Climate Risk, Credit, and Food Security*

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Abstract

We test whether climate risk affects credit origination. Anticipated climate anomalies in a county explain a 2.6% reduction in agricultural loan volume. These effects exceed the impact of realized climate conditions, align with products' vulnerabilities to different anomalies, and strengthen in months when climate is more salient to production decisions. The reduction in credit is driven by a decline in demand more than supply. Through their impact on credit origination, anticipated climate anomalies also reduce investment and agricultural productivity. Take-up of hedging instruments mitigates these effects. Overall, we find that climate risk threatens food security through a finance channel.

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1. Introduction

A growing literature studies the effects of climate shocks on a variety of economic outcomes.[1] While studies often focus on the physical consequences of climate shocks, less is known about how anticipation (as opposed to realization) of climate conditions affects economic activities.[2] These responses can be as important as the physical costs of climate change, yet the financial economics literature provides relatively little evidence on their consequences.

This paper tests how perceptions of climate risk affect capital allocation. The direction of the effect is unclear. On the one hand, credit volume could decrease as both demand and supply sides worry about heightened (climate) risk. On the other hand, demand for capital could increase as producers seek to retool operations in the face of a changing climate. Further, capital supply could increase if investors exhibit a willingness to accept lower returns in exchange for funding a desired social objective, such as supporting industries that are sensitive to climate risk.[3]

We address this question by studying bank credit in the U.S. agricultural industry in anticipation of forecasted climate anomalies. Agriculture is ground zero for the consequences of climate change and food security. Lipper et al. (2014) discuss the need for "climate-smart agriculture" to achieve food security in response to climate change. These authors identify the link between climate and finance as one of four key pathways to improving food security. We test the

[1] A large literature examines the effects of weather and climate change on agricultural productivity. See, e.g., Schlenker and Roberts (2009), Fisher et al. (2012), Lesk et al. (2016), Bergman, Iyer, and Thakor (2020), and Ortiz-Bobea et al. (2021). For effects on financial assets, see, e.g., Dietz et al. (2016), Hong, Li, and Xu (2019), Bolton and Kacperczyk (2021), Ilhan, Saunter, and Vilkov (2021), and Pastor, Stambaugh, and Taylor (2021). Dell et al. (2012), Burke et al. (2015), Addoum, Ng, and Ortiz-Bobea (2020), Acharya et al. (2024), and Ponticelli et al. (2024) study the impact of temperature shocks on economic productivity and growth. Brown, Gustafson, and Ivanov (2021) study the impact of severe winter weather on credit line financing. Cramer, Ghosh, Kulkarni, and Vats (2025) study fintech lenders' responses to weather shocks.

[2] The *Stern Review* (Stern, 2007) defines "socially contingent" responses to climate change as dynamic effects on socio-economic activities that are distinct from the physical, or "static", effects of climate change.

[3] The literature refers to this as a "willingness to pay". See for example, Baker, Egan, and Sarkar (2024), who quantify investors' willingness to pay for the psychic and societal benefits of ESG objectives. Goldstein, Kopytov, Shen, and Xiang (2024) develop a rational expectations model in which traditional and green investors have different preferences for financial and ESG risks.

importance of this pathway by examining the sensitivity of credit in the agricultural industry to anticipated climate conditions.

This setting provides several advantages for studying climate and finance. First, a key challenge to studying the effects of climate risk perceptions is finding an agreed-upon benchmark of climate expectations, as people's beliefs about climate are diverse (Choi, Gao, and Jiang, 2020). We use data from the National Oceanic and Atmospheric Administration (NOAA) because survey evidence indicates it is the most popular source of information about climate for farmers (Cabrini et al., 2023). The NOAA's Seasonal Climate Outlooks provide forecasts of climate anomalies. These forecasts are among the most scientific and authoritative projections of seasonal climate risks available to the public.

Another advantage is the opportunity to isolate the effect of anticipated climate anomalies from that of physical climate shocks. The two are often correlated and affect decision making independently (Alok et al., 2020; and Alekseev et al., 2021), yet existing empirical literature does little to separate them.[4] Exploiting data on anomalies forecasted for certain periods together with anomalies that actually happen in these periods, we measure the simultaneous yet independent effects of anticipated and actual climate anomalies.

The third advantage of our setting is the relatively short-run nature of financing cycles in the agriculture industry. Policy makers hope to influence long-run climate change over the coming decades. Therefore, attempts to measure the effects of long-run climate change must consider the influence of climate policy made in the present. Producers in the agriculture industry typically make financing decisions with annual growing seasons in mind. This means financing decisions

[4] Recent papers study how projected sea level rise affects real estate prices and municipal bonds. See Bernstein, Gustafson, and Lewis (2019), Baldauf, Garlappi, and Yannelis (2020), Ilhan (2020), Murfin and Spiegel (2020), and Painter (2020).

are based on climate conditions that will materialize in a matter of months, if not the present month. Such time horizons are too short for climate policy to play a role, facilitating cleaner measurement of the effects of anticipated climate conditions apart from policy interventions.

