considered as extensive damage to or destruction of physical farm property, including buildings, equipment, infrastructure, livestock, and poultry and their products, as well as growing and harvested crops. Severe production losses refer to a minimum of a 30% reduction of the normal annual value of crops that could not be replanted or replaced by a substitute crop, 30% of a single farm annual enterprise's value, or conditions that have caused significant production losses or generated extenuating circumstances warranting a finding that a natural disaster event has occurred.

Since 2012, the USDA Secretary can automatically designate a county as affected when, during the growing season, any portion of a county meets the severe drought (D2) intensity value for eight consecutive weeks or a higher drought intensity value for any length of time, as reported by the USDM. [3]

Emergency loan funds can be used for several purposes, including replacing or restoring essential property, paying some or all of the cost of production in the disaster year, covering essential family living expenditures, reorganizing the farming operation, and refinancing specific non-real estate operating debts. Loan amounts are limited to $500,000, and loans exceeding $300,000 require two letters of credit declination from commercial lending institutions, while those below $300,000 but above $100,000 require one letter. For loans below $100,000, this requirement is determined on a case-by-case basis at the FSA's discretion. It should be noted that loan applications must be received no later than eight months after the date of the disaster designation.

The terms of repayment are based on the useful life of the loan, the applicant's repayment ability, and the category of loss involved. The repayment schedule must include at least one payment per year. Loans intended to cover annual operating expenditures must be repaid within a year, although this can be extended to up to 18 months depending on the production cycle of the involved commodity. The interest rate is the lower of the rates at the time of loan approval or the closing of the loan, with interest rates calculated and posted on the first of each month. Borrowers who are unable to meet their scheduled payments may be authorized to have certain amounts set aside.

In addition, more than 1,000 credit unions were eligible to provide unlimited lending to small business owners, including farmers in drought-designated areas. Small business lending by credit unions is typically capped at 12.25% of their total assets, but this cap does not apply to institutions serving low-income communities. Despite these inroads made by credit unions, the U.S. banking industry remains the primary credit provider to the agricultural sector.

We sourced the list of primary and contiguous counties designated by the US Secretary of Agriculture due to drought from the U.S. Department of Agriculture (USDA) for the years 2012-

[3] See information on Disaster Protection and Recovery at https://www.fsa.usda.gov/news-room/fact-sheets/index

2020.

2.2. *Banking data*

We have employed three distinct datasets, each offering different levels of geographic precision. The first dataset, derived from the Community Reinvestment Act (CRA), operates at the bank-county level. Established by Congress in 1977 under 12 U.S.C. 2901 and executed through Regulations 12 CFR parts 25, 228, 345, and 195, the CRA has been an invaluable resource.

Our second dataset, referred to as the Call Report data, originates from the Commercial Bank Database of the Federal Reserve Bank of Chicago. Functioning at the bank level, it encompasses all banks that file the Report of Condition and Income, supervised by entities such as the Federal Reserve System, Federal Deposit Insurance Corporation (FDIC), and the Comptroller of the Currency.

Our final dataset zooms in on the branch level, offering detailed data about individual bank branches, right down is at the branch level and provides granular data on individual bank branches, including their exact geographic locations. This dataset is a combination of two different databases: the FDIC's Summary of Deposits (SoD) and Rate Watch's records on deposit and loan interest rates.

Subsequent sections offer more detailed information about these datasets and elucidate the variables pivotal to our analyses.

2.2.1. *Community Reinvestment Act*

We utilize data from the Community Reinvestment Act (CRA) which pertains to new loans at the county-level for small farms and businesses. The CRA, enacted by Congress in 1977, stipulates that banks are required to report on their lending activities in the areas of business, farming, and community development at a county level. The aim of the CRA was to ensure banks were meeting the credit requirements of their operational localities.

Banks must report their small business lending activities to the FDIC, but to alleviate regulatory burdens on smaller entities, asset size thresholds were put in place. These were initially set at $250 million for independent banks and $1 billion for affiliates of bank holding companies. These thresholds were raised to $1 billion for independent banks in 2005, though smaller banks were encouraged to continue reporting voluntarily. Since 2007, these thresholds have been adjusted annually to account for inflation, ranging from $1 billion to $1.252 billion in 2018 (Cole and Damm, 2021).

One limitation of this data is that it primarily covers larger, diversified banks that are less susceptible to the impact of locally concentrated droughts. Thus, using this data could potentially underestimate the overall impact, as we anticipate local banks to be more significantly affected by drought.

The CRA data categorizes loans into those under $100,000, between $100,000 and $250,000, and between $250,000 and $1 million. The U.S. Federal Financial Institutions Examination Council collects this data periodically on behalf of the Federal Reserve System. It defines small farm and business loans as those that originate with amounts up to US $1 million. This categorization may include loans to medium and larger businesses and excludes loans to small businesses originated above US $1 million. However, the dataset also includes information on loans issued to very small farms and businesses generating less than $1 million in revenue.

Table 1 presents the summary statistics for our sample of small farm loans. As shown, the average loan amounts relative to the banks' assets are quite minimal, e.g., small farm loans totaling less than $100,000 constitute merely 0.04% of assets, peaking at 13.2%. This can be attributed to our data being on the bank and county level. Conversely, our drought variables are relatively substantial, averaging between 1 to 3 weeks depending on drought intensity, and peaking at 27 weeks. This suggests that our coefficients will be very small; hence, we divide our drought variables by 100 for the regressions.

Table 1

2.2.2. Call Reports

Our study draws upon bank-level loan information from the Consolidated Reports of Condition and Income (Call Reports) for the period from 2000 to 2019. All federally insured banks are mandated to submit these reports to the Federal Deposit Insurance Corporation (FDIC), providing us with financial data at the state level. Our analysis exclusively considers loans issued by domestic branches (rcon data). Our primary measure represents the total loans, which corresponds to the aggregate gross book value of all loans. Additionally, we extract data from the Call

Reports detailing the loans to farmers, consumer loans, household loans, and commercial loans. The data also encompasses various measures of mortgage loans and loan performance. Lastly, to complement our third dataset, we also retrieve data on bank deposits.

2.2.3. FDIC Deposits and Ratewatch

Our third dataset is organized at the branch level, offering granular data on individual bank branches, inclusive of their precise geographic location. This dataset is formed by merging two others: the Summary of Deposits (SoD) from the FDIC, and Rate Watch's interest rate data.

Rate Watch offers interest rate quotes from banks at the branch level for a range of loan and deposit products, encompassing the most common interest-bearing checking, savings, and term deposits in the US. We focus our analysis on three commonly offered core deposit products across nearly all branches of US depository institutions: an interest-bearing checking account with a minimum balance of $0 (INTCK0K), a money market deposit account with a minimum balance of $25,000 as a saving deposit (MM25K), and a certificate of deposit with an account size of $10,000 for a tenor of 12 months (12CD10K). The data is merged with the SoD database using the unique FDIC branch identifier.

The Rate Watch data covers approximately three-quarters of the branches in the SoD database. Not all branches actively set deposit rates; many follow the rate established by another branch, referred to as a rate setter. To prevent duplication, our analysis is limited to active rate setters, which constitute close to 10% of the branches represented in the Rate Watch data.

3. New Loans to Small Farms and Small Businesses

The existing research indicates that natural disasters amplify local credit demand due to the need to rebuild damaged or destroyed physical capital Berg and Schrader (2012); Cortés and Strahan (2017); Koetter et al. (2020); Rajan and Ramcharan (2023). This is further supported by Cortes (2014), which demonstrates that regions with a stronger presence of local lenders witness quicker post-disaster recovery. Meanwhile, Rajan and Ramcharan (2023) demonstrates an increase in bank lending in response to drought, facilitating farm investment in productivity. They show that banks, reacting to heightened demand, shift assets towards loans in response to drought-induced credit demand.

Our analysis begins with the CRA dataset, covering the period from 2000 to 2019, to assess the impact of droughts on bank lending to small farms and small businesses. The dataset allows us to investigate new bank loan issuances to small farms and small firms during drought periods. Opaq small farms and firms rely heavily on relationship lending, a reliance that may intensify following a natural disaster due to asymmetric information. Cortes (2014) demonstrates that small and medium-sized enterprises (SMEs) that rely on relationships with local banks play a pivotal role in economic recovery in terms of improved job retention and creation patterns after a natural disaster.

The importance of relationship lending was underlined by Berg and Schrader (2012), who found that, following the volcanic eruption in Ecuador, credit demand increased, yet access to credit remained constrained. They discovered that bank-borrower relationships could mitigate these lending restrictions during natural disasters. Specifically, they report that clients familiar to the bank are about equally likely to receive loans after volcanic eruptions.

Our dataset does not allow us to distinguish the different relationships; however, it covers primarily relatively large banks that that depend more on hard information for lending decisions. Berger, Miller, Petersen, Rajan and Stein (2005) provide evidence that large banks shy away from small-business lending as this activity relies especially heavily on the production of soft information, something that small banks are better on. Accordingly, we hypothesize that these larger banks are more likely to restrict lending to small farms and small businesses in areas affected by drought. Our baseline regressions are structured as follows:

$$\mathit{loans}_{i,c,s,t} = \beta_0 + \beta_1 \,\mathrm{Drought}_{i,c,t} + \alpha_{i,c} + \mu_{s,t} + \varepsilon_{i,c,s,t} \tag{1}$$

In this equation, $\mathit{loans}_{i,c,s,t}$ signifies the amount (or number) of small loans originated by bank *i* in county *c* within state *s* in year *t*. The drought variable is a bank-county specific measure of drought exposure, weighted by deposits of the bank branches situated in the drought area. It represents the number of weeks during which a county has experienced a drought. We utilize two drought indicators: (i) at least D3 (D3=extreme and D4=exceptional) and (ii) at least D2 (D2=severe, D3=extreme, and D4=exceptional). The regressions control for bank-county fixed effects $\alpha_{i,c}$ and state-year fixed effects $\mu_{s,t}$; the former accounts for unobserved time-invariant bank-county factors, and the latter addresses common time- and state-specific shocks.

It is crucial to note that the remaining variation in the drought variable can be considered as random realizations from the location-specific drought distribution after accounting for bank-county specific effects. In other words, while banks and their branches may choose their locations based on expected drought shock distributions, this variation is absorbed by the bank-county specific effects as long as the distribution remains unchanged over time or changes over time unbeknownst to the banks. Importantly, the drought variable is rooted solely in the climatic characteristics of the droughts and pre-event weights of the branch sizes within the affected area.

The standard errors of the error term $\varepsilon_{i,c,s,t}$ are clustered by bank and year to allow for the clustering of shocks within a bank. Clustering at the county level, considering that our primary variable of interest (the drought variable) is county-specific, only enhances the precision of our estimates, hence our choice for a more conservative approach.

The baseline model is subsequently modified to include interactions with a post-2012 indicator variable. This alteration accounts for potential changes in the impact of droughts on bank lending due to modifications in the regulation concerning the designation of counties as extreme drought areas and government aid. In 2012, North America experienced one of the severest droughts in the history (Rajan and Ramcharan, 2023), leading to the legal declaration of 1,692 counties across 36 U.S. states as primary natural disaster areas. This drought affected over 62% of the contiguous U.S. and resulted in the designation of hundreds of additional counties as "contiguous" disaster areas, making them eligible for federal aid. This devastating drought cost the Midwest over \$35 billion and reduced the U.S. GDP by 0.5–1%, equating to a loss of \$75 to \$150 billion. As a response, the U.S. Government implemented aid instruments for the impacted farmers, ranchers, small businesses, and communities, which included lowering borrower interest rates for emergency loans and allowing credit unions to lend unlimited amounts to small business owners, including farmers. To account for these changes, we utilize the following augmented model:

$$\mathrm{loans}_{i,c,s,t} = \beta_0 + \beta_1\ \mathrm{Drought}_{i,c,t} + \beta_2\ \mathrm{Drought}_{i,c,t} * \mathrm{Post}^{2012} + \alpha_{i,c} + \mu_{s,t} + \varepsilon_{i,c,s,t} \quad (2)$$

In this model, Post^{2012} is an indicator variable that takes the value of 1 for the years 2012–2019 and zero otherwise. This variable is interacted with our drought measure to account for the easing of access to emergency loans in drought-affected counties.

The results pertaining to small farm loans are presented in Table 2. Columns (1) - (3) display results for different types of new small loans to farms, categorized based on amounts granted by banks. In contrast, column (4) details results for new loans to farms with revenues less than $1 million. Generally, the results show a decrease in new loans issued by banks to small farms in drought areas. In Panel A, coefficients for droughts of at least level D3 are negative and statistically significant across all columns. Similar results are evident in Panel C, where the coefficients account for droughts of at least level D2. These findings suggest a decrease in the number of new small loans to farms during drought seasons. Moreover, the results in column 4 confirm a reduction in loans to small-revenue farms during droughts.

In Panels B and D, we introduce an interaction term between the drought index and the dummy variable representing post-2012 reforms. While the coefficient for the drought remains negative across all specifications, it is only statistically significant in Panel D in columns (1) and (4). The coefficient for the interaction term is statistically insignificant across all specifications. Thus, these findings suggest that new bank loans to farms were not impacted during post-2012 drought periods, indicating that the implemented reforms effectively mitigated bank funding declines during drought periods.

Table 2 here

In their study, Berger, Frame and Miller (2005) highlighted that credit scoring enabled larger banks to extend their market presence, specifically targeting small business loans. However, uncertainties induced by drought cast shadows over the future profitability of these enterprises, heightening the information asymmetry between lenders and borrowers. Given these circumstances, it's reasonable to hypothesize that the trends observed for small businesses might parallel those noted for small farms. However, it's crucial to recognize that small firms aren't directly impacted by droughts. Therefore, any observed reduction might be indicative of bank-related decisions, potentially stemming from increased risk aversion in light of the drought.

In Table 3, we present the results on new loans to small businesses during drought periods. Like before, columns (1)–(3) display the results for different categories of new loans, whereas column (4) presents results for new loans to firms with revenues less than one million. In general, the results affirm our hypothesis showing that banks curtailed new lending to small businesses in drought-stricken areas. In panels A and C, the coefficients for the drought index are negative and statistically significant across all specifications.

In Panels B and D, we incorporate the interaction between the drought index and the dummy variable representing post-2012 reforms. Aligning with our prior results, the interaction term consistently lacks significance across all specifications. These observations imply that, post-2012, lending to small businesses was no longer influenced by drought conditions. This can be linked to the government's decision to extend aid programs to non-farm small businesses economically impacted by drought. [4]

Table 3

3.1. Emergency loans

To further explore the government's assistance to farmers, we introduce controls for counties designated for emergency loan eligibility. The data sample begins in 2012 due to data constraints. We incorporate a dummy variable, set to 1 for designated counties and 0 otherwise, as well as an interaction term with the drought indicator. The revised model is as follows:

$$\mathrm{loans}_{i,c,s,t} = \beta_0 + \beta_1\ \mathrm{Drought}_{i,c,t} + \beta_2\ \mathrm{Drought}_{i,c,t} * D^{desig}_{c,t} + \beta_3\ D^{desig}_{c,t} + \alpha_{i,c} + \mu_{s,t} + \varepsilon_{i,c,s,t} \tag{3}$$

Table 4 illustrates the outcomes for new loans to small farms, factoring in areas eligible for government emergency loans. Contrasting with the results shown in Table 2, we now find that the coefficients of drought are positively associated with new farm loans exceeding $100,000. However, the coefficients for drought are only significant in columns (2) and (3) in panels A and C, respectively. In line with Scott et al. (2022), the results indicate that farmers seek new funding during challenging periods. On introducing the designation dummy and its interaction with drought, all variables are statistically insignificant. This suggests the government's drought relief initiative is effective as no changes in new loans to farmers by banks are observable. Concurrently, the findings reaffirm that the prior reduction in lending was primarily driven by bank decisions.