Our main result is that anticipation of climate risk has a significantly negative effect on credit origination. When a county-month's projected probability of having abnormal temperature or precipitation is in the top decile, the annual amount of loan origination in the county drops by 2.6% from the mean. For an average county, this effect translates into a ~$150,000 decline in annual loan volume. The effects of realized anomalies on financing tend to be weaker, both economically and statistically. Thus, the results suggest that credit declines substantially in anticipation of potential climate shocks. It drops further when actual anomalies hit, but the impact is smaller.

We examine results in the cross section by parsing the data by product. We find significantly negative effects of projected climate anomalies on financing across product categories. However, these effects vary in predictable ways, depending on a product's vulnerability to certain climate extremes. For example, corn and soybean are particularly sensitive to heat and cold while hay and cotton are sensitive to drought. We further investigate the effects of projected climate anomalies over different months of the year. We find that the effects are significantly negative in most months and are particularly strong when anomalies are forecasted for the planting and growing seasons. The patterns are consistent with climate extremes being more damaging to products at times of the year when climate conditions are most consequential.

Our main analysis studies credit originated by commercial banks, which are the largest source of credit to the U.S. agricultural industry. We further collect and geolocate data on agricultural loans issued by the Farm Credit System (FCS). FCS institutions, whose statutes are

set by Congress and are mandated to serve agriculture-related borrowers, are the other primary agricultural lender in the U.S. Combined, commercial banks and FCS institutions originate 84% of the country's farm debt.[5] We replicate our main analysis and find that forecasted climate anomalies have a similar, significantly negative effect on FCS loans. When most territories of a FCS lender are projected to be hit by climate anomalies, the annual amount of loans from the lender drops by 2.7% from the mean. Thus, the reduction of credit in anticipation of climate risk is commonplace in the agriculture sector. To our knowledge, we are the first to geolocate and study the majority of agricultural loans in the U.S.

Next, we test whether the drop in loan origination is driven by demand or supply factors. Using Federal Reserve Surveys of Agricultural Credit Conditions, we find that in Federal districts where most counties experience large increases in forecasted anomalies, bankers report a significant decline in demand for agricultural loans. Meanwhile, the availability of funds to agricultural loans increases. We also exploit two credit supply shocks that have been widely adopted in the banking literature: 1) local markets' openness to outside lenders that varies by state-year following the Interstate Banking and Branching Efficiency Act of 1994, and 2) banks' deposits windfall following the shale boom that varies by a bank's presence in shale-boom counties. We find that neither positive credit supply shock mitigates the reduction of credit in anticipation of climate anomalies. Taken together, our findings indicate that a reduction in demand for credit is the primary channel affecting loan origination. Our findings echo Lane (2024), who shows that farmers in Bangladesh reduce investment when they are concerned about being affected by climate shocks.

[5] CRS Report RS21977, *Agricultural Credit: Institutions and Issues* (published in March 2018).

Next, we turn to real effects. Does the reduction in credit in response to anticipated climate anomalies have implications for agricultural output and, therefore, food security? We find expected climate anomalies have a significantly negative impact on investment. Agricultural producers use fewer inputs and plant fewer acres, and do not successfully change crop concentrations. We follow these results by testing whether reduced financing can further hinder productivity, as some investment opportunities may be lost due to deleveraging. To tackle the potential endogeneity of financing, we use anticipated climate anomalies as instruments. Anticipated climate anomalies affect credit origination but are unlikely related to productivity after controlling for actual climate conditions and production inputs. We find that credit has a positive and significant effect on productivity. Therefore, a decline in financing due to anticipated climate anomalies reduces agricultural productivity apart from any harm done by actual climate shocks. This result is consistent with papers showing that credit has a positive effect on economic activity (e.g., Jayaratne and Strahan,1996; and Butler and Cornaggia, 2011). However, our evidence of a credit demand channel is new to this literature. Overall, our findings stress the role of finance in food security threatened by climate change.

Finally, we test whether hedging strategies mitigate the negative effects of anticipated climate anomalies on financing. Crop insurance is a primary tool for agricultural producers to manage risk (Cornaggia, 2013). Sales closing dates for insuring different crops are predetermined once a year, usually a few months before the planting season for the crop concerned.[6] Therefore, variation in financing due to forecasted climate anomalies during the growing season cannot be affected by the insurance decision. We find that insurance take-up offsets 27-55% of the negative

[6] For example, in 2025, initial plant dates for corn range from 3/20 to 4/15, and final plant dates range from 5/15 to 5/31, depending on area. The sales closing date for insurance for all areas is 3/15, which precedes even the earliest initial plant date. Source: Farm Credit Services of America. URL accessed August 8, 2025: Key Crop Insurance Deadlines 2025 | FCSAmerica

impact of anticipated climate anomalies on financing, depending on which dimension of insurance we examine. The results indicate that risk management helps maintain financing in the face of climate risk.

This paper contributes to several literatures. First, a growing climate economics literature addresses the immediate impact of adverse climate conditions on economic activities (see footnote 1). Our paper examines how anticipation of future climate anomalies affects present economic decisions. We show the role of anticipated effects relative to direct effects of realized climate shocks. As such, our evidence fills a gap in the literature on the costs of climate change (Frankhauser and Tol, 2005; Stern, 2007; Rising et al., 2022). We also provide evidence of how hedging helps producers mitigate climate risk.

Second, we contribute to the literature on the effect of environmental risk on financial and economic activities. Chava (2014) documents that firms with higher environmental hazards tend to pay higher costs of capital. Bolton and Kacperczyk (2021) find that stocks of firms with high carbon emissions earn higher returns. Huynh and Xia (2021) show that corporate bonds with potential to hedge climate risk are priced higher. Ilhan, Sautner, and Vilkov (2021) find that the cost of option protection against downside carbon tail risks is larger for firms with more carbon-intense business models.[7] To our knowledge, we are the first to study how climate risk affects firm financing in terms of credit origination. Importantly, the effects of climate risk on economic outcomes are exacerbated by discouraging capital origination and reducing productivity (a feedback risk as per Rising et al., 2022). While this literature often measures firms' environmental

[7] Also see Matsumura, Prakash, and Vera-Munoz (2014) on the effects of carbon disclosure and carbon emissions on firm value, Ratnadiwakara and Venugopal (2023) on how climate risk perceptions affect demand for flood insurance, Capasso, Gianfrate, and Spinelli (2020) on how carbon emissions affect firms' credit risk, Javadi and Masum (2021) on the effect of drought exposure on firms' cost of bank loans, and Dang, Gao, and Yu (2023) on how cap-and-trade policies targeting power plants affect manufacturers' capital structure.

risk using firms' business profiles, we use direct measures of producers' risk exposure to climate anomalies. The exogenous nature of the Seasonal Climate Outlook coupled with large cross-sectional and time-series variations in agricultural producers' risk exposure helps enhance the quality of measurement.[8] Moreover, our paper focuses on the effect of climate risk per se, as opposed to policy risk associated with regulatory actions directed at curbing carbon emissions.

Third, we contribute to the literature on the impact of climate on agriculture and food security. The global agricultural industry will encounter significant challenges as it adapts to climate change (Adams et al., 1990; Piao et al., 2010; Burke and Emerick, 2016; and Hong, Li, and Xu, 2019). As Vermeulen et al. (2012) note:

> "*The impacts of global climate change on food systems are expected to be widespread, complex, geographically and temporally variable, and profoundly influenced by socioeconomic conditions*" (Vermeulen et al., 2012, pp. 195).

Our results indicate that credit allocation is a channel through which climate change affects food production. Beyond its direct consequences for food security, the agricultural industry is important because it affects savings and investment, leading to economic growth in other sectors (Bustos, Caprettini, and Ponticelli, 2016; Bustos, Garber, and Ponticelli, 2020). Our findings show that capital markets and financial instruments have an important role to play as the agricultural industry contends with climate change.

2. Data

2.1. Climate Data

Each month, on a Thursday around the middle of the month, the NOAA publishes a Seasonal Climate Outlook. Each outlook contains the probability of deviations from normal

[8] Alekseev et al. (2024) show that information from a large cross-section of climate events can greatly improve the efficacy of hedging strategies in comparison to the relatively limited cases of climate risks in the time series.

temperature and precipitation across the continental United States, for a total of 13 periods in the future. Each period (or "season") contains 3 months and is one month further into the future than the previous period. For example, the outlook published in December 2021 provides a forecast for the next 13 periods, with the first period being Jan-Feb-Mar 2022, the second being Feb-Mar-Apr 2022, the third being Mar-Apr-May 2022, …, and the thirteenth being Jan-Feb-Mar 2023. The outlook published in January 2022 provides a forecast for Feb-Mar-Apr 2022, Mar-Apr-May 2022, all the way to Feb-Mar-Apr 2023. Figure IA.1 in the Internet Appendix provides an example. It shows the Seasonal Climate Outlook published on February 17, 2022, which provides a forecast for Mar-Apr-May 2022.