[4] https://obamawhitehouse.archives.gov/blog/2012/08/08/assistance-small-businesses-affected-drought

Table 4

In 2012, the U.S. experience an extreme drought, resulting in at least abnormally dry conditions (D0) covering roughly 81% of the country. This year also marks the beginning of our subsample using designated counties, and consequently, our results may be skewed by the extraordinary drought and the novel fast-track program. Therefore, we rerun the regression excluding the year 2012. Table 5 presents the results for the period 2013-2019. The coefficients for the variables don't change sign compared to the previous results, but exhibit heightened statistical significance.

The findings corroborate that banks ramped up new lending to farmers during the drought season. In panel A, the coefficients for drought are positive and now statistically significant across all specifications. In panel C, the coefficient for drought is only significant in columns (2)–(3). The data upholds that the demand for new loans intensifies in drought-affected areas, particularly for small farms.

However, when the designation dummy is introduced, the coefficients lose significance in all specifications. The data attests that bank lending to small farms in designated areas remained steady during the drought following the introduction of expedited aid in 2012. Thus, our results demonstrate the effectiveness of the government program in stabilizing farm funding in drought-stricken areas.

Column 1 indicates that banks provide fewer small credits, less than $100,000, in drought and designated areas. The coefficient for drought and designated areas is negative and significant in panels C and D, respectively. Furthermore, when bank-time fixed effects are utilized in panel D, the results are even stronger, with both coefficients significant at least at the 5% level.

Adams et al. (2021) propose that small-dollar loans differ from larger loans, asserting that loans less than $100,000 are likely credit card loans, not directly comparable to other types of small business loans. Therefore, the data illustrates that small farms in drought areas augmented credit card loans during drought periods, but this trend reversed with the reforms and expedited aid introduced in 2012. We infer that the aid reduces current debt levels, which could account for the decline in loans less than $100,000 in designated drought areas.

So far, our data solely captures new loans to small farmers and small firms mainly from large banks. We therefore broaden our examination of the drought's impact on bank lending in this section.

Table 5

4. Changes in Banks' Loan Portfolio

So far, our results indicate that banks, particularly single-state or single-county banks, provide fewer new loans to small farms and enterprises in drought areas. However, the existing literature suggests that local credit increases in response to disasters because residents need to rebuild destroyed or damaged physical capital. Koetter et al. (2020) shows that banks in areas exposed to flooding increased their lending after the Elbe flood in Germany relative to unexposed local banks. Bos et al. (2022), using a theoretical model, documents that natural disasters destroy firm fixed capital, leading to a surge in loan demand and an increased borrowing rate. They confirm the validity of the model using US data and observe that banks increase post-disaster lending at a higher interest rate. Moreover, they observe a change in the composition of the assets of the banks following the natural disaster. Consequently, the model and empirical results confirm that banks increase lending following a disaster, yet at the same time, adjust their asset structure.

In our study, we assume that drought will affect, in the first place, the agriculture sector, and consequently, lending to the agriculture sector. While we do not expect that drought will directly affect other types of loans, we assume that banks may change their portfolio. We investigate the impact of droughts on the composition of bank loan portfolios by calculating different types of credit as a percentage of total loans. The baseline regressions adopt the following format:

$$share_{i,c,s,t} = \beta_0 + \beta_1\ Drought_{i,c,t} + \alpha_i + \upsilon_t + \varepsilon_{i,t} \tag{4}$$

Here, $share_{i,t}$ represents the ratio of a specific type of bank loan *i* to total bank loans in year *t*. The drought variable corresponds to a bank-specific measure of drought exposure, which is determined by the deposits in a bank's branches located in drought-affected areas. The regression controls for bank-specific effects α_i and year-fixed effects υ_t, with the former accounting for unobserved time-invariant bank-specific factors and the latter accommodating common time-specific shocks. The error term $\varepsilon_{i,t}$'s standard errors are clustered by county, given that our main variable of interest—the drought variable—is county-specific.

In continuation with our earlier approach, we include interactions post-2012. To ascertain whether the results differ among banks with varying degrees of geographic diversification, we partition the sample between single- and multi-state (county) banks. We also focus exclusively on the post-2012 period, and introduce a dummy variable for designated counties and an interaction term of this dummy with the drought variable.

4.1. Total loans

Our previous results indicated that banks extend fewer loans to small farms and businesses during drought periods. Consequently, a downturn in the bank's loan volume during such times would be anticipated. Building on this, our analysis first seeks to ascertain the impact of drought on the overall magnitude of the bank's loan portfolio.

Table 6 presents the results where the dependent variable in equation (4) represents the ratio of total loans to total assets. At first sight, we find that drought generally does not seem to strongly affect the level of bank lending. Contrary to our expectations, the coefficient for drought is positive in all specifications. Nonetheless, its statistical significance is only in panel A, column (6). This suggests that multicounty banks amplify their overall lending in drought-stricken areas. Conversely, other bank types maintain consistent loan levels regardless of drought conditions.

Notably, the situation changed after the 2012 reforms. In panel A, the coefficients for the interaction between drought and post-2012 consistently yield negative values and are statistically significant in most specifications at 10% level. An exception is the coefficient for the interaction term concerning single-county banks; although it's negative, it isn't statistically significant. These findings imply that single-county banks, known for their robust community ties, showed a diminished propensity to curtail lending during drought spells following the 2012 reforms. This relationship-centric trend gains traction considering the negative and statistically significant coefficients observed for multi-county banks in panels A and B.

The findings from panel C reveal that lending remained largely unaltered in counties benefiting from the drought aid program introduced in 2012. Although the coefficient for drought is negative, it's only statistically significant for multi-state banks. Of greater significance, however, is that the interaction term between drought and the designated county is statistical insignificant across specifications, with the exception being multi-state banks. Intriguingly, the interaction coefficient is now positive and statistically significant. This suggests that multi-state banks exhibit an increased inclination to augment their loan portfolios in drought-affected areas that are also designated for aid.

In general, the results show that the level of bank lending does not change due to drought. In other words, we do not find evidence that the general supply of bank loans is affected by drought. These findings contrast with the prevailing literature suggesting an increase in loan demand following natural disasters. One potential explanation for this deviation is that droughts primarily lead to the devastation of farmlands rather than infrastructure, thereby eliminating the need for reconstruction loans, which is typically necessary following other types of natural disasters.

Table 6

Our earlier findings indicated that banks extend fewer loans to small farms and enterprises. However, given that our results now reveals consistent lending levels during droughts, it suggests a potential shift in the composition of the bank's loan portfolio due to drought conditions. We delve further into this aspect in the subsequent sections.

4.2. Agricultural Production and Farm Loans

Our exploration commences with the examination of the influence of droughts on the proportion of agricultural loans in bank portfolios. Table 7 outlines the results of the analysis, revealing a contraction in the share of agricultural loans following a drought. In columns (1)-(2), the coefficient for drought is negative and significant at the 1% level, suggesting that banks generally minimize their exposure to the agricultural sector during drought periods.

Upon further scrutiny, we observe some discrepancies between different types of banks. The credit reduction seems predominantly led by single-state and single-county banks. These institutions continue to reduce lending to the agricultural sector during drought periods even post the 2012 reforms, as shown by the negative and statistically significant coefficient of the interaction term (droughts and post-2012) in columns (3) and (5). Yet, we found that these banks increase their portfolio in designated drought countries, indicated by the positive and statistically significant coefficient for the interaction term (drought and designated).

These findings diverge for multi-state and multi-county banks, emphasizing the differences between local banks and larger entities. In columns (4) and (5), the coefficient for drought is statisticall insignificant across most specifications. Notably, in panel B column (4), it emerges as positive but is statistically significant only at the 10% level.

In Panel C, we find that the interaction term for drought and designated areas is positive and statistically significant for single-state and single-county banks. However, the positive results primarily derive from the year 2012. In Panel D, we rerun the regression excluding the year 2012. This reveals that the coefficient for drought for single-state banks is positive and statistically significant, while for single-county banks, it is statistically insignificant. Furthermore, the coefficient for the interaction term (designated and drought) is negative and statistically significant for single-state banks, but again statistically insignificant for single-county banks.

In contrast, results in Panels A and B do not change in terms of the signs and significance of the coefficients when we replace the post-2012 dummy with a post-2013 dummy [5]. Consequently, our findings demonstrate that banks generally reduced their lending in drought areas, although we did not find differences in the designated counties, attesting to the effectiveness of the reforms.

Table 7

We extended our analysis by categorizing the banks in our sample into agricultural banks and other banks. We define agricultural banks as those commercial banks with agricultural loans constituting at least 15% and 25% of total loans. We set two thresholds given the variable density of agricultural banks reported in the literature (Scott et al., 2022). However, the results in Table 8 assert that different thresholds do not influence the findings. We observe that agricultural banks curtailed their lending in drought-ridden countries, with the coefficient of drought being significant only in counties with extreme drought. While the coefficient for drought for other banks is negative and significant in all specifications at the 1% level, the coefficients for agricultural banks are larger, indicating a more pronounced reduction in lending to the agricultural sector relative to other loans. Additionally, we find that both agricultural and other commercial banks scaled back lending in drought areas post the 2012 reforms, as evidenced by the negative and statistically significant coefficient for the interaction term between drought and the post-2012 dummy.

However, Panel C reveals that agricultural banks did not alter their lending to the agricultural sector in designated counties. In fact, the coefficient for the interaction term for drought and designated dummy is positive but statistically significant only for other banks. Thus, the findings suggest that other commercial banks even augmented their agricultural loan portfolio relative to

[5] We omit these results for brevity, but they can be made available upon request.

total loans due to government aid, whereas agricultural banks' farm loans remained unaffected by drought in designated counties, thereby reaffirming the effectiveness of the aid reforms.

Table 8

Rajan and Ramcharan (2023) reports that farmers in drought-afflicted areas in the 1950s, who had better access to credit, invested in new technologies, including the recently developed irrigation technology. This technological adoption proved advantageous, as Kuwayama et al. (2019) showed that the average impact of drought on crop yields is smaller in irrigated counties than in dryland counties. Accordingly, we reiterate our estimations, now accounting for irrigated and dryland counties using the data Kuwayama et al. (2019).

The results are shown in IA Table A1 for dryland and in Table A2 for irrigated counties, respectively. Generally, the results align with those presented in Table 7. We find that single-state and single-county banks reduce lending in drought areas, with larger coefficients for dryland counties. Moreover, the coefficient for drought is negative and statistically significant for multi-county banks for dryland counties. This suggests a more potent impact of droughts on loans in dryland counties. Interestingly, in Table A2, Panels A and B reveal that the coefficient for drought is positive and statistically significant for multistate banks. This suggests that these banks might be substituting for local banks, as farms in irrigated counties are less impacted by drought and can therefore receive new loans, potentially for further productivity investments. Hence, our findings not only highlight the existing disparities between dryland and irrigated counties but also, following Rajan and Ramcharan (2023), suggest that these differences result from past financial access. Simultaneously, we find that irrigated counties have better access to finance, which may create further divisions in the future between the two types of farms.

Overall, the findings validate that banks reduced lending to drought-affected farmers prior to the 2012 reforms. Post these reforms, both local and agricultural banks maintained their lending patterns in drought-stricken areas. In a contrasting move, non-specialized banks seized the opportunity to increase their lending to farmers now benefiting from government assistance due to the drought.

This reaffirms that the previous decrease in lending to the drought affected farmers was a conscious decision by the banks. Furthermore, the uptick in lending to the agricultural sector in designated areas by non-specialized banks underscores the persistent funding demand from drought affected farmers.

4.3. Commercial and Industrial Loans

In our preceding analysis, we demonstrated that banks reduced lending to small enterprises located in drought-stricken counties. Supporting this, Ding et al. (2011) posited that droughts might affect the business operations of firms outside the agricultural sector, especially those with substantial water consumption. Consequently, we now investigate the influence of drought on the proportion of commercial and industrial loans within a bank's total lending portfolio.

The results, presented in Table 9, indicate that drought does not alter the proportion of bank lending to non-agricultural firms. We only observe an increase in lending by multi-county banks in designated areas during a drought. In Panel C, the coefficient of the interaction term for drought and designated areas is significant and statistically significant at the 5% level.

Overall, the results imply that the non-agricultural sector, in general, remains resilient to droughts. Concurrently, the data reaffirms that banks become more risk-averse during drought periods, accounting for the decreased lending to drought-impacted small firms.

Table 9

4.4. Loans to Individuals

Our principal findings revealed that the banks' share of loans in relation to total assets remains unchanged during a drought, yet the share of agricultural loans in banks' portfolios decreases. Previous results indicated that the proportion of commercial and industrial loans in total loans does not change during a drought. Thus, we hypothesize that banks' lending to consumers may alter in drought-affected areas.

Table 10 confirm our assumptions as the coefficient of drought is positive and significant at the 1% level in almost all specifications. The exception is for multi-state banks, where the coefficient is positive but statistically insignificant in panels A and B, while in panel C, it is significant at the 10% level. This suggests that commercial banks increase the share of loans to individuals in drought-affected areas. A plausible explanation for this is that banks augment consumer lending to counterbalance the decline in agricultural lending in the afflicted counties (Borsuk et al., 2020).

This could also account for the results for multi-state banks, which contrast with other banks, as the drought coefficient had a positive association with farm lending and was statistically significant.

Nevertheless, we find that the situation underwent changes following the reforms of the aid programs in 2012. The coefficient for the interaction term between drought and post-2012 is negative and statistically significant for the whole sample in panel A. A more detailed analysis shows that the results are primarily driven by single-state banks and multi-county banks. The interaction terms for these banks are negative and statistically significant at least at the 5% level. In panel B, we observe that the coefficients are almost uniformly negative, but they are not statistically significant. In panel C, we find that the coefficient for the interaction term drought and designated is negative and statistically significant for the whole sample. A closer examination shows that the results are primarily driven by multi-county banks. The coefficient for the interaction term for this type of banks is negative and statistically significant at the 5% level. Interestingly, we find that the coefficient of the designated dummy is negative and statistically significant for single-county banks. This may imply that single-county banks reduced consumer lending in counties that received government aid but were not directly affected by the drought. A possible explanation is that in these areas, the supplemental funds permitted consumers to lower their existing bank debt.

Table 10

Up to this point, our analyses have illustrated that banks, in response to drought conditions, pivoted their portfolios away from the agricultural sector, increasing their stake in consumer lending. The 2012 governmental aid reforms, seem to have been curtailed these adaptive strategies. This strongly hints at the role of banks' increased risk aversion, particularly towards entities operating within drought-stricken regions. To ensure the robustness of our conclusions, we extended our analyses to dissect whether these findings held consistently across various consumer loan sub-categories. The detailed breakdown, available in Appendix Tables A3-A6, aligns consistently with the overarching trends presented in Table 10.

4.5. Real Estate Secured Loans

Cortés and Strahan (2017) document that bank lending, in the form of home mortgage originations, significantly increases in the months following disasters as residents in affected communities rebuild damaged physical capital. Bos et al. (2022) confirms the finding showing that the U.S. commercial banks increase real estate lending after disasters.

Although drought does not directly damage real estate, it may affect real estate prices during drought (Baldauf et al., 2020). Bernstein et al. (2019) showed that properties vulnerable to sea level rise fetch lower prices compared to those unaffected by climate change. This assertion was not only validated by Baldauf et al. (2020), but they also highlighted that perceptions and beliefs about climate change play a pivotal role in influencing property values. Building on this theme, Nguyen et al. (2022) revealed that for properties facing heightened climate change-related risks, lenders tend to levy higher mortgage interest rates.

Consequently, the existing research shows that natural disaster may effect real estates, yet its effect on mortgage loans is ambigius. Contrary to our assumptions, the results depicted in Table 11 don't align with our expectations. In Panel A, the coefficients for drought remain statistically insignificant across all specifications. This insinuates that drought conditions don't substantially influence the proportion of real estate-secured loans within bank portfolios. However, Panel B presents a slightly different picture. Here, the coefficients for drought for both single-state and multi-county banks are positive and statistically significant, suggesting that these types of banks increased their share of real estate-secured loans in areas impacted by drought.

However, this finding is not supported by the results presented in Panel C. We observe that multi-state and single-county banks reduced the shares of loans secured by real estate by designated counties affected by drought. At the same time, single-county banks increased lending in counties that were only designated as drought-affected. A possible explanation is that single-county banks are especially exposed to drought and therefore reduce their lending to real estate in these areas. Concurrently, in counties that are not directly affected by drought but benefit from being designated as such, the additional funds may be used for investment, financed by real estate secured loans. Furthermore, the changes in bank behavior post-2012 could be attributed to increasing climate change awareness and its impact on real estates used as collateral.

Table 11

Although our findings so far reflect minimal impact of drought conditions on real estate-secured lending, we chose to further investigate this aspect given literature-based evidence demonstrating the influence of climate change on real estate prices. We did by investigating the effect of drought on loans secured by diverse types of mortgages. These subsequent results are presented in the Online Appendix A7–A11.

The results shows that during periods of drought, the share of loans secured by farmland and construction land within the overall bank's loan portfolio tend to increase. As evidenced in Tables A7-A8, the coefficients for drought are positive and statistically significant across most specifications. Essentially, this implies an augmentation in loans extended to farmers and construction enterprises, with a crucial caveat that these loans are collateralized by real estate. By demanding real estate as collateral, banks signal their heightened risk awareness amidst drought conditions.

This phenomenon isn't uniformly observed across all banking institutions. Our findings point towards single-state and single-county banks as the primary drivers of this trend. Such banks, owing to their concentrated operational geographies, may be more sensitive and responsive to local climatic disruptions and their associated economic implications.

In contrast, banks scaled down the share of loans secured by 1-4 family residential properties during drought periods, as demonstrated by the positive and statistically significant coefficients for drought at a 1% level across all specifications in Table A9. Interestingly, this trend pivoted post-2012, as the coefficients for the interaction term between drought and the post-2012 period turned to be positive and highly statistically significant.

The influence of drought seems to be mitigated in designated counties where government aid is in place, implying the effectiveness of such intervention in countering the drought effect. Additionally, drought conditions appeared to have no significant impact on loans secured by multi-family (5 or more) residential properties and non-farm non-residential properties. This is reflected in Tables A10–A11, where the drought coefficient remains statistically insignificant for most of the specifications.

Generally, these results indicate that drought influences the nature of real estate-secured lending, but this impact is not universal. Instead, it is largely contingent on the type of real estate offered as collateral and the segment of borrowers. Furthermore, our findings reaffirm the hypothesis that banks exhibit increased risk aversion, in particular towards agriculture sector, during drought periods, a trend mitigated to some extent by the implementation of government aid post-2012.

4.6. Construction loans rates

Given the well-established relationship between drought and its effect on loans secured by real estate, we carried out a more granular analysis on the impact of drought on mortgage lending, specifically targeting construction loan rates. Our focus narrowed down to construction loans amounting to $175K due to their prominent representation within our dataset. We postulated that this standardized loan value would not exhibit significant disparities across the banks encompassed in our sample. The data to ascertain shifts in loan rates is from Bankrate, and the methodology employed to estimate these changes is discussed in the following section on deposits.

Our analysis, as illustrated in Table A12 of the Online Appendix, unexpectedly points out that drought does not have a significant bearing on construction loan rates. This implies that even though drought significantly influences real estate-secured loans, it does not directly trigger notable shifts in construction loan rates across different type of banks. This observation could offer critical insights into the intricate interplay of drought's impact on different aspects of real estate financing.

4.7. Non-Performing Loans

Until now, our analysis has operated under the assumption that droughts predominantly influence the lending behavior of banks. However, the degradation of a bank's loan portfolio quality during drought periods might also drive changes in lending behavior. Huljak et al. (2022) found that an exogenous surge in non-performing loans typically leads to a reduction in bank lending volumes, an expansion of bank lending spreads, and a decline in both real GDP growth and residential real estate prices.

Klomp (2014) posited that a heightened share of non-performing loans, potentially accompanied by a bank run in the immediate aftermath of a disaster, can amplify the risk of a bank defaulting. Drawing from a comprehensive dataset of natural disasters, he demonstrated that geophysical and meteorological disasters elevate the risk of bank failures, primarily due to the extensive damage they inflict. For instance, the environmental devastation wrought by the 2004 Indian Ocean earthquake and tsunami in Indonesia, particularly in Nias, was pinpointed as a primary catalyst for the surge in non-performing loans. The Nias community, predominantly agrarian, relies heavily on bank loans to acquire crops, livestock, machinery, and land. Brahmana et al. (2016) highlighted that the tsunami's impact on Nias severely compromised the residents' ability to repay their loans, leading to an increase in non-performing loans in local banks.

The deteriorating quality of loans, especially those extended to the agricultural sector, might underpin the observed reduction in lending during drought periods. To delve deeper into this hypothesis, we assess the influence of droughts on non-performing loans, presenting our findings in Table 12.

We observe that the coefficient for drought is negative in all specifications and statistically significant at least at the 5% level. Consequently, the results indicate an improvement of the quality of the nonperforming loans across the different types of banks. The only exception is for multi-state banks, where the coefficients are insignificant in Panels A and B. In Panels A and B, the results also show a decrease in non-performing loans following the 2012 reforms, with the interaction term for drought and post-2012 being negative and statistically significant in most specifications at the 5% level. Hence, the results shows overall an improvement in the quality of the loan portfolio during drought periods, indicating that this was not a cause for loan reduction.

However, Panel C shows an increase in non-performing loans in both drought-affected and designated areas. This rise in non-performing loans in designated regions might be attributed to an expansion of the loan portfolio. At the same time, we observed a decline in household loans, which could be indicative of a deteriorating performance of the loan portfolio. To ensure the robustness of our findings, we excluded the data from the 2012 drought year in our analysis. The outcomes, presented in Panel D, mirror those from Panel C but emphasize that single-state and single-county banks primarily drive the results.

In general, the findings suggest that reforms intended to support drought-stricken areas may have inadvertently increased the stability of the local banking sector. These results align with Brei et al. (2019), who also found no evidence of an increase in loan defaults following a hurricane in the Caribbean.

Table 12

We took our analysis a step further by examining more specific data, focusing on non-performing loans secured by farmland. We illustrate the results in the Online Appendix Table A13-14. We found that the coefficients for drought were statistically insignificant across all specifications. Interestingly, the coefficient for the interaction term between drought and post-2012 is negative across all specifications. However, it is statistically significant only for multi-state banks and multi-county banks. This suggests that the quality of such loans did not deteriorate during drought conditions, which could account for why banks decided to increase lending to farmers using their real estate as collateral.

Additionally, for multi-state banks, the coefficient for the interaction term between drought and designated counties is positive and statistically significant. This implies that the government aid program, while beneficial in many respects, also had some inadvertent adverse impacts on the stability of the banking sector.

5. Deposits

Ivashina and Scharfstein (2010) demonstrated that during the 2008 financial crisis, banks with better access to deposit financing were less inclined to curtail lending. In a related observation, Brei et al. (2019) found that banks experienced deposit withdrawals after a hurricane struck the Caribbean. These banks responded to this negative funding shock by reducing their lending supply and drawing on liquid assets. They posited that, in the region, deposits rather than bank loans became the primary funding source for post-hurricane recovery.

Steindl and Weinrobe (1983) investigated the impact of major natural disasters on bank deposits within the US context. Contrary to anticipated bank runs in the aftermath of such disasters, he found that banks witnessed a marked increase in deposits following four significant events. This observation aligns with the findings of Skidmore (2001), who identified a positive relationship between the extent of damage from natural disasters and the rate of household savings. Such behavior suggests that households might be resorting to self-insurance in the face of catastrophic events, particularly when traditional insurance markets fall short in providing comprehensive coverage against potential losses. In a related vein, Barth, Miller, Sun and Zhang (2022) noted that both local and non-local US banks, when confronted with a disaster, exhibit a rise in the proportion of brokered to total deposits, signaling a pivot to this market as an alternative funding avenue during times of natural crises.

Moreover, Barth, Miller, Sun and Zhang (2022) noted that bank exposure to disasters is associated with a rise in both deposit and loan rates. Notably, the surge in loan rates surpasses the rise in deposit rates, resulting in a greater net interest margin. Dlugosz et al. (2022) examined the deposit dynamics of banks, focusing on the discretion of bank branches in disaster-affected communities to set local deposit rates. This autonomy potentially allows them to elevate these rates to attract additional deposits, thereby drawing in more deposits to meet the amplified loan demand for reconstruction. Their findings indicates that branches with the capability to set local rates do, in fact, hike these rates and experience a surge of deposits in counties affected by natural disasters.

To gauge the influence of droughts on deposit volumes, we utilize data from the FDIC's Summary of Deposits (SOD). We also evaluate shifts in deposit rates using data sourced from Rate Watch. Both datasets are branch-level and encompass all commercial banks operating in the US. The baseline regressions are structured as follows:

$$\mathtt{rate}_{i,b,c,s,t} = \beta_0 + \beta_1 \ \mathtt{Drought}_{b,i,c,s,t} + \alpha_{i,b,c,s} + \mu_{s,t} + \varepsilon_{i,b,c,s,t} \tag{5}$$

where $\mathtt{rate}_{i,b,c,s,t}$ signifies the changes in deposit levels or deposit rates of bank *i*'s branch *b* located in county *c* of state *s* in year *t*. We also employ deposit volumes of bank *i*'s branch *b* located in county *c* of state *s* in year *t* as a dependent variable. We concentrate on three deposit variables: (i) interest-bearing checking account with a minimum balance of $0 (INTCK0K), (ii) money market deposit account with a minimum balance of $25,000 as a saving deposit (MM25K), and (iii) certificates of deposit with an account size of $10,000 for a tenor of 12 months (12CD10K). We also examine the impact on the annual growth rate of branch deposits. As previously stated, we only focus on active rate setters (approximately 10% of the sample) when using Rate Watch data to avoid double-counting. Therefore, the number of observations will be significantly lower in the case of interest rates compared to the analysis of deposits.

As in prior analyses, we control for branch-specific factors ($\alpha_{i,b,c,s}$) and state-year fixed effects ($\mu_{s,t}$). The former controls for unobserved time-invariant branch-specific factors, while the latter accounts for common state-time specific shocks. The standard errors of the error term $\varepsilon_{i,b,c,s,t}$ are robust, i.e., clustered by branch, as our primary variable of interest, the drought variable, is branch-specific.

5.1. Deposits

Table 13 illustrates the impact of droughts on the growth rate of branch deposits. The results indicate that deposit levels have risen in single-state and single-county banks during droughts. In Panels A and B, the coefficients for drought are positive and statistically significant at the 1% level. However, we find that the interaction term between drought and post-2012 is negative and statistically significant, but only in Panel A. To assess the sensitivity of the results, we adjusted the post-2012 dummy to post-2013, though the results are not presented for brevity. We discovered that the coefficients for the interaction term between drought and post-2013 are now negative and statistically significant for single-state and single-county banks. Consequently, the data show that these two types of banks experienced a decline in deposit growth in drought-affected areas following the reforms of 2012.

In Panel C, the coefficients for drought and designated areas are not statistically significant for single-state and single-county banks. However, when we exclude the year of the 2012 drought, the results in Panel D are now analogous to the previous findings. We observe that the coefficients for drought are positive for single-state and single-country banks, while the interaction term for drought and designated areas is negative. Contrarily, the coefficients are only statistically significant for single-state banks. At the same time, we find that the interaction term is positive and statistically significant for multi-state and multi-county banks. Therefore, these results suggest that local banks experienced an increase in deposits during the drought period prior to the 2012 reforms, which could be attributed to liquidity hoarding by depositors. In fact, we find that local banks lend their surplus deposits to other banks during the drought period. In the Online Appendix, Table A16 presents the results of bank lending to other depository institutions. The coefficient of drought is positive and statistically significant for single-state banks.

Following the 2012 reforms, the scenario changed; we note a decline in deposit growth in local banks, while multi-state and multi-county banks saw an increase. In Table A13, the interaction term for drought and post-2012 or designated areas is insignificant. Hence, the results confirm that the 2012 reforms impacted the local banking sector.

Table 13

5.2. Deposit rates

The prior results revealed that deposit growth in local banks increased during drought periods, but this trend reversed following the 2012 reforms. This increase could be attributed to banks' liquidity hoarding behavior rather than depositor actions. Existing literature documents that banks precautionarily hoard liquidity during periods of economic uncertainty (Berger et al., 2022), particularly during crisis periods (Acharya and Merrouche, 2013).

Following Berger et al. (2022), we analyze deposit interest rates to identify whether liquidity hoarding is driven by depositors or banks. If depositors are the ones deciding to save more, we should observe a decrease in deposit rates as banks respond to growing liquidity. Conversely, if banks are driving the increase in deposits, we should observe a rise in deposit rates as they seek to attract new and additional deposits from households and non-financial entities.

We commence our analysis with checking account rates (INTCK0K), which are primarily held for transactional purposes. Consequently, we anticipate that the balance on these accounts will be less sensitive to interest rate changes. Table 14 presents the results, indicating that banks increased their interest rates during drought periods. In Panels A and B, the coefficient for drought is positive and statistically significant for single-state and multi-county banks. However, we observe a shift following the 2012 reforms; the coefficient for the interaction term is now negative and significant at the 1% level for single-state, single-county, and multi-county banks. Interestingly, none of the coefficients in Panel C are statistically significant.

Table 14

Next, we explored the impact of drought on interest rate changes for saving products. Table 15 presents the results for 12-month CDs (12MCD10K) with a minimum account size of $10,000, one of the most common savings products in the US (Granja et al., 2021). As a robustness check, we also examined money market accounts with a minimum account size of $25,000 (MM25K), with results shown in Table A15.

The outcomes for savings products mirror those for checking accounts. In Table 15, Panels A and B, the drought coefficient is positive and statistically significant at the 1% level. Conversely, the interaction term for post-2012 and drought is negative and statistically significant at the 1% level. However, the coefficients are not significant for multi-state banks.

Granja et al. (2021) established that banks tend to apply uniform deposit rates across their branch networks for different deposit products, including savings accounts and money market accounts. They also found significant variation in deposit rates among branches of different banks located in the same county. This suggests that local banks are more likely to adjust their deposit rates in response to changes in local economies. Our results align with the findings of Granja et al. (2021) as we notice changes in deposit rates for local banks, while results for multi-state banks are statistically insignificant.

This implies that the observed changes in deposit interest rates are primarily driven by drought and local banks' adaptive policies. The results in (Table 13) indicate that local banks increased deposit rates during drought periods to boost liquidity, leading to an increase in the level of deposits in drought affected areas. We theorize that this is a precautionary measure, as we observed local banks beginning to lend their funds to other financial institutions during the drought period (Table A16).