The NOAA is the most popular source of information about climate for farmers (Cabrini et al., 2023). The NOAA's forecasts of climate anomalies are among the most scientific and authoritative projections of seasonal climate risks available to the public, and Shafiee-Jood, Deryugina, and Cai (2021) show that users' trust affects the adoption of climate and weather forecasts. Recent cuts to the federal workforce threaten to undermine farmers' trust in the NOAA for the long-range forecasts that guide their operations.[9]

Seasonal Climate Outlooks provide probabilities of temperature (or precipitation) to be above, within, or below the climatological norm of a location.[10] We use these probabilities to construct measures of forecasted climate anomalies. Because the NOAA publishes new outlooks each month, we use the most recent outlook when constructing measures for county-year-month observations in the sample.[11]

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[9] *Farmers, meteorologists fear forecast gaps as Trump-era layoffs hit NOAA*, WHRO public media, URL accessed August 4, 2025: Farmers, meteorologists fear forecast gaps as Trump-era layoffs hit NOAA.

[10] The NOAA defines climatological norms with the middle tercile of the temperature (or precipitation) distribution of a location in the past 30 years.

[11] The NOAA also publishes outlooks that provide forecasts that begin at longer time horizons. For example, the 2-month lead outlook issued in December 2021 provides a forecast for Feb-Mar-Apr 2022. Our main analysis uses 1-month outlooks because these provide forecasts for the months that immediately follow. These forecasts should be

Panel A, B, C, and D of Figure 1 show the distributions of forecast probabilities of above-normal temperature, below-normal temperature, above-normal precipitation, and below-normal precipitation, respectively, for the county-year-months in our sample. The modes of the forecast probabilities of these anomalies are all 0.33, represented by the tallest bars in the graphs. These forecasts are the most common, typically corresponding to equal probabilities of above-normal, normal, and below-normal climate outcomes.[12] Climate extremes are consequential for agricultural production (Vogel et al., 2019). The 90th percentile of the forecast probability of above-normal temperature (below-normal temperature, above-normal precipitation, below-normal precipitation) is 0.434 (0.335, 0.360, 0.359). Producers should anticipate significant risk of an anomaly in the local area when the forecast probability of this anomaly is above the 90th percentile (e.g., see the heat stress indicator in Zampieri et al., 2017).

We define four indicators to capture producers' anticipation of different climate anomalies in their counties over the following months. Specifically, based on the outlook for a county-year-month, *Forecast High Temp* (*Forecast Low Temp*) is an indicator that equals 1 if the probability that the county-year-month's average temperature will be above (below) normal is in the top decile of the sample. Similarly, *Forecast High Precip* (*Forecast Low Precip*) is an indicator that equals 1 if the probability that the county-year-month's precipitation will be above (below) normal is in the top decile of the sample. To summarize forecast anomalies for a county-year-month in one variable, we define *Forecast Anomalies*, an indicator that equals 1 if any of the four indicators defined above equals 1.

more salient than forecasts that begin at longer time horizons. We use 2-month outlooks in robustness tests and find results that are similar in sign, magnitude, and statistical significance to the baseline findings.

[12] In principle, the probability of normal temperature or precipitation could be 33%, while the probability of above-normal temperature or precipitation could be, for example, 67%, and the probability of below-normal temperature or precipitation could be 0%. However, this kind of asymmetry is uncommon in the data. When the probability of normal temperature or precipitation is 33%, the probabilities of both above- and below-normal temperature or precipitation are almost always also 33%.

The NOAA also provides historical data on actual average temperature and total precipitation in a month for a location. We define four indicators to capture actual climate anomalies. *Actual High Temp* (*Actual Low Temp*) equals 1 if average temperature of a county-year-month is above (below) the county-month's climatological norm. Similarly, *Actual High Precip* (*Actual Low Precip*) equals 1 if precipitation of a county-year-month is above (below) the county-month's climatological norm. To summarize actual anomalies for a county-year-month in one variable, we define *Actual Anomalies*, an indicator that equals 1 if any of the four indicators for actual anomalies equals 1. Therefore, for a given location, we measure anomalies forecasted for a month and anomalies that actually happened in the month and examine their simultaneous yet independent explanatory power. This approach is distinct from Islam and Singh (2023), who study the relationship between recent historical realizations of temperature and agricultural financing. We feature most results using *Forecast Anomalies* and *Actual Anomalies* because this approach is succinct. For completeness, we also report results using the more detailed sets of four indicators.

Seasonal Climate Outlook data are published at the forecast division level, while actual climate data are at the more detailed climate division level. Figure IA.2 in the Internet Appendix provides a visual comparison of the forecast and climate divisions in the continental U.S. There are 102 forecast divisions and 344 climate divisions. Most states have 7-10 climate divisions depending on the size and climate diversity of the state. Climate divisions usually include several counties. We measure a county's forecasted climate conditions with the Seasonal Climate Outlook for the county's forecast division. We measure a county's actual climate conditions with the actual climate data for the county's climate division.

Figure 2 visualizes the relationship between forecasted anomalies and actual anomalies. Our main measures of forecasted and actual anomalies are indicator variables, and the binary nature of these variables coarsens the data. Therefore, on the x-axis, we use the forecasted percentage values of climate anomalies for this visualization: *Forecasted Probability of Temperature Above Norm*, *Forecasted Probability of Temperature Below Norm*, *Forecasted Probability of Precipitation Above Norm*, and *Forecasted Probability of Precipitation Below Norm*. On the y-axis, we use *Actual Temperature Minus Norm* and *Actual Precipitation Minus Norm* to measure actual anomalies.[13] These continuous variables make the figure easier to interpret.

In Panel A, the correlation between *Forecasted Probability of Temperature Above Norm* and *Actual Temperature minus Norm* is 0.077. The R^2 of a univariate regression is 0.006. As expected, the relationship is positive, but it is noisy. In Panel B, the correlation between *Forecasted Probability of Temperature Below Norm* and *Actual Temperature minus Norm* is -0.073. The R^2 of a univariate regression is 0.005. Again, this relation is negative as expected but noisy. Panels C and D show similar patterns regarding precipitation anomalies. Although forecasted and actual conditions correlate according to expectations, forecasted conditions often do not materialize. This lack of predictive power suggests significant risk for agricultural producers who rely on the NOAA's forecasts when making financial and operational decisions.

2.2. Bank Loans and Deposit Data

County-level farm financing data are from Community Reinvestment Act (CRA) filings maintained by the Federal Financial Institutions Examination Council (FFIEC). These data allow us to geolocate credit from commercial banks, which are the largest providers of credit to farmers

[13] "Norm" refers to the average temperature or total precipitation of the same month averaged over the recent 30 years.

in the U.S.[14] The CRA database covers loans with amounts up to $1 million issued to farms by banks and savings associations. Although it is mandatory for banks with approximately $1 billion or more of total assets to file CRA data (this threshold adjusts every year based on the Consumer Price Index), many smaller banks file their data either voluntarily or because they elect to be evaluated as "large" institutions during CRA examinations. As banks with $1 billion or more of assets hold 95% of the industry's assets, the CRA data cover a large portion of agricultural financing in the U.S. The main dependent variable is *Loan Volume*, defined as the annual amount of farm financing originating in a county divided by the acres operated in the county. We also collect county-level small business loan data from the CRA. We obtain data on bank deposits in a county from the Summary of Deposits data maintained by the Federal Deposit Insurance Corporation.

2.3. FCS Institutions and Loans

The Farm Credit System (FCS) is a nationwide network of borrower-owned lenders that serves farmers. It is the second-largest agriculture lender in the U.S., just behind commercial banks. For FCS institutions, we obtain agriculture loan volumes as well as lender characteristics such as size, leverage, and profitability from call reports maintained by the Farm Credit Administration (FCA). We focus on "agriculture production and intermediate term" loans reported in the call reports. We define *FCS Loan Volume* as the total amount of such loans issued by an FCS institution in a year-quarter.

Unlike the CRA data for commercial banks, call reports do not geolocate FCS loans at the county level. However, the FCS provides maps of each institution's territory counties. Figure IA.3 in the Internet Appendix provides examples. Some FCS institutions serve only a few counties,

[14] Commercial banks hold 42% of total farm debt in the U.S. Source: Congress.gov. URL accessed June 12, 2025: https://www.congress.gov/crs-product/RS21977

such as Legacy Ag Credit, which provides credit to nine counties in northeast Texas. Others serve non-contiguous territories across state lines. For example, AgSouth Farm Credit provides credit to 147 counties across parts of Georgia, North Carolina, and South Carolina. Still others serve larger territories encompassing multiple states. For example, Farm Credit Mid-America serves the entire states of Indiana and Tennessee, 11 counties in Arkansas, three counties in Missouri, all but nine counties in Ohio, and all but eight counties in Kentucky.

We manually tabulate the counties in each of the 65 FCS institutions' territories. This approach allows us to coarsely geolocate FCS institutions' loans and test whether *FCS Loan Volume* is sensitive to the forecasted and realized climate conditions in FCS institutions' service territories. To the extent that responses to climate anomalies in some counties mix with nonevents in other counties, any relation will be muted in the data. Overall, by collecting and geolocating loan volumes from commercial banks with the CRA data, and borrower-owned lenders with the FCS data, we study the two main sources of agricultural credit in the U.S., which combine to provide over 80 percent of all debt to U.S. farmers.

2.4. Farm Operations and County Characteristics

We obtain county-year level farm characteristics such as size, asset value, and acres operated from the United States Department of Agriculture (USDA). To measure crop investment and diversity, we also collect acres planted and acres harvested for different crops at the county-year level from the USDA. We collect data on farm inputs, farm outputs, farm employment, and per capita income from the Bureau of Economic Analysis. We also obtain data on population density and population education levels (percent of population with a high school diploma or higher education) from the U.S. Census Bureau. We take the intersection of the above datasets to

construct our baseline sample. It covers a total of 3,032 counties from December 1997 to April 2015.