However, the situation shifted following the 2012 government reforms. From 2012 onwards, local banks have been reducing interest rates, a trend we attribute to increased liquidity due to rapid transfers of aid to drought areas. On one hand, we see a decrease in deposits in drought areas following the 2012 reforms. On the other hand, there is an increase in bank deposits in designated counties, those eligible for immediate state aid. Interestingly, we did not observe a change in deposit rates in these areas. In fact, Panel C shows insignificant results in all regressions, suggesting that banks no longer respond to drought in designated areas, likely due to confidence in their liquidity status thanks to state aid transfers. In contrast, Panel C reveals that results are only significant for multi-county banks, which increase their deposit rates in designated drought counties. We theorize that these banks formulate their policies based on anticipated changes in local markets and overall experience, reflecting their weaker understanding of local economies.

Table 15

In conclusion, our results reveal that local banks adjust their deposit policies in response to shifts in local economies. We found that local banks elevate deposit interest rates during drought periods. Although this points to local banks stockpiling liquidity, evidenced by an increase in deposits, we do not believe this impacts the banks' lending activities. In fact, we note that the surplus liquidity is lent to other banks through the interbank market during drought periods.

6. Conclusion

This research provides insights into the adaptation strategies of commercial banks in response to drought periods within the US. We observe a surprising decrease in the issuance of new loans to small farms during drought conditions, diverging from the commonly held belief that loan demand increases following natural disasters. We posit that this anomaly stems from the unique characteristics of droughts which primarily affect agricultural yields rather than physical infrastructure, consequently decreasing the requirement for reconstruction-oriented loans.

An intriguing aspect of our analysis lies in the differential lending responses of banks in dryland versus irrigated counties. Single-state and single-county banks curtail lending in drought affected areas, particularly in dryland counties. Meanwhile, multistate banks step in to fill the lending void in irrigated counties, potentially catering to the productivity enhancement needs of less affected farms.

Our exploration into the impact of droughts on non-agricultural sectors uncovers that such climatic events do not significantly modify the distribution of bank lending to these sectors. However, we note a strategic shift in lending behavior, as banks appear to increase their share of loans to individuals within drought-impacted regions. We hypothesize that this may be an intentional move to offset the decline in agricultural lending in these locales.

In assessing the efficacy of government intervention, we discern a stabilizing effect on new bank loans to farms during post-2012 drought periods, attributable to reforms aimed at improving access to emergency loans. This finding underscores the important role of policy measures in mitigating the financial impacts of climate shocks on the farming sector.

Interestingly, our findings indicate that drought conditions also induce changes in bank deposit behaviors. Local banks experience an increase in deposit growth during drought periods, which reversely post-2012 reforms. This, combined with an observed elevation in deposit rates during droughts, suggests that these banks may be adopting precautionary liquidity hoarding strategies.

Regarding deposit interest rates, our research indicates that local banks boost rates during drought seasons, perhaps as a mechanism to attract increased deposits and thereby strengthen their liquidity positions. Post-2012, however, these institutions seem to reduce their deposit rates, a trend which we speculate may be a response to enhanced liquidity brought about by expedited state-aid transfers to drought-impacted areas.

In essence, our findings illuminate the nuanced ways in which banks navigate local economic fluctuations and emphasize the crucial role of government intervention in alleviating the adverse effects of natural disasters on banking operations. These results underscore the necessity for carefully tailored policy responses to climatic events, which adequately account for variations in bank types and their geographical purview.

In the face of mounting climate change challenges, where increased incidence and severity of droughts are becoming a pressing reality, our understanding of banking adaptations to such conditions is crucial for the development of robust agricultural and financial policies. Future research that delves into the long-term consequences of shifts in lending behavior on agricultural sectors and rural economies could offer valuable direction for policy design.

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Table 1 Summary statistics

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
Panel A: CRA dataset						
Amount <100k	Total amount of small farm loans originated with loan amount at origination of less than $100,000, in percentage of assets	119294	0.04	0.21	0	13.19
Amount >100k <250k	Total amount of small farm loans originated with loan amount at origination in the range of $100000-$250000, in percentage of assets	119294	0.04	0.18	0	9.08
Amount >250k<1m	Total amount of small farm loans originated with loan amount at origination in the range of $250000-1 million, in percentage of assets	119294	0.03	0.16	0	8.16
Amount firms revenue <1m	Total amount of Loans Originated to Small Businesses with Gross Annual Revenues < $1 million, in percentage of assets	119294	0.10	0.44	0	22.10
Droughts$_{3-4}$	Number of weeks within the growing season for which the drought index is at least level D3	119294	0.03	0.06	0	0.27
Droughts$_{2-4}$	Number of weeks within the growing season for which the drought index is at least level D2.	119294	0.01	0.04	0	0.27

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
Panel B Call Reports dataset						
Total loans	Total loans in percent of total assets	136453	63.75	15.93	0.01	91.40
Agriculture loans	Loans to finance agricultural production and other loans to farmers in percent of total loans, in percent of total loans	136453	7.26	12.33	0	55.91
Industry loans,	Commercial and industrial loans to U.S. address, in percent of total loans	136453	3,46	7,99	0	53,87
Individual loans	Loans to individuals for household, family, and other personal expenditures	136453	2,62	5,26	0	33,02
Real estate loans	Loans secured by real estate, in percent of total loans	136453	58,62	25,49	0,91	99,66
Loans, RE, farmland	Loans secured by real estate, secured by farmland, in percent of total loans	136453	6,97	9,28	0	39,56
Loans, RE, 1-4 residential	Loans secured by real estate, secured by 1–4 family residential properties, in percent of total loans	136453	29,04	19,65	0	92,34
Loans, RE, multi-residential	Loans secured by real estate, secured by multifamily (5 or more) residential properties, in percent of total loans	136453	2,39	3,63	0	21,17
Loans, RE, non-farm	Loans secured by real estate, secured by nonfarm nonresidential property, in percent of total loans	136453	15,58	17,27	0	65,74
NPL, RE, farmland, non-accrual	Loans secured by real estate (in domestic offices): secured by farmland - nonaccrual, in percent of total loans	136453	0,05	0,18	0	1,29
$Droughts_{3\text{-}4}$	Number of weeks within the growing season for which the drought index is at least level D3.	136453	1.11	3.91	0	27
$Droughts_{2\text{-}4}$	Number of weeks within the growing season for which the drought index is at least level D2.	136453	2.60	5.97	0	27

Variable	Definition	Obs.	Mean	Std. Dev.	Min	Max
Panel C SoD dataset						
Deposit growth	Annual growth rate of branch deposits	1672750	11.44	35.95	-100	248.15
$Droughts_{3\text{-}4}$	Number of weeks within the growing season for which the drought index is at least level D3.	1672750	1.17	4.46	0	27
$Droughts_{2\text{-}4}$	Number of weeks within the growing season for which the drought index is at least level D2.	1672750	2.63	6.44	0	27
Panel D Rate Watch dataset						
MM25K	Money market deposit account with minimum balance $25.000	131804	0.73	0.78	0	5.40
12MCD10K	Certificates of deposit with an account size $10.000 for a tenor of 12 month	138303	1.52	1.32	0	6.60
INTCK0K	Interest-bearing checking account with minimum balance $0	132855	0.27	0.34	0.001	10.47
Construction loans 175K	Construction loans of less than $170,000	14025	5.95	1.39	0	11.98
$Droughts_{3\text{-}4}$	Number of weeks within the growing season for which the drought index is at least level D3.	131804	1.08	3.91	0	27
$Droughts_{3\text{-}4}$	Number of weeks within the growing season for which the drought index is at least level D2.	131804	2.55	6.01	0	27

Table 2 Droughts and lending to small farms by types of loans and firms

The estimation period is 2000-2019. The estimations are done with the fixed effects estimator including bank-county and state-year fixed effects. The data covers lending to small businesses reported by CRA regulations. "<100k" is the logarithm of one plus the number (100*total amount/total assets) of small business loans originated with loan amount at origination of less than $100,000. Similar definitions apply to columns (2) -(3) with higher loan amounts. The column 4 "revenue <1m" is the logarithm of one plus the number (100*total amount/total assets) of loans originated to small businesses with gross annual revenues of less than $1 million. Standard errors are clustered by bank and year. Standard errors are clustered by bank and year. In brackets t-statistics are shown. *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)
		Loan amount		Revenue
	<100k	>100k <250k	>250k <1m	<1m
Panel A: Drought index at least of level D3				
$Droughts_{3\text{-}4}$	-0.011*	-0.012**	-0.016***	-0.038**
	(-1.93)	(-2.03)	(-2.75)	(-2.55)
Observations	119,294	119,294	119,294	119,294
R^2	11141	11141	11141	11141
Panel B: Drought index at least of level D3 with interaction				
$Droughts_{3\text{-}4}$	-0.010	-0.009	-0.015	-0.033
	(-0.99)	(-0.95)	(-1.59)	(-1.27)
$Droughts_{3\text{-}4}$*post 2012	-0.002	-0.006	-0.003	-0.011
	(-0.22)	(-0.46)	(-0.26)	(-0.36)
Observations	119,294	119,294	119,294	119,294
R^2	0.875	0.846	0.817	0.860
Panel C: Drought index at least of level D2				
$Droughts_{2\text{-}4}$	-0.016***	-0.009*	-0.013**	-0.039***
	(-2.90)	(-1.69)	(-2.39)	(-2.71)
Observations	119,294	119,294	119,294	119,294
R^2	11141	11141	11141	11141
Panel D: Drought index at least of level D2 with interaction				
$Droughts_{2\text{-}4}$	-0.020**	-0.007	-0.011	-0.042*
	(-2.40)	(-0.88)	(-1.34)	(-1.83)
$Droughts_{2\text{-}4}$*post 2012	0.011	-0.004	-0.004	0.007
	(1.25)	(-0.46)	(-0.46)	(0.27)
Observations	119,294	119,294	119,294	119,294
R^2	0.875	0.846	0.817	0.860

Table 3 Droughts and lending to small businesses

The estimation period is 2000-2019. The estimations are done with the fixed effects estimator including bank-county and state-year fixed effects. The data covers lending to small businesses reported by CRA regulations. "<100k" is the amount (100*total amount/total assets) of small business loans originated with loan amount at origination of less than $100,000. Similar definitions apply to columns (2) to (3) with higher loan amounts. Column (4) is the amount (100*total amount/total assets) of loans originated to small businesses with gross annual revenues of less than $1 million. Standard errors are clustered by bank and year. Standard errors are clustered by bank and year. In brackets t-statistics are shown. *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)
		Loan amount		Revenue
	<100k	>100k <250k	>250k <1m	<1m
Panel A: Drought index at least of level D3				
$Droughts_{3-4}$	-0.023*	-0.034**	-0.108***	-0.085**
	(-1.90)	(-2.21)	(-3.29)	(-2.38)
Observations	248989	248989	248989	248989
R^2	20153	20153	20153	20153
Panel B: Drought index at least of level D3 with interaction				
$Droughts_{3-4}$	-0.020	-0.033	-0.110**	-0.107*
	(-1.00)	(-1.27)	(-2.17)	(-1.76)
$Droughts_{3-4}$*post 2012	-0.005	-0.002	0.005	0.047
	(-0.24)	(-0.08)	(0.09)	(0.70)
Observations	248989	248989	248989	248989
R^2	0.797	0.759	0.733	0.753
Panel C: Drought index at least of level D2				
$Droughts_{2-4}$	-0.025***	-0.026**	-0.071***	-0.078***
	(-2.69)	(-2.19)	(-2.76)	(-2.71)
Observations	248989	248989	248989	248989
R^2	20153	20153	20153	20153
Panel D: Drought index at least of level D2 with interaction				
$Droughts_{2-4}$	-0.030**	-0.025	-0.062	-0.101**
	(-2.08)	(-1.39)	(-1.63)	(-2.28)
$Droughts_{2-4}$*post 2012	0.012	-0.002	-0.022	0.056
	(0.72)	(-0.09)	(-0.50)	(1.20)
Observations	248989	248989	248989	248989
R^2	0.797	0.759	0.733	0.753

Table 4 Droughts and lending to small farms, post-2012

The estimation period is 2012-2019. The estimations are done with the fixed effects estimator including bank-county and state-year fixed effects. The data covers lending to small farms reported by CRA regulations. "Num. <100k" ("Amount <100k") is the logarithm of one plus the number of small farm loans (100*total amount/total assets) originated with loan amount at Origination of less than $100,000. Similar definitions apply to columns (3) to (6) with higher loan amounts. "Num. firms revenue <1m" (Amount firms revenue <1m) is the logarithm of one plus the number (100*total amount/total assets) of loans originated to small businesses with gross annual revenues of less than $1 million. Standard errors are clustered by bank and year. In brackets t-statistics are shown. *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)
		Loan amount		Revenue
	<100k	>100k <250k	>250k <1m	<1m
Panel A: Drought index at least of level D3				
$Droughts_{3\text{-}4}$	0.001	0.007**	0.007*	0.008
	(0.59)	(2.51)	(1.77)	(1.46)
Observations	49630	49630	49630	49630
R^2	0.962	0.942	0.930	0.963
Panel B: Drought index at least of level D3 with interaction				
$Droughts_{3\text{-}4}$	0.005	0.011	0.009	0.008
	(0.60)	(0.92)	(0.53)	(0.33)
Designated	0.000	0.000	0.000	0.000
	(1.31)	(0.75)	(0.73)	(0.54)
$Drought_{3\text{-}4}$*Designated	-0.005	-0.005	-0.002	-0.001
	(-0.58)	(-0.41)	(-0.12)	(-0.03)
Observations	49630	49630	49630	49630
R^2	0.962	0.942	0.930	0.963
Panel C: Drought index at least of level D2				
$Droughts_{2\text{-}4}$	0.001	0.005**	0.006*	0.005
	(0.96)	(2.33)	(1.86)	(1.11)
Observations	49630	49630	49630	49630
R^2	0.962	0.942	0.930	0.963
Panel D: Drought index at least of level D2 with interaction				
$Droughts_{2\text{-}4}$	0.006	0.009	0.013	0.015
	(0.96)	(1.12)	(1.10)	(0.80)
Designated	0.000	0.000	0.000	0.000
	(1.37)	(0.64)	(0.71)	(0.77)
$Drought_{2\text{-}4}$*Designated	-0.006	-0.006	-0.010	-0.014
	(-0.94)	(-0.69)	(-0.78)	(-0.69)
Observations	49630	49630	49630	49630
R^2	0.962	0.942	0.930	0.963
Includes in addition bank-time fixed effects				
Droughts	0.003	0.002	0.003	-0.002
	(0.95)	(0.47)	(0.60)	(-0.32)
Designated	0.000	0.000	0.000	0.000
	(1.32)	(0.19)	(0.54)	(0.95)
$Drought_{2\text{-}4}$*Designated	-0.002	0.0001	0.0003	0.006
	(-0.84)	(0.03)	(0.06)	(0.71)
Observations	49061	49061	49061	49061
R^2	0.962	0.952	0.946	0.966