2.5. Credit Demand and Supply Conditions

For analysis of loan demand and supply, we collect credit conditions at the Federal Reserve District level from the Federal Reserve District Surveys of Agricultural Credit Conditions. We then geolocate each county to a Fed District using the shape files provided by the Federal Reserve Bank of Kansas City. *Loan Renewals, Loan Demand*, and *Loan Supply* are diffusion indexes. Bankers responded to each item by indicating whether loan renewals or extensions, demand for loans, and loan fund availability, respectively, during the current quarter were higher than, lower than, or the same as in the year-earlier period. The index numbers are computed by subtracting the percent of bankers that responded "lower" from the percent that responded "higher" and adding 100. Take *Loan Demand* as an example. If there are more bankers who believe that loan demand has increased over the year than those who believe that loan demand has decreased, then the diffusion index is greater than 100. The greater the percentage of bankers who believe loan demand has increased, the greater this index. These variables measure bankers' first-hand experience regarding credit conditions. Importantly, the credit demand and supply conditions are reported as separate items, i.e., *Loan Demand* and *Loan Supply*. As such, we can directly examine how the demand side and supply side, respectively, respond to climate risks.

2.6. Credit Supply Shocks

We use two proxies for credit supply shocks that vary by time and geography and have been widely adopted in the banking literature. First, in 1994, the Interstate Banking and Branching Efficiency Act (IBBEA) was passed at the federal level, which allowed bank holding companies (BHCs) to enter another state without the state's permission. However, under the new law, states

still had the authority to impose restrictions on interstate branching by out-of-state banks. These restrictions can be categorized into four types of provisions regarding: (1) the minimum age of the target institution, (2) de novo interstate branching, (3) the acquisition of individual branches, and (4) a statewide deposit cap. States erected some or all of these barriers and made adjustments in later years. We follow Rice and Strahan (2010) and define a *Branching Restrictions Index* (BRI). The index is set to zero for states that are most open to branching by out-of-state banks. We add one to the index when a state adds any of the four barriers mentioned above. Areas with a lower BRI are more open to outside banks and therefore have greater availability of credit.

The second proxy uses Shale Well Data from Wharton Research Data Services (WRDS). We obtain data on new well activities in seven states with major shale discoveries since 2003 (Arkansas, Louisiana, North Dakota, Oklahoma, Pennsylvania, Texas, and West Virginia). Following Gilje, Loutskina, and Strahan (2016), we define *Share of Branches in Boom Counties* as the fraction of branches owned by a bank in a shale-boom county. A county is considered as a shale-boom county if the county is in the top quartile of all county-years with shale well activity. The shale boom brought wealth windfalls to landowners in boom counties and resulted in an exogenous increase in bank deposits (Plosser, 2015; Gilje, Loutskina, and Strahan, 2016; Gilje, 2019). Thus, banks with a greater *Share of Branches in Boom Counties* have more liquidity to supply credit.

2.7. Risk Management and Government Subsidies Data

For extended analysis, we collect crop insurance data from the Summary of Business prepared by the Risk Management Agency of the USDA. We obtain policy types (buyup versus catastrophe, or "CAT"), coverage levels, and insured acres at the county-year level from this dataset. We obtain farm subsidies data from Farm Payment Files at the USDA. We aggregate

payments to individual recipients at the county-year level to make measures of subsidies that are compatible with the rest of the sample.

2.8. Summary Statistics

Appendix Table A.1 in the Appendix provides definitions for the variables in our analysis. We report summary statistics in Table 1. The average *Loan Volume* is $20 per acre, with a standard deviation of $27 per acre. The means of *Forecast High Temp*, *Forecast Low Temp*, *Forecast High Precip*, and *Forecast Low Precip* are approximately 0.10. These values are not exactly 0.10 because forecasted climate extremes are defined for a forecast division, not a county. Some forecast divisions have more counties than other divisions. The summary statistics are based on all county-years in the sample. Therefore, the mean of an anomaly indicator can be higher (lower) than 0.10 if forecast divisions with the indicator equal to 1 tend to contain a greater (smaller) number of counties. The means of *Actual High Temp*, *Actual Low Temp*, *Actual High Precip*, and *Actual Low Precip* are close to 0.33, the steady state if the historical temperature and precipitation distributions remained stable. Consistent with temperature increasing in recent decades, *Actual High Temp* (*Actual Low Temp*) has a mean of 0.40 (0.27), somewhat higher (lower) than 0.33. Because *Forecast Anomalies* is the union of four indicators for different climate extremes, its mean is necessarily higher than the mean of any one of the four. The same logic applies to *Actual Anomalies*.

3. Forecasted Climate Anomalies and Financing

3.1. Baseline

We begin by testing whether forecasted climate anomalies explain financing. Because loan volumes are annual observations, whereas forecast anomalies are monthly, we stack *Loan Volume* for each month of the year and match it with each month's *Forecast Anomalies* and *Actual*

Anomalies. We conduct OLS regressions to estimate the following relationship. Each observation is a county-year-month (*c-y-m*).

$$Loan\ Volume_{cy} = \alpha_{ym} + \gamma_{cm} + \beta_1 Forecast\ Anomalies_{cym} + \beta_2 Actual\ Anomalies_{cym} + \boldsymbol{\delta} \cdot \boldsymbol{X} + \varepsilon_{cym} \quad (1)$$

α_{ym} and γ_{cm} are year-month and county-month fixed effects, respectively. $\boldsymbol{X}$ is a vector of control variables that capture county-year economic and agricultural conditions. We refer to this set of control variables as "County-Year Controls". β_1 captures the effect of *Forecast Anomalies* predicted for a county-year-month on *Loan Volume* of that county-year. β_2 captures the effect of *Actual Anomalies* occurring in a county-year-month on *Loan Volume* of that county-year. Because *Loan Volume* is stacked for each month of a county-year, we cluster standard errors by county-year.[15] This specification places a heavy burden on the data to uncover any effect of forecast anomalies. This is partly because we only observe financing at annual intervals. Even though forecast anomalies in a couple of months may significantly impact those months' financing outcomes, normal forecasts in other months of the year should have no significant impact on those months' financing outcomes. Given that we only observe financing aggregated for the year, salient effects from a few abnormal months will be muted by other months of the year. Thus, an effect identified in this specification can be thought of as a conservative estimate of the true effect.[16] We also conduct OLS regressions to estimate the following relationship. This approach captures the relationship between financing and individual effects of different types of anomalies.

[15] Results are robust to clustering at other levels, including county, division, and division-year. See Table IA.1 in the Internet Appendix.

[16] An alternative specification is to use county-year observations and regress the annual *Loan Volume* on all twelve months' *Forecast Anomalies* of that year as explanatory variables. We execute this approach and report results in Figure IA.4 in the Internet Appendix. Although key results are very similar, this approach produces a cumbersome regression output, and the specification is prone to collinearity. We thus use equation (1) as the preferred baseline.

$$Loan\ Volume_{cy} \tag{2}$$
$$= \alpha_{ym} + \gamma_{cm} + \beta_1 Forecast\ High\ Temp_{cym}$$
$$+ \beta_2 Forecast\ Low\ Temp_{cym} + \beta_3 Forecast\ High\ Precip_{cym}$$
$$+ \beta_4 Forecast\ Low\ Precip_{cym} + \boldsymbol{\delta} \cdot \boldsymbol{X} + \varepsilon_{cym}$$

We report the results in Table 2. *Forecast Anomalies* has a significantly negative impact on *Loan Volume*. When a month of a year is forecasted to have high risk of abnormal climate conditions, the annual amount of financing drops by $0.51 per acre on average, or a 2.6% decrease from the mean. Given that an average county in our sample has ~300,000 acres operated by farms, this effect translates to a ~$153,000 decline in financing in the county. *Actual Anomalies* has a negative but statistically insignificant impact on *Loan Volume*.

Further examining the effects of different types of anomalies, we find that abnormally high temperature, abnormally low temperature, abnormally high precipitation, and abnormally low precipitation forecasted for a month of a year lead to 1.8%, 3.7%, 1.1%, and 3.2% declines in annual financing from the mean, respectively. For realized anomalies, abnormally high and low temperatures in a month are associated with a 0.8% to 0.9% decline in annual loans from the mean. Although abnormally high and low actual precipitation have positive signs, they are statistically insignificant and economically small. While extreme temperatures often cause damage to crops and are difficult to deter, producers could alleviate damage from abnormally high and low precipitation through drainage and irrigation. The simultaneous possibilities of damage and remedy drive financing in opposite directions and hence could make the net effect insignificant. Overall, the findings indicate that while realized extreme temperatures directly reduce financing, anticipated climate anomalies have even stronger negative explanatory power for credit

origination. Thus, when policy makers assess the overall cost of climate change, these results highlight the role of contingent responses to perceived climate risks.

3.2. Effects across Crops, Months, and States

We further examine the explanatory power of forecast climate anomalies on financing when we consider different products. We focus on four major crop clusters in the U.S.: (1) hay, (2) corn and soybean, (3) wheat, sorghum, and sunflower, and (4) cotton and peanuts. We classify county-years in our sample according to which of these four clusters is the major crop and estimate equation (2) for each subsample. Mapping of county-years to crop clusters follows Wagner, Niles, and Roy (2019).