Table 5 Droughts and lending to small farms, post-2013

The estimation period is 2013-2019. The estimations are done with the fixed effects estimator including bank-county and state-year fixed effects. The data covers lending to small farms reported by CRA regulations. "Num. <100k" ("Amount <100k") is the logarithm of one plus the number of small farm loans (100*total amount/total assets) originated with loan amount at Origination of less than $100,000. Similar definitions apply to columns (3) to (6) with higher loan amounts. "Num. firms revenue <1m" (Amount firms revenue <1m) is the logarithm of one plus the number (100*total amount/total assets) of loans originated to small businesses with gross annual revenues of less than $1 million. Standard errors are clustered by bank and year. In brackets t-statistics are shown. *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)
		Loan amount		Revenue
	<100k	>100k <250k	>250k <1m	<1m
Panel A Drought index at least of level D3				
Droughts$_{3\text{-}4}$	0.003*	0.010***	0.011***	0.015**
	(1.91)	(3.44)	(2.59)	(2.50)
Observations	43908	43908	43908	43908
R^2	0.963	0.943	0.934	0.967
Panel B Drought index at least of level D3 with interactions				
Droughts$_{3\text{-}4}$	0.200	0.134	-0.0372	-0.197
	(0.69)	(0.62)	(-0.08)	(-0.91)
Designated	0.000	0.000	0.000	-0.000
	(0.63)	(0.51)	(0.87)	(-0.20)
Droughts$_{3\text{-}4}$ * Designated	-0.198	-0.124	0.048	0.213
	(-0.68)	(-0.57)	(0.10)	(0.98)
Observations	43908	43908	43908	43908
R^2	0.963	0.943	0.934	0.967
Panel C Drought index at least of level D2				
Droughts$_{2\text{-}4}$	0.002*	0.007***	0.008***	0.007**
	(1.90)	(3.51)	(3.06)	(2.11)
Observations	43908	43908	43908	43908
R^2	0.963	0.943	0.934	0.967
Panel D Drought index at least of level D2 with interactions				
Droughts$_{2\text{-}4}$	0.076**	0.073	-0.003	0.014
	(2.00)	(1.33)	(-0.07)	(0.32)
Designated	0.000	0.000	0.000	-0.000
	(0.74)	(0.25)	(0.38)	(-0.32)
Droughts$_{2\text{-}4}$ *Designated	-0.075*	-0.066	0.011	-0.007
	(-1.96)	(-1.21)	(0.25)	(-0.15)
Observations	43908	43908	43908	43908
R^2	0.963	0.943	0.934	0.967
Includes in addition bank-time fixed effects				
Droughts$_{2\text{-}4}$	0.078**	0.066	-0.020	0.059
	(2.07)	(1.38)	(-0.38)	(1.41)
Designated	0.000	0.000	0.000	0.000
	(1.31)	(0.41)	(0.60)	(0.93)
Drought$_{2\text{-}4}$ *Designated	-0.079**	-0.064	0.023	-0.056
	(-2.09)	(-1.36)	(0.44)	(-1.37)
Observations	43439	43439	43439	43439
R^2	0.960	0.952	0.945	0.967

Table 6 Total loans

The estimation period is 2001-2020. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable are total loans in percent of assets reported in the call reports. "Single state banks" (multi) are banks that operate in one (more than one) state. "Single county banks" (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown. *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A Drought index at least of level D3						
$Droughts_{3\text{-}4}$	0.001	0.015	0.012	0.046	0.006	0.021*
	(0.09)	(1.47)	(1.15)	(1.40)	(0.41)	(1.89)
Droughts*post 2012		-0.039*	-0.038*	-0.075*	-0.032	-0.061***
		(-1.89)	(-1.85)	(-1.84)	(-1.17)	(-3.32)
Observations	136322	136322	126108	10087	67698	68165
R^2	0.787	0.787	0.789	0.842	0.816	0.787
Panel B Drought index at least of level D2						
$Droughts_{2\text{-}4}$	-0.002	0.003	0.004	-0.019	-0.001	0.005
	(-0.32)	(0.53)	(0.58)	(-0.97)	(-0.06)	(0.70)
Droughts*post 2012		-0.028	-0.030	-0.009	-0.025	-0.045**
		(-1.43)	(-1.56)	(-0.29)	(-1.02)	(-2.57)
Observations	136322	136322	126108	10087	67698	68165
R^2	0.787	0.787	0.789	0.842	0.816	0.787
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2\text{-}4}$	-0.023***	-0.019	-0.019	-0.069**	-0.040	-0.014
	(-2.91)	(-1.21)	(-1.09)	(-2.14)	(-1.39)	(-0.82)
Designated		-0.126	-0.153	-0.297	-0.321*	0.003
		(-1.38)	(-1.54)	(-1.27)	(-1.96)	(0.03)
Drought*Designated		-0.001	-0.002	0.077**	0.031	-0.010
		(-0.07)	(-0.12)	(2.01)	(1.00)	(-0.53)
Observations	52471	52471	46865	5524	22508	29783
R^2	0.902	0.902	0.901	0.916	0.909	0.896

Table 7 The impact of droughts on agricultural production and farm loans

The estimation period is 2001-20. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable are loans to finance agricultural production and other loans to farmers in percent of total loans reported in the call reports. "Single state banks" (multi) are banks that operate in one (more than one) state. "Single county banks" (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown. *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A Drought index at least of level D3						
$Droughts_{3\text{-}4}$	-0.023***	-0.010***	-0.013***	0.014	-0.017***	-0.006
	(-6.39)	(-3.06)	(-3.74)	(1.41)	(-3.39)	(-1.41)
Droughts* post 2012		-0.035***	-0.033***	-0.016	-0.031***	-0.028***
		(-5.15)	(-4.67)	(-1.37)	(-2.92)	(-4.56)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.946	0.946	0.947	0.968	0.955	0.952
Panel B Drought index at least of level D2						
$Droughts_{2\text{-}4}$	-0.014***	-0.006***	-0.008***	0.010*	-0.010***	-0.004
	(-5.83)	(-2.88)	(-3.59)	(1.84)	(-3.19)	(-1.51)
Droughts* post 2012		-0.038***	-0.037***	-0.014	-0.037***	-0.030***
		(-5.57)	(-5.17)	(-1.57)	(-3.38)	(-5.20)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.946	0.946	0.947	0.968	0.955	0.952
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2\text{-}4}$	-0.007**	-0.017***	-0.020***	0.003	-0.040***	0.002
	(-2.39)	(-3.19)	(-3.26)	(0.31)	(-4.28)	(0.32)
Designated		-0.061	-0.063	-0.028	-0.089	-0.010
		(-1.57)	(-1.50)	(-0.42)	(-1.34)	(-0.23)
Drought* Designated		0.015**	0.017***	0.001	0.037***	-0.006
		(2.46)	(2.61)	(0.05)	(3.69)	(-0.79)
Observations	52817	52817	46805	5929	22384	30251
R^2	0.973	0.973	0.974	0.979	0.976	0.974
Drought index at least of level D2, post-2013						
$Droughts_{2\text{-}4}$	-0.003	0.020	0.048*	-0.004	0.082	0.006
	(-0.78)	(1.32)	(1.67)	(-0.40)	(1.39)	(0.60)
Designated		-0.070*	-0.073*	-0.032	-0.086	-0.024
		(-1.77)	(-1.68)	(-0.46)	(-1.28)	(-0.53)
Drought* Designated		-0.021	-0.049*	0.006	-0.087	-0.008
		(-1.37)	(-1.69)	(0.58)	(-1.45)	(-0.72)
Observations	45792	45792	40409	5289	19111	26510
R^2	0.976	0.976	0.976	0.981	0.979	0.975

Table 8 The impact of droughts on agricultural production and farm loans at agricultural banks

The estimation period is 2001-2020. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable are loans to finance agricultural production and other loans to farmers in percent of total loans reported in the call reports. In column (1) and (3) agricultural bank are defined as banks were agricultural production and farm loans represent at least 15% and 25% of total loans, respectively. In brackets, t-statistics are shown, and *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1) Agricultural banks	(2) Other banks	(3) Agricultural banks	(4) Other banks
Panel A Drought index at least of level D3				
$Droughts_{3\text{-}4}$	-0.044**	-0.006***	-0.052*	-0.008***
	(-2.38)	(-2.83)	(-1.84)	(-2.80)
Droughts*post 2012	-0.115***	-0.012***	-0.102***	-0.024***
	(-4.52)	(-3.14)	(-2.72)	(-4.40)
Observations	24884	111569	13309	123144
R^2	0.809	0.825	0.705	0.884
Panel B Drought index at least of level D2				
$Droughts_{2\text{-}4}$	-0.012	-0.006***	-0.017	-0.006***
	(-1.02)	(-4.63)	(-0.98)	(-3.44)
Droughts*post 2012	-0.144***	-0.011***	-0.135***	-0.026***
	(-6.01)	(-3.24)	(-4.09)	(-4.70)
Observations	24884	111569	13309	123144
R^2	0.809	0.825	0.705	0.884
Panel C Drought index at least of level D2, post-2012				
$Droughts_{2\text{-}4}$	-0.026	-0.017***	-0.011	-0.020***
	(-0.84)	(-4.76)	(-0.23)	(-4.89)
Designated	-0.095	-0.032	-0.133	-0.027
	(-0.53)	(-1.45)	(-0.50)	(-0.87)
Drought*Designated	0.018	0.013***	0.017	0.013***
	(0.62)	(3.28)	(0.37)	(2.76)
Observations	9600	43217	5098	47719
R^2	0.907	0.924	0.852	0.950

Table 9 Commercial and industrial loans to U.S. address

The estimation period is 2001-20. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable are loans secured by real estate in percent of loans reported in the call reports. "Single state banks" (multi) are banks that operate in one (more than one) state. "Single county banks" (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown. *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A Drought index at least of level D3						
$Droughts_{3-4}$	0.005	-0.000	-0.002	0.000	-0.000	0.006
	(0.81)	(-0.08)	(-0.32)	(0.01)	(-0.07)	(0.81)
Droughts*post 2012		0.014	0.016	-0.035	0.018	0.001
		(1.08)	(1.33)	(-1.04)	(0.78)	(0.09)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.729	0.729	0.701	0.819	0.684	0.759
Panel B Drought index at least of level D2						
$Droughts_{2-4}$	0.003	0.001	-0.000	-0.005	-0.001	0.006
	(0.94)	(0.22)	(-0.02)	(-0.32)	(-0.22)	(1.32)
Droughts*post 2012		0.013	0.015	-0.030	0.018	0.001
		(1.01)	(1.21)	(-1.06)	(0.80)	(0.11)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.729	0.729	0.701	0.819	0.684	0.759
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2-4}$	0.011*	0.005	0.009	-0.032	0.012	-0.000
	(1.74)	(0.59)	(1.21)	(-1.25)	(1.19)	(-0.01)
Designated		0.016	0.0107	-0.031	-0.008	-0.037
		(0.24)	(0.16)	(-0.14)	(-0.09)	(-0.41)
Drought*Designated		0.009	0.003	0.051	-0.014	0.030**
		(0.75)	(0.23)	(1.63)	(-0.96)	(2.13)
Observations	52817	52817	46805	5929	22384	30251
R^2	0.820	0.820	0.792	0.873	0.790	0.827

Table 10 Loans to individuals for household, family, and other personal expenditures

The estimation period is 2001-20. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable are loans secured by real estate in percent of loans reported in the call reports. "Single state banks" (multi) are banks that operate in one (more than one) state. "Single county banks" (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown. *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A Drought index at least of level D3						
$Droughts_{3-4}$	0.039***	0.050***	0.050***	0.022	0.050***	0.045***
	(6.99)	(10.46)	(10.29)	(1.27)	(7.06)	(8.77)
Droughts*post 2012		-0.029**	-0.027**	-0.025	-0.013	-0.034***
		(-2.27)	(-1.99)	(-1.19)	(-0.60)	(-3.42)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.657	0.657	0.661	0.738	0.691	0.680
Panel B Drought index at least of level D2						
$Droughts_{2-4}$	0.026***	0.028***	0.028***	0.007	0.032***	0.022***
	(8.24)	(10.34)	(10.24)	(0.87)	(7.80)	(7.46)
Droughts*post 2012		-0.011	-0.008	-0.011	0.003	-0.012
		(-0.93)	(-0.65)	(-0.76)	(0.17)	(-1.48)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.657	0.657	0.660	0.738	0.691	0.679
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2-4}$	0.023***	0.033***	0.034***	0.019*	0.038***	0.027***
	(7.99)	(5.70)	(5.40)	(1.66)	(3.62)	(4.71)
Designated		-0.016	-0.028	0.033	-0.128**	0.046
		(-0.46)	(-0.76)	(0.50)	(-2.22)	(1.38)
Drought*Designated		-0.013*	-0.013	-0.006	-0.011	-0.015**
		(-1.82)	(-1.64)	(-0.51)	(-0.87)	(-2.27)
Observations	52817	52817	46805	5929	22384	30251
R^2	0.919	0.919	0.921	0.929	0.929	0.920

Table 11 Loans secured by real estate

The estimation period is 2001-20. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable are loans secured by real estate in percent of loans reported in the call reports. "Single state banks" (multi) are banks that operate in one (more than one) state. "Single county banks" (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown, and *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Drought index at least of level D3						
$Droughts_{3-4}$	0.007	-0.020	-0.012	0.070	-0.029	0.029
	(0.34)	(-0.88)	(-0.56)	(1.24)	(-0.98)	(1.11)
Droughts*post 2012		0.070	0.062	-0.066	0.058	0.001
		(1.60)	(1.42)	(-1.04)	(0.98)	(0.02)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.819	0.819	0.821	0.883	0.828	0.853
Panel B: Drought index at least of level D2						
$Droughts_{2-4}$	0.026*	0.021	0.029*	-0.003	0.015	0.039***
	(1.84)	(1.42)	(1.90)	(-0.09)	(0.77)	(2.67)
Droughts*post 2012		0.030	0.019	0.005	0.015	-0.013
		(0.77)	(0.51)	(0.11)	(0.29)	(-0.51)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.819	0.819	0.821	0.883	0.828	0.853
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2-4}$	-0.036***	-0.020	-0.019	0.010	0.023	-0.052***
	(-4.14)	(-1.48)	(-1.36)	(0.29)	(1.09)	(-3.17)
Designated		0.094	0.123	0.042	0.315**	-0.082
		(1.10)	(1.32)	(0.20)	(2.17)	(-0.83)
Drought* Designated		-0.025	-0.025	-0.061*	-0.056**	0.0002
		(-1.60)	(-1.53)	(-1.72)	(-2.41)	(0.01)
Observations	52817	52817	46805	5929	22384	30251
R^2	0.940	0.940	0.941	0.943	0.948	0.936