Figure 3A shows that in counties where hay is the major crop, *Forecast Low Temp* and *Forecast Low Precip* have significantly negative effects on financing. Cold temperatures tend to hinder plant growth in general. There is also evidence that droughts significantly reduce hay yields (Smit, Metzger, and Ewert, 2008). Figure 3B shows that all four types of forecast anomalies hurt financing significantly in counties whose major crop cluster is corn and soybean. The findings are consistent with existing research on the consequences of climate anomalies on corn and soybean yields (Swan et al., 1990; Wang et al., 1997; Shaw, 2018; Li et al., 2019; and Thomey et al., 2019). Figure 3C shows that counties with wheat, sorghum, and sunflowers as major crops experience significantly reduced financing when drought is expected, consistent with evidence of drought hurting wheat yields (Helman and Bonfil, 2022; and Wan et al., 2022). Figure 3D shows that financing significantly decreases in anticipation of low precipitation in counties where cotton and peanuts are major crops. That drought hurts cotton yields is well documented (Wang et al., 2016; and Li et al., 2021). Overall, Figure 3 indicates that financing responds negatively to projected climate shocks in accordance with local products' vulnerabilities to different types of anomalies.

Figure 3 also shows that actual anomalies have mixed effects on agriculture financing. Their impacts generally have comparable or lower significance than the impacts of forecast anomalies.

Next, we estimate equation (1) on separate samples for each month from January to December and plot the effects of forecast climate anomalies over the course of a year. As Figure 4 shows, the impacts of forecast anomalies on financing are negative in most months' subsamples. The negative coefficients are particularly large in magnitude in April, the planting season, and June and July, the prime growing season for many crops. Figure IA.4 in the Internet Appendix shows very similar results when we use county-year observations and regress the annual *Loan Volume* on a set of 12 variables that capture the months' *Forecast Anomalies* of that year, as below.

$$\begin{aligned} Loan\ Volume_{cy} &= \alpha_y + \gamma_c + \beta_1 Forecast\ Anomalies_{cyJan} \\ &+ \beta_2 Forecast\ Anomalies_{cyFeb} + \cdots + \beta_{12} Forecast\ Anomalies_{cyDec} \\ &+ \beta_{13} Actual\ Anomalies_{cyJan} + \beta_{14} Actual\ Anomalies_{cyFeb} + \cdots \\ &+ \beta_{24} Actual\ Anomalies_{cyDec} + \boldsymbol{\delta} \cdot \boldsymbol{X} + \varepsilon_{cy} \end{aligned} \quad (3)$$

where α_y and γ_c are year and county fixed effects, respectively, and $\boldsymbol{X}$ is the same set of county-year control variables as in equation (1).

Next, we examine the relation between forecast anomalies and agriculture financing in different states in the continental U.S. We estimate equation (1) on separate samples for each state and plot a heat map of each state's percentage change of *Loan Volume* when *Forecast Anomalies* changes from 0 to 1. As shown in Figure 5A, *Forecast Anomalies* has negative relation with agriculture financing in most states. Even if we only consider states where *Forecast Anomalies* is statistically significant, as shown in Figure 5B, the negative relation is still prevalent.

3.3. Robustness

The evidence above paints a consistent picture that financing responds negatively to projected climate anomalies. In Table IA.2 in the Internet Appendix, we further show that our results remain robust in several additional tests.

First, we test whether our results are pronounced for smaller, short-term loans, as the Seasonal Climate Outlook concerns climate conditions that will materialize in a matter of months. We conjecture that very large loans are more likely geared for long-term capital expenditures rather than farms' annual operating cycles. Thus, we use *Loan <= 250K* as the dependent variable, which is defined in the same way as *Loan Volume* except that it considers loans with amounts less than or equal to $250,000, effectively excluding loans in the top tier of amounts in the CRA data. As shown in column 1, the results are very similar to the baseline results. *Forecast Anomalies* has a negative and significant relation with credit origination, and *Actual Anomalies* has a negative but insignificant relation.

Second, to consider the possibility that producers may utilize forecasts with longer lead times in their operating and financing decisions, we use 2-month lead forecasts to measure projected anomalies, instead of the 1-month lead used in the baseline regressions. The results, reported in column 2, are qualitatively unchanged from the baseline.

Third, we relax the screen for climate risks. Specifically, we define *Forecast High Temp* (*Forecast Low Temp*, *Forecast High Precip*, and *Forecast Low Precip*) as equal to 1 if the forecast probability of abnormally high temperature (abnormally low temperature, abnormally high precipitation, and abnormally low precipitation) is above its 75th percentile, instead of the 90th percentile used in the baseline regressions. *Forecast Anomalies* is redefined accordingly. Column 3 shows that the results are similar to the baseline results.

Fourth, we examine the effects of climate anomalies on loan growth instead of level. The new dependent variable, *Loan Volume Growth*, is defined as the growth rate of farm loan amounts in the county from last year to this year. Accordingly, as control variables, we use *Small Business Loan Growth* and *Deposit Growth* in place of *Small Business Loan* and *Deposit*, respectively, Again, *Forecast Anomalies* has a significantly negative relation with *Loan Volume Growth*. A significant risk of abnormal temperature or precipitation is associated