Table 12 The impact of droughts on non-performing loans

The estimation period is 2001-20. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable is 100*NPL/TL reported in the call reports. "Single state banks" (multi) are banks that operate in one (more than one) state. "Single county banks" (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets, t-statistics are shown, and *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A: Drought index at least of level D3						
$Droughts_{3\text{-}4}$	-0.017***	-0.014***	-0.014***	-0.003	-0.014***	-0.011***
	(-6.90)	(-4.36)	(-4.22)	(-0.22)	(-3.49)	(-3.04)
Droughts* post 2012		-0.009**	-0.009**	-0.008	-0.005	-0.014***
		(-2.20)	(-2.18)	(-0.62)	(-0.92)	(-2.94)
Observations	134572	134572	125054	9390	66949	67167
R^2	0.490	0.490	0.487	0.660	0.496	0.546
Panel B: Drought index at least of level D2						
$Droughts_{2\text{-}4}$	-0.009***	-0.006***	-0.006***	-0.002	-0.007**	-0.005**
	(-4.68)	(-2.84)	(-2.71)	(-0.27)	(-2.19)	(-2.33)
Droughts* post 2012		-0.015***	-0.015***	-0.009	-0.012**	-0.019***
		(-4.22)	(-4.10)	(-0.91)	(-2.30)	(-4.56)
Observations	134572	134572	125054	9390	66949	67167
R^2	0.490	0.490	0.487	0.660	0.496	0.546
Panel C: Drought index at least of level D2, post-2012						
$Droughts_{2\text{-}4}$	-0.017***	-0.028***	-0.027***	-0.024**	-0.025**	-0.029***
	(-6.96)	(-4.52)	(-4.03)	(-2.04)	(-2.46)	(-4.60)
Designated		-0.078***	-0.087***	-0.010	-0.073	-0.084***
		(-2.93)	(-2.95)	(-0.18)	(-1.50)	(-3.12)
Drought* Designated		0.017***	0.017**	0.016	0.017*	0.016**
		(2.74)	(2.40)	(1.29)	(1.72)	(2.49)
Observations	52170	52170	46636	5453	22282	29708
R^2	0.665	0.666	0.661	0.760	0.661	0.687
Panel D: Drought index at least of level D2, post-2013						
$Droughts_{2\text{-}4}$	-0.016***	-0.037***	-0.063***	0.000	-0.063**	-0.031***
	(-6.32)	(-3.81)	(-4.63)	(0.02)	(-2.56)	(-3.11)
Designated		-0.076***	-0.086***	0.019	-0.081*	-0.068**
		(-2.90)	(-3.00)	(0.35)	(-1.71)	(-2.48)
Drought* Designated		0.024**	0.050***	-0.012	0.053**	0.015
		(2.44)	(3.65)	(-0.87)	(2.13)	(1.50)
Observations	45236	45236	40269	4875	19026	26041
R^2	0.683	0.683	0.677	0.785	0.676	0.703

Table 13 The impact of droughts on deposits

The estimation period is 2001-20. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable is the annual growth rate of branch deposits. "Single state banks" (multi) are banks that operate in one (more than one) state. "Single county banks" (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown, and *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A: Drought index at least of level D3						
$Droughts_{3\text{-}4}$	0.0171	0.0280	0.144***	-0.0382*	0.212***	0.0071
	(1.56)	(1.62)	(4.92)	(-1.77)	(3.35)	(0.39)
Droughts* post 2012		-0.022	-0.076*	0.0145	-0.183**	-0.0024
		(-1.03)	(-1.95)	(0.54)	(-2.28)	(-0.11)
Observations	1672750	1672750	594728	1072780	129378	1541466
R^2	0.194	0.194	0.253	0.201	0.295	0.196
Panel B: Drought index at least of level D2						
$Droughts_{2\text{-}4}$	0.0163**	0.0308**	0.0886***	0.0020	0.130***	0.0204
	(1.99)	(2.43)	(4.24)	(0.13)	(2.97)	(1.54)
Droughts* post 2012		-0.0307*	-0.0252	-0.0400**	-0.0785	-0.0253
		(-1.92)	(-0.89)	(-2.02)	(-1.32)	(-1.52)
Observations	1672750	1672750	594728	1072780	129378	1541466
R^2	0.194	0.194	0.253	0.201	0.295	0.196
Panel C: Drought index at least of level D2, post-2012						
$Droughts_{2\text{-}4}$	-0.0162	-0.108	0.0253	-0.157	0.0102	-0.110
	(-1.51)	(-1.38)	(0.20)	(-1.62)	(0.05)	(-1.32)
Designated		-0.472***	-0.326	-0.641***	-0.231	-0.512***
		(-3.04)	(-1.21)	(-3.33)	(-0.45)	(-3.15)
Drought* Designated		0.101	0.0153	0.126	-0.0168	0.104
		(1.28)	(0.12)	(1.31)	(-0.09)	(1.26)
Observations	679516	679516	205383	471219	40850	637645
R^2	0.286	0.286	0.347	0.277	0.364	0.286
Panel D: Drought index at least of level D2, post-2012						
$Droughts_{2\text{-}4}$	-0.0162***	-0.0373***	-0.0633***	0.00025	-0.0633**	-0.0309***
	(-6.32)	(-3.81)	(-4.63)	(0.02)	(-2.56)	(-3.11)
Designated		-0.0756***	-0.0862***	0.0193	-0.0811*	-0.0676**
		(-2.90)	(-3.00)	(0.35)	(-1.71)	(-2.48)
Drought* Designated		0.0238**	0.0498***	-0.0124	0.0527**	0.0150
		(2.44)	(3.65)	(-0.87)	(2.13)	(1.50)
Observations	45236	45236	40269	4875	19026	26041
R^2	0.683	0.683	0.677	0.785	0.676	0.703

Table 14 The impact of droughts on the interest rate on checking accounts (INTCK0K)

The estimation period is 2001-20. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable is the interest rate on 0k interest checking accounts. “Single state banks” (multi) are banks that operate in one (more than one) state. “Single county banks” (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown. *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A: Drought index at least of level D3						
$Droughts_{3\text{-}4}$	0.0001	0.0008**	0.0012***	0.0003	0.0007	0.0009**
	(0.53)	(2.14)	(2.88)	(0.37)	(1.15)	(1.98)
Droughts* post 2012		-0.0016***	-0.0017***	-0.0013	-0.0013*	-0.0018***
		(-3.74)	(-3.50)	(-1.60)	(-1.73)	(-3.42)
Observations	132841	132841	92332	30690	40027	82838
R^2	0.730	0.731	0.743	0.751	0.737	0.753
Panel B: Drought index at least of level D2						
$Droughts_{2\text{-}4}$	0.0001	0.0006**	0.0010***	0.0001	0.0007	0.0007**
	(0.36)	(2.44)	(3.39)	(0.15)	(1.56)	(2.34)
Droughts* post 2012		-0.0013***	-0.0015***	-0.0009	-0.0014***	-0.0013***
		(-4.53)	(-4.36)	(-1.61)	(-2.58)	(-3.79)
Observations	132841	132841	92332	30690	40027	82838
R^2	0.730	0.731	0.743	0.751	0.737	0.753
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2\text{-}4}$	-0.0001	-0.0001	-0.0001	-0.0003	0.0001	-0.0003
	(-1.52)	(-0.84)	(-0.63)	(-1.49)	(0.20)	(-1.24)
Designated		-0.0028	-0.0046	-0.00004	-0.0101	-0.0010
		(-1.03)	(-1.17)	(-0.02)	(-1.04)	(-0.74)
Drought* Designated		0.0001	0.00002	0.0002	-0.0003	0.0002
		(0.29)	(0.07)	(0.76)	(-0.88)	(1.00)
Observations	56266	56266	37297	12468	15968	33693
R^2	0.635	0.635	0.573	0.707	0.510	0.728

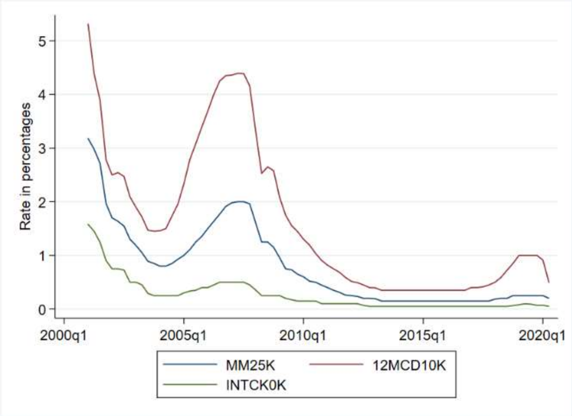
Table 15 The impact of droughts on the interest rate of certificates of deposits (12MCD10K)

The estimation period is 2001-20. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable is the interest rate on 12-month 10k certificates of deposits. “Single state banks” (multi) are banks that operate in one (more than one) state. “Single county banks” (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown. *,**, *** denote significance at the 10, 5 and 1% level, respectively.

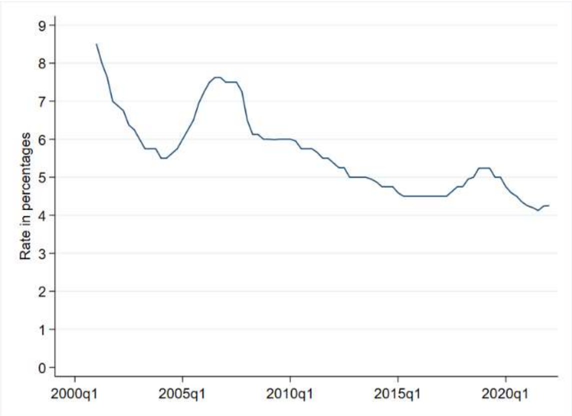
	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A: Drought index at least of level D3						
$Droughts_{3\text{-}4}$	0.0016***	0.0030***	0.0034***	0.0016	0.0043***	0.0019***
	(5.32)	(6.62)	(6.65)	(1.60)	(5.39)	(3.41)
Droughts* post 2012		-0.0032***	-0.0032***	-0.0028**	-0.0039***	-0.0026***
		(-5.78)	(-4.84)	(-2.24)	(-3.78)	(-3.72)
Observations	138284	138284	94884	31845	41202	85384
R^2	0.958	0.958	0.959	0.962	0.961	0.959
Panel B: Drought index at least of level D2						
$Droughts_{2\text{-}4}$	0.0011***	0.0020***	0.0023***	0.0011	0.0024***	0.0017***
	(4.84)	(6.04)	(5.97)	(1.57)	(3.99)	(4.08)
Droughts* post 2012		-0.0022***	-0.0026***	-0.0010	-0.0028***	-0.0020***
		(-5.22)	(-5.27)	(-1.10)	(-3.63)	(-3.78)
Observations	138284	138284	94884	31845	41202	85384
R^2	0.958	0.958	0.959	0.962	0.961	0.959
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2\text{-}4}$	-0.0001	-0.0004	-0.00003	-0.0007	0.0006	-0.0012**
	(-0.28)	(-0.84)	(-0.06)	(-0.72)	(0.87)	(-2.22)
Designated		-0.0002	-0.0038	0.0096	-0.0073	0.0024
		(-0.04)	(-0.79)	(1.20)	(-0.98)	(0.47)
Drought* Designated		0.0004	-0.00001	0.0010	-0.0008	0.0012*
		(0.75)	(-0.01)	(0.83)	(-0.87)	(1.89)
Observations	59874	59874	39024	13155	16678	35394
R^2	0.753	0.753	0.756	0.763	0.770	0.761

Figure 1 Median deposit and loan rates

Deposits



Loans - Construction Loan @ 175K



Online Appendix

CRA data

Adams, Brevoort and Driscoll (2021): We use a dataset where each observation provides a bank's lending activity in a county in a single year ("bank-county-year" data). This dataset includes all counties regardless of whether the bank made loans there. These zero-loan county observation are included to reduce sample selection bias that comes from only examining the counties to which loans are made (if permanent they do not have to be included…). Since every bank could, hypothetically, lend to every county in the U.S., the fact that they do not lend in particular counties provides useful information about the importance of distance.

Total small business lending, shown in Figure 1, increased substantially during the first half of our sample period, peaking at over $320 billion in 2007. During the ensuing recession, lending fell sharply and remains below pre-recession levels. Large and small loans both exhibit the same general pattern with two notable exceptions.

The first is the effect of the 2005 changes in CRA reporting thresholds (in principle the time dummy show take care of this…; as a robustness check, re-define the threshold; exclude the ones that drop, i.e. that are below the 2005 threshold; one could argue that this should be the base sample). While large-loan volumes dropped sharply in 2005, small-loan volumes continued to increase, suggesting that the small lenders exempted from CRA reporting were more heavily involved in large-loan lending.

The second notable difference is that small-loan volumes grew more rapidly than large loans over the entire sample, increasing small loans as a share of lending. This growth is particularly remarkable given that the CRA's $100,000 threshold does not adjust for inflation. As discussed above, according to the Consumer Price Index, prices in 2017 were 56% higher than in 1996. This means that the equivalent of a $65,000 loan in 1996, which would then have been safely below the threshold, would not be considered a small loan in 2017 (the threshold changes in economic terms, not in absolute terms…).

Our figure below is more or less similar to Figure 1 of Adams, Brevoort and Driscoll (2021).

Figure A1 CRA Loan Volumes

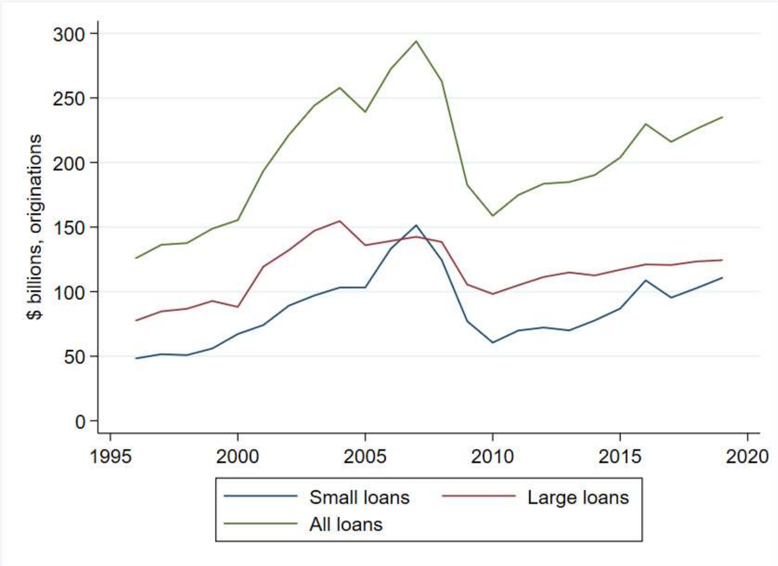


Table A1 The impact of droughts on loans to agriculture for dryland

The estimation period is 2001-20. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable is loans to agriculture in percent of total loans reported in the call reports. "Single state banks" (multi) are banks that operate in one (more than one) state. "Single county banks" (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets, t-statistics are shown. *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A Drought index at least of level D3						
$Droughts_{3-4}$	-0.032***	-0.018***	-0.019***	-0.010	-0.021***	-0.013***
	(-5.86)	(-4.15)	(-4.24)	(-1.16)	(-3.05)	(-2.90)
Droughts *post 2012		-0.052***	-0.054***	0.021	-0.058***	-0.042***
		(-4.44)	(-4.45)	(1.21)	(-3.15)	(-3.67)
Observations	92803	92803	85980	6698	46106	46402
R^2	0.944	0.944	0.944	0.968	0.950	0.953
Panel B Drought index at least of level D2						
$Droughts_{2-4}$	-0.017***	-0.009***	-0.009***	0.003	-0.009*	-0.007**
	(-5.14)	(-3.00)	(-3.21)	(0.36)	(-1.91)	(-2.51)
Droughts *post 2012		-0.058***	-0.0605***	0.008	-0.068***	-0.045***
		(-4.84)	(-4.80)	(0.40)	(-3.62)	(-3.72)
Observations	92803	92803	85980	6698	46106	46402
R^2	0.944	0.944	0.944	0.968	0.950	0.953
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2-4}$	-0.018***	-0.022***	-0.026***	0.0182	-0.039***	-0.002
	(-3.61)	(-2.97)	(-3.23)	(1.49)	(-3.59)	(-0.21)
Designated		-0.058	-0.052	-0.104	-0.065	-0.018
		(-1.21)	(-1.00)	(-1.16)	(-0.76)	(-0.34)
Drought *Designated		0.009	0.012	-0.004	0.021	-0.011
		(1.11)	(1.34)	(-0.26)	(1.63)	(-1.15)
Observations	36411	36411	32587	3750	15707	20566
R^2	0.974	0.974	0.974	0.982	0.975	0.977

Table A2 The impact of droughts on loans to agriculture for irrigated counties

The estimation period is 2001-2020. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable is loans to agriculture in percent of total loans reported in the call reports. "Single state banks" (multi) are banks that operate in one (more than one) state. "Single county banks" (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets, t-statistics are shown. *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A Drought index at least of level D3						
$Droughts_{3\text{-}4}$	-0.021***	-0.0123**	-0.0161***	0.0354*	-0.019**	-0.004
	(-3.97)	(-2.12)	(-2.72)	(1.74)	(-2.57)	(-0.55)
Droughts *post 2012		-0.0196**	-0.0151*	-0.0392*	-0.015	-0.020**
		(-2.41)	(-1.78)	(-1.80)	(-1.25)	(-2.16)
Observations	37716	37716	34728	2895	18978	18542
R^2	0.950	0.950	0.951	0.971	0.960	0.952
Panel B Drought index at least of level D2						
$Droughts_{2\text{-}4}$	-0.015***	-0.010***	-0.013***	0.017*	-0.016***	-0.004
	(-4.23)	(-2.81)	(-3.40)	(1.70)	(-3.30)	(-0.78)
Droughts *post 2012		-0.022***	-0.019**	-0.021*	-0.019	-0.020***
		(-2.84)	(-2.35)	(-1.74)	(-1.59)	(-2.88)
Observations	37716	37716	34728	2895	18978	18542
R^2	0.950	0.950	0.951	0.971	0.960	0.952
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2\text{-}4}$	-0.003	-0.015	-0.015	-0.009	-0.045**	0.008
	(-0.70)	(-1.58)	(-1.42)	(-0.47)	(-2.58)	(0.67)
Designated		-0.004	-0.042	0.208	-0.043	0.062
		(-0.05)	(-0.51)	(1.37)	(-0.36)	(0.66)
Drought *Designated		0.014	0.016	0.002	0.046***	-0.011
		(1.35)	(1.34)	(0.12)	(2.60)	(-0.87)
Observations	13811	13811	12153	1601	5892	7852
R^2	0.972	0.972	0.973	0.979	0.978	0.970

Table A3 Loans to individuals (credit cards)

The estimation period is 2001-2020. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable are loans secured by real estate in percent of loans reported in the call reports. “Single state banks” (multi) are banks that operate in one (more than one) state. “Single county banks” (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown. *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A: Drought index at least of level D3						
$Droughts_{3\text{-}4}$	-0.0001	0.0002	0.0003*	-0.0005	-0.0001	0.001**
	(-0.90)	(1.19)	(1.72)	(-0.25)	(-0.37)	(2.12)
Droughts*post 2012		-0.0010**	-0.001***	0.0008	-0.0005	-0.001***
		(-2.53)	(-2.65)	(0.43)	(-0.91)	(-2.97)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.821	0.821	0.834	0.821	0.875	0.787
Panel B: Drought index at least of level D2						
$Droughts_{2\text{-}4}$	0.0001	0.0002**	0.0004***	-0.001	0.00006	0.0005**
	(0.52)	(1.97)	(2.89)	(-1.08)	(0.45)	(2.29)
Droughts*post 2012		-0.001***	-0.001***	0.001	-0.001	-0.001***
		(-2.91)	(-3.05)	(1.33)	(-1.25)	(-3.01)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.821	0.821	0.834	0.821	0.875	0.787
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2\text{-}4}$	-0.0001	0.0004	0.0003	0.0018*	0.0010	-0.0001
	(-0.50)	(0.92)	(0.59)	(1.65)	(1.21)	(-0.36)
Designated		0.0007	-0.001	0.0101	-0.0039	0.0035
		(0.40)	(-0.72)	(1.33)	(-1.54)	(1.56)
Drought*Designated		-0.0006	-0.0005	-0.0015	-0.0011	-0.0002
		(-1.33)	(-0.97)	(-1.20)	(-1.22)	(-0.44)
Observations	52817	52817	46805	5929	22384	30251
R^2	0.929	0.929	0.925	0.946	0.934	0.925

Table A4 Loans to individuals (Other revolving credit plans)

The estimation period is 2001-2020. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable are loans secured by real estate in percent of loans reported in the call reports. "Single state banks" (multi) are banks that operate in one (more than one) state. "Single county banks" (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown. (*,**, ***) denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A: Drought index at least of level D3						
$Droughts_{3-4}$	0.000	0.001***	0.001***	-0.000	0.001	0.001**
	(1.05)	(3.68)	(3.51)	(-0.04)	(1.60)	(2.44)
Droughts* post 2012		-0.002***	-0.002***	0.002	-0.002***	-0.001***
		(-3.81)	(-4.43)	(1.47)	(-2.73)	(-2.68)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.649	0.649	0.645	0.761	0.659	0.698
Panel B: Drought index at least of level D2						
$Droughts_{2-4}$	0.000*	0.001***	0.001***	0.000	0.001**	0.001***
	(1.90)	(3.85)	(3.66)	(0.44)	(2.33)	(2.65)
Droughts* post 2012		-0.002***	-0.002***	0.002	-0.002***	-0.001***
		(-3.88)	(-4.54)	(1.39)	(-3.09)	(-2.68)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.649	0.649	0.645	0.761	0.659	0.698
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2-4}$	-0.000	-0.001*	-0.001*	0.0002	-0.000	-0.001
	(-1.28)	(-1.73)	(-1.83)	(0.21)	(-0.84)	(-1.47)
Designated		0.0007	0.0015	-0.004	-0.003	0.004
		(0.31)	(0.64)	(-0.79)	(-0.82)	(1.37)
Drought* Designated		0.000	0.000	0.000	0.001	0.001
		(1.29)	(1.15)	(0.33)	(0.82)	(1.01)
Observations	52817	52817	46805	5929	22384	30251
R^2	0.810	0.810	0.794	0.891	0.787	0.843

Table A5 Loans to individuals (Automobile loans)

The estimation period is 2001-20. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable are loans secured by real estate in percent of loans reported in the call reports. “Single state banks” (multi) are banks that operate in one (more than one) state. “Single county banks” (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown. (*,**, ***) denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A: Drought index at least of level D3						
$Droughts_{3\text{-}4}$	0.023***	0.051***	0.051***	0.037*	0.051***	0.047***
	(7.33)	(12.00)	(11.76)	(1.66)	(7.52)	(10.00)
Droughts* post 2012		-0.042***	-0.041***	-0.034	-0.043***	-0.038***
		(-9.35)	(-8.85)	(-1.49)	(-6.16)	(-7.83)
Observations	59480	59480	52919	6462	25565	33741
R^2	0.898	0.899	0.899	0.932	0.905	0.907
Panel B: Drought index at least of level D2						
$Droughts_{2\text{-}4}$	0.018***	0.026***	0.026***	0.016***	0.026***	0.024***
	(9.38)	(11.85)	(11.63)	(2.83)	(7.49)	(10.22)
Droughts* post 2012		-0.020***	-0.019***	-0.015**	-0.021***	-0.018***
		(-7.70)	(-7.14)	(-2.00)	(-4.84)	(-6.30)
Observations	59480	59480	52919	6462	25565	33741
R^2	0.898	0.898	0.898	0.932	0.905	0.907
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2\text{-}4}$	0.010***	0.014***	0.013***	0.014***	0.011**	0.016***
	(5.44)	(4.60)	(3.95)	(2.86)	(2.04)	(5.01)
Designated		-0.021	-0.023	0.023	-0.063*	0.016
		(-1.05)	(-1.03)	(0.57)	(-1.80)	(0.90)
Drought* Designated		-0.004	-0.003	-0.012*	0.001	-0.010***
		(-1.19)	(-0.69)	(-1.76)	(0.12)	(-2.83)
Observations	52817	52817	46805	5929	22384	30251
R^2	0.910	0.910	0.909	0.939	0.916	0.918

Table A6 Loans to individuals (Other consumer loans)

The estimation period is 2001-20. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable are loans secured by real estate in percent of loans reported in the call reports. “Single state banks” (multi) are banks that operate in one (more than one) state. “Single county banks” (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown. (*,**, ***) denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A: Drought index at least of level D3						
$Droughts_{3\text{-}4}$	0.019***	0.035***	0.035***	0.034**	0.028***	0.039***
	(7.06)	(8.42)	(8.28)	(2.23)	(3.91)	(8.72)
Droughts* post 2012		-0.025***	-0.024***	-0.033**	-0.018**	-0.029***
		(-5.64)	(-5.24)	(-2.13)	(-2.49)	(-6.10)
Observations	59480	59480	52919	6462	25565	33741
R^2	0.872	0.872	0.874	0.869	0.885	0.872
Panel B: Drought index at least of level D2						
$Droughts_{2\text{-}4}$	0.016***	0.021***	0.021***	0.007	0.022***	0.017***
	(7.11)	(7.55)	(7.35)	(1.31)	(4.44)	(7.59)
Droughts* post 2012		-0.012***	-0.012***	-0.007	-0.013***	-0.010***
		(-4.48)	(-4.03)	(-1.03)	(-2.78)	(-3.48)
Observations	59480	59480	52919	6462	25565	33741
R^2	0.872	0.872	0.874	0.869	0.885	0.871
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2\text{-}4}$	0.011***	0.013***	0.015***	-0.002	0.014**	0.011***
	(4.91)	(3.86)	(3.87)	(-0.34)	(2.39)	(2.90)
Designated		0.0145	0.0101	0.0176	-0.026	0.0254
		(0.62)	(0.40)	(0.39)	(-0.62)	(1.08)
Drought* Designated		-0.003	-0.003	0.002	0.001	-0.005
		(-0.74)	(-0.76)	(0.30)	(0.07)	(-1.12)
Observations	52817	52817	46805	5929	22384	30251
R^2	0.884	0.884	0.886	0.875	0.896	0.883

Table A7 Loans secured by real estate (Secured by farmland)

The estimation period is 2001-20. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable are loans secured by real estate in percent of loans reported in the call reports. "Single state banks" (multi) are banks that operate in one (more than one) state. "Single county banks" (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown. (*,**, ***) denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A: Drought index at least of level D3						
$Droughts_{3-4}$	0.006**	0.010***	0.010***	0.003	0.007*	0.015***
	(2.22)	(3.03)	(3.07)	(0.30)	(1.65)	(3.74)
Droughts*post 2012		-0.009	-0.010	0.004	-0.006	-0.013**
		(-1.32)	(-1.37)	(0.35)	(-0.58)	(-1.96)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.901	0.901	0.900	0.951	0.906	0.919
Panel B: Drought index at least of level D2						
$Droughts_{2-4}$	0.004**	0.005**	0.005**	-0.001	0.002	0.010***
	(2.06)	(2.38)	(2.34)	(-0.18)	(0.80)	(4.15)
Droughts*post 2012		-0.005	-0.005	0.007	-0.002	-0.009
		(-0.78)	(-0.82)	(0.86)	(-0.16)	(-1.62)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.901	0.901	0.900	0.951	0.906	0.919
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2-4}$	-0.009***	-0.029***	-0.031***	-0.006	-0.019*	-0.030***
	(-2.88)	(-4.90)	(-4.62)	(-0.79)	(-1.89)	(-4.26)
Dummy, designated		-0.132***	-0.138***	-0.030	-0.030	-0.215***
		(-3.33)	(-3.18)	(-0.45)	(-0.41)	(-4.99)
Drought*Designated		0.031***	0.033***	0.008	0.018	0.032***
		(4.59)	(4.37)	(0.78)	(1.64)	(3.94)
Observations	52817	52817	46805	5929	22384	30251
R^2	0.956	0.956	0.955	0.974	0.954	0.963

Table A8 Loans secured by real estate (Constr, land dev, other land loans)

The estimation period is 2001-20. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable are loans secured by real estate in percent of loans reported in the call reports. "Single state banks" (multi) are banks that operate in one (more than one) state. "Single county banks" (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown. *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A: Drought index at least of level D3						
$Droughts_{3-4}$	0.016**	0.028***	0.027***	0.091***	0.022*	0.041***
	(2.40)	(2.75)	(2.61)	(3.48)	(1.83)	(3.46)
Droughts*post 2012		-0.032***	-0.032***	-0.094***	-0.027**	-0.043***
		(-2.92)	(-2.79)	(-3.31)	(-2.00)	(-3.44)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.631	0.631	0.628	0.755	0.612	0.699
Panel B: Drought index at least of level D2						
$Droughts_{2-4}$	0.018***	0.024***	0.025***	0.017	0.020***	0.030***
	(3.83)	(4.05)	(4.09)	(1.32)	(2.73)	(4.77)
Droughts*post 2012		-0.030***	-0.031***	-0.023	-0.026***	-0.035***
		(-3.79)	(-3.79)	(-1.28)	(-2.73)	(-3.84)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.631	0.632	0.628	0.754	0.612	0.699
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2-4}$	0.005*	0.021***	0.024***	-0.001	0.030***	0.013*
	(1.73)	(3.65)	(3.78)	(-0.06)	(3.56)	(1.77)
Dummy, designated		0.079*	0.098**	-0.084	0.062	0.093*
		(1.86)	(2.19)	(-0.93)	(0.92)	(1.90)
Drought*Designated		-0.023***	-0.027***	-0.001	-0.028***	-0.019**
		(-3.55)	(-3.79)	(-0.05)	(-2.71)	(-2.38)
Observations	52817	52817	46805	5929	22384	30251
R^2	0.846	0.846	0.847	0.864	0.840	0.856

Table A9 Loans secured by real estate (Secured by 1–4 family residential properties)

The estimation period is 2001-20. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable are loans secured by real estate in percent of loans reported in the call reports. "Single state banks" (multi) are banks that operate in one (more than one) state. "Single county banks" (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown. (*,**, ***) denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A: Drought index at least of level D3						
$Droughts_{3\text{-}4}$	-0.012**	-0.042***	-0.038***	-0.106***	-0.030***	-0.049***
	(-1.96)	(-5.79)	(-5.12)	(-3.57)	(-3.05)	(-4.93)
Droughts*post 2012		0.081***	0.076***	0.116***	0.060***	0.074***
		(6.35)	(5.93)	(3.29)	(2.98)	(6.09)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.908	0.908	0.911	0.916	0.925	0.910
Panel B: Drought index at least of level D2						
$Droughts_{2\text{-}4}$	-0.009**	-0.020***	-0.018***	-0.046**	-0.015***	-0.026***
	(-2.09)	(-4.69)	(-4.24)	(-2.54)	(-2.60)	(-4.46)
Droughts*post 2012		0.062***	0.058***	0.062**	0.046***	0.055***
		(5.95)	(5.48)	(2.01)	(2.58)	(5.53)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.908	0.908	0.911	0.916	0.925	0.910
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2\text{-}4}$	-0.022***	-0.030**	-0.027*	-0.031	-0.008	-0.043***
	(-3.59)	(-2.26)	(-1.92)	(-0.97)	(-0.36)	(-3.02)
Designated		0.084	0.092	0.264	0.158	0.016
		(1.12)	(1.16)	(1.60)	(1.24)	(0.19)
Drought*Designated		0.007	0.007	-0.021	-0.008	0.018
		(0.51)	(0.49)	(-0.60)	(-0.36)	(1.15)
Observations	52817	52817	46805	5929	22384	30251
R^2	0.959	0.959	0.960	0.959	0.964	0.959

Table A10 Loans secured by real estate (by multifamily (5 or more) residential properties)

The estimation period is 2001-2020. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable are loans secured by real estate in percent of loans reported in the call reports. “Single state banks” (multi) are banks that operate in one (more than one) state. “Single county banks” (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown. *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A: Drought index at least of level D3						
$Droughts_{3\text{-}4}$	-0.0002	0.001	-0.000	0.021***	-0.002	0.003
	(-0.11)	(0.27)	(-0.03)	(3.11)	(-0.73)	(1.09)
Droughts* post 2012		-0.002	0.0003	-0.029***	0.005	-0.004
		(-0.34)	(0.06)	(-3.10)	(0.48)	(-0.80)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.764	0.764	0.762	0.849	0.784	0.789
Panel B: Drought index at least of level D2						
$Droughts_{2\text{-}4}$	0.001	0.002	0.001	0.016***	0.001	0.003*
	(0.80)	(1.34)	(0.90)	(3.36)	(0.47)	(1.70)
Droughts* post 2012		-0.003	-0.001	-0.026***	0.002	-0.004
		(-0.61)	(-0.16)	(-3.62)	(0.23)	(-0.94)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.764	0.764	0.762	0.849	0.784	0.789
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2\text{-}4}$	0.005**	0.017***	0.013***	0.033***	0.006	0.024***
	(2.19)	(4.01)	(2.96)	(3.29)	(0.86)	(4.86)
Designated		0.049**	0.052**	0.003	0.076**	0.024
		(2.20)	(2.26)	(0.04)	(2.10)	(0.90)
Drought* Designated		-0.018***	-0.014***	-0.024**	-0.005	-0.024***
		(-3.84)	(-2.87)	(-2.21)	(-0.70)	(-4.33)
Observations	52817	52817	46805	5929	22384	30251
R^2	0.879	0.879	0.878	0.905	0.877	0.890

Table A11 Loans secured by real estate (secured by nonfarm nonresidential property)

The estimation period is 2001-2020. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable are loans secured by real estate in percent of loans reported in the call reports. "Single state banks" (multi) are banks that operate in one (more than one) state. "Single county banks" (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown. *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A: Drought index at least of level D3						
$\text{Droughts}_{3\text{-}4}$	-0.014	-0.032**	-0.027**	0.028	-0.030	-0.009
	(-0.95)	(-2.29)	(-2.01)	(0.68)	(-1.53)	(-0.53)
Droughts*post 2012		0.046	0.042	-0.034	0.021	0.017
		(1.56)	(1.40)	(-0.72)	(0.52)	(0.90)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.796	0.796	0.793	0.889	0.780	0.850
Panel B: Drought index at least of level D2						
$\text{Droughts}_{2\text{-}4}$	0.004	0.002	0.007	-0.002	0.003	0.009
	(0.42)	(0.18)	(0.71)	(-0.09)	(0.23)	(0.93)
Droughts*post 2012		0.014	0.009	-0.005	-0.010	-0.001
		(0.53)	(0.33)	(-0.15)	(-0.29)	(-0.04)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.796	0.796	0.793	0.889	0.780	0.850
Panel C Drought index at least of level D2, post-2012						
$\text{Droughts}_{2\text{-}4}$	-0.012**	0.003	0.003	0.010	0.017	-0.017
	(-2.17)	(0.25)	(0.30)	(0.33)	(1.02)	(-1.27)
Designated		-0.006	0.007	-0.166	0.007	-0.002
		(-0.08)	(0.09)	(-1.06)	(0.06)	(-0.03)
Drought*Designated		-0.020	-0.023	-0.005	-0.033*	-0.001
		(-1.51)	(-1.64)	(-0.17)	(-1.73)	(-0.06)
Observations	52817	52817	46805	5929	22384	30251
R^2	0.940	0.940	0.940	0.947	0.939	0.944

Table A12 The impact of droughts on rates of construction loans 175K

The estimation period is 2001-20. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable is the interest rate on construction loans @ 175K. "Single state banks" (multi) are banks that operate in one (more than one) state. "Single county banks" (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown. *,**, *** denote significance at the 10, 5 and 1% level

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A: Drought index at least of level D3						
$Droughts_{3\text{-}4}$	0.003	0.003	-0.004	0.012	-0.015	0.006
	(1.02)	(0.71)	(-0.93)	(1.61)	(-1.38)	(1.35)
Droughts*post 2012		0.002	0.008	-0.010	0.031*	-0.001
		(0.26)	(1.03)	(-0.53)	(1.90)	(-0.19)
Observations	14019	14019	8920	4004	2476	10516
R^2	0.848	0.848	0.854	0.862	0.877	0.846
Panel B: Drought index at least of level D2						
$Droughts_{2\text{-}4}$	0.000	-0.001	-0.005	0.001	-0.004	0.000
	(0.01)	(-0.38)	(-1.31)	(0.24)	(-0.53)	(0.03)
Droughts*post 2012		0.004	0.011*	-0.001	0.025*	-0.001
		(0.91)	(1.72)	(-0.11)	(1.81)	(-0.10)
Observations	14019	14019	8920	4004	2476	10516
R^2	0.848	0.848	0.854	0.862	0.877	0.846
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2\text{-}4}$	0.003	0.007	0.019	-0.002	0.049***	-0.010
	(0.65)	(0.61)	(1.48)	(-0.05)	(2.82)	(-0.61)
Designated		0.122**	0.150**	-0.0178	-0.080	0.100*
		(2.31)	(2.39)	(-0.16)	(-0.51)	(1.75)
Drought*Designated		-0.008	-0.017	0.003	-0.041**	0.007
		(-0.69)	(-1.23)	(0.08)	(-2.17)	(0.40)
Observations	3951	3951	2606	776	639	2801
R^2	0.852	0.852	0.862	0.876	0.907	0.849

Table A13 NPL Loans secured by real estate (in domestic offices): secured by farmland - past due 30 through 89 days and still accruing

The estimation period is 2001-20. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable are loans secured by real estate in percent of loans reported in the call reports. "Single state banks" (multi) are banks that operate in one (more than one) state. "Single county banks" (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown. (*,**, ***) denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A: Drought index at least of level D3						
$Droughts_{3\text{-}4}$	-0.00002	0.00003	0.00003	0.000007	0.00004	0.00003
	(-0.20)	(0.20)	(0.22)	(0.01)	(0.18)	(0.16)
Droughts* post 2012		-0.0001	-0.00007	-0.0011**	0.0002	-0.0004*
		(-0.63)	(-0.31)	(-1.98)	(0.61)	(-1.71)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.282	0.282	0.281	0.389	0.298	0.303
Panel B: Drought index at least of level D2						
$Droughts_{2\text{-}4}$	0.00003	0.00006	0.00007	-0.0001	0.0001	0.00007
	(0.37)	(0.71)	(0.82)	(-0.55)	(0.69)	(0.66)
Droughts* post 2012		-0.0002	-0.0001	-0.00096**	0.0002	-0.0005**
		(-0.88)	(-0.54)	(-2.28)	(0.51)	(-2.15)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.282	0.282	0.281	0.389	0.298	0.303
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2\text{-}4}$	-0.0001	-0.0001	-0.0001	-0.0006	0.0004	-0.0006**
	(-0.54)	(-0.49)	(-0.29)	(-1.59)	(0.85)	(-2.31)
Designated		-0.005***	-0.005**	-0.005	-0.004	-0.007***
		(-2.62)	(-2.23)	(-1.26)	(-0.94)	(-3.10)
Drought* Designated		0.0003	0.0002	0.00002	-0.0004	0.0009***
		(0.83)	(0.70)	(0.04)	(-0.73)	(2.61)
Observations	52817	52817	46805	5929	22384	30251
R^2	0.353	0.353	0.350	0.454	0.358	0.368

Table A14 NPL Loans secured by real estate (in domestic offices): secured by farmland - past due 90 days or more and still accruing

The estimation period is 2001-2020. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable are loans secured by real estate in percent of loans reported in the call reports. "Single state banks" (multi) are banks that operate in one (more than one) state. "Single county banks" (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown. *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A: Drought index at least of level D3						
$Droughts_{3\text{-}4}$	-0.0000	-0.0000	-0.0000	0.0001	-0.0001	0.0000
	(-1.34)	(-0.92)	(-0.93)	(0.47)	(-1.09)	(0.01)
Droughts*post 2012		-0.0000	-0.0000	-0.0000	0.0001	-0.0001
		(-0.29)	(-0.39)	(-0.05)	(0.43)	(-1.21)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.188	0.188	0.186	0.300	0.193	0.222
Panel B: Drought index at least of level D2						
$Droughts_{2\text{-}4}$	-0.0000	0.0000	0.0000	0.0000	-0.0000	0.0000
	(-0.15)	(0.32)	(0.28)	(0.16)	(-0.06)	(0.80)
Droughts*post 2012		-0.0001	-0.0001	0.0000	-0.0000	-0.0001*
		(-0.99)	(-1.07)	(0.24)	(-0.06)	(-1.75)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.188	0.188	0.186	0.300	0.193	0.222
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2\text{-}4}$	0.0000	0.0000	0.0000	-0.0000	0.0002	-0.0001
	(0.07)	(0.22)	(0.47)	(-0.29)	(1.29)	(-1.54)
Designated		-0.0009	-0.0008	-0.0010	0.0012	-0.0022***
		(-1.38)	(-1.13)	(-0.89)	(0.93)	(-3.07)
Drought*Designated		0.0000	-0.0000	0.0001	-0.0001	0.0002*
		(0.10)	(-0.23)	(0.54)	(-0.90)	(1.66)
Observations	52817	52817	46805	5929	22384	30251
R^2	0.262	0.262	0.260	0.352	0.272	0.278

Table A15 NPL Loans secured by real estate (in domestic offices): secured by farmland – non accrual

The estimation period is 2001-2020. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable are loans secured by real estate in percent of loans reported in the call reports. "Single state banks" (multi) are banks that operate in one (more than one) state. "Single county banks" (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown. *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A: Drought index at least of level D3						
$Droughts_{3\text{-}4}$	-0.000***	-0.000	-0.000	-0.000	-0.000	-0.000
	(-2.73)	(-1.53)	(-1.41)	(-0.54)	(-0.30)	(-1.11)
Droughts *post 2012		-0.000	-0.000	0.000	-0.000	-0.000
		(-1.24)	(-1.34)	(0.14)	(-1.48)	(-0.46)
Observations	136453	136453	125790	10538	67307	68688
R2	0.275	0.275	0.271	0.505	0.282	0.319
Panel B: Drought index at least of level D2						
$Droughts_{2\text{-}4}$	-0.000***	-0.000***	-0.000**	-0.001*	-0.0001	-0.000***
	(-3.49)	(-2.75)	(-2.49)	(-1.92)	(-0.73)	(-2.64)
Droughts *post 2012		-0.000	-0.000	0.001	-0.001	-0.000
		(-1.16)	(-1.29)	(0.68)	(-1.54)	(-0.09)
Observations	136453	136453	125790	10538	67307	68688
R2	0.275	0.275	0.271	0.505	0.282	0.319
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2\text{-}4}$	-0.000**	-0.000*	-0.000	-0.000	-0.000	-0.001
	(-2.31)	(-1.79)	(-1.45)	(-1.05)	(-1.33)	(-1.13)
Designated		-0.003	-0.0036	-0.003	-0.0052	-0.002
		(-1.41)	(-1.32)	(-0.54)	(-1.24)	(-0.74)
Drought *Designated		0.000	0.000	0.001	0.001	0.000
		(0.94)	(0.69)	(0.92)	(0.97)	(0.33)
Observations	52817	52817	46805	5929	22384	30251
R2	0.446	0.446	0.436	0.626	0.449	0.460

Table A16 Loans to depository institutions

The estimation period is 2001-2020. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable are loans secured by real estate in percent of loans reported in the call reports. "Single state banks" (multi) are banks that operate in one (more than one) state. "Single county banks" (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown, and *,**, *** denote significance at the 10, 5 and 1% level, respectively.

	(1) Whole sample	(2) Whole sample	(3) Single state banks	(4) Multi state banks	(5) Single county banks	(6) Multi county banks
Panel A: Drought index at least of level D3						
$Droughts_{3\text{-}4}$	0.000	-0.000	0.000	-0.002	-0.000	-0.000
	(0.14)	(-0.17)	(0.26)	(-1.33)	(-0.16)	(-0.17)
Droughts*post 2012		0.000	0.000	0.001	0.000	-0.000
		(0.40)	(0.52)	(0.19)	(1.21)	(-0.11)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.608	0.608	0.613	0.637	0.676	0.592
Panel B: Drought index at least of level D2						
$Droughts_{2\text{-}4}$	0.000*	0.000*	0.000**	-0.000	0.000	0.000
	(1.71)	(1.81)	(2.27)	(-0.49)	(0.64)	(1.64)
Droughts*post 2012		-0.000	-0.000	-0.001	0.000	-0.000
		(-0.29)	(-0.21)	(-0.27)	(1.01)	(-0.68)
Observations	136453	136453	125790	10538	67307	68688
R^2	0.608	0.608	0.613	0.636	0.676	0.592
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2\text{-}4}$	0.0001	0.001	0.0002**	0.003	0.0001	0.0009
	(0.54)	(1.31)	(2.21)	(0.78)	(0.85)	(1.22)
Designated		0.001	-0.001	0.018	-0.003	0.003
		(0.04)	(-1.18)	(1.31)	(-1.50)	(0.97)
Drought*Designated		-0.001	-0.000	-0.006	0.000	-0.001
		(-1.30)	(-0.14)	(-1.48)	(1.15)	(-1.54)
Observations	52817	52817	46805	5929	22384	30251
R^2	0.732	0.732	0.800	0.663	0.800	0.699

Table A17 The impact of droughts on the interest rate of money market accounts (MM25K)

The estimation period is 2001-2020. The estimations are done with the fixed effects estimator including bank- and year-fixed effects. The dependent variable is the interest rate on money market 25k accounts. "Single state banks" (multi) are banks that operate in one (more than one) state. "Single county banks" (multi) are banks that operate in one (more than one) county. Standard errors are clustered by county. In brackets t-statistics are shown. (*,**, ***) denote significance at the 10, 5 and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample		Single state banks	Multi state banks	Single county banks	Multi county banks
Panel A: Drought index at least of level D3						
$Droughts_{3\text{-}4}$	0.001***	0.002***	0.003***	-0.000	0.003**	0.001
	(3.01)	(3.11)	(3.92)	(-0.22)	(2.53)	(1.28)
Droughts*post 2012		-0.002**	-0.003***	-0.000	-0.002*	-0.001
		(-2.52)	(-2.86)	(-0.14)	(-1.67)	(-1.10)
Observations	131826	131826	90773	30756	38712	82660
R^2	0.806	0.806	0.812	0.813	0.816	0.808
Panel B: Drought index at least of level D2						
$Droughts_{2\text{-}4}$	0.000	0.001	0.001**	-0.002	0.001	0.000
	(0.94)	(1.07)	(2.43)	(-1.46)	(1.40)	(0.37)
Droughts*post 2012		-0.001	-0.001*	0.001	-0.001	-0.000
		(-0.99)	(-1.96)	(1.07)	(-1.02)	(-0.33)
Observations	131826	131826	90773	30756	38712	82660
R^2	0.806	0.806	0.812	0.813	0.816	0.808
Panel C Drought index at least of level D2, post-2012						
$Droughts_{2\text{-}4}$	-0.00	-0.000	-0.000	-0.000	0.0001	-0.001**
	(-0.98)	(-1.22)	(-1.22)	(-0.24)	(0.17)	(-1.98)
Designated		0.000	-0.000	0.006	-0.001	0.002
		(0.33)	(-0.21)	(1.28)	(-0.18)	(0.61)
Drought*Designated		0.000	0.000	0.000	-0.000	0.001*
		(0.81)	(0.67)	(0.31)	(-0.50)	(1.71)
Observations	56411	56411	37018	12634	15524	34025
R^2	0.726	0.726	0.723	0.711	0.756	0.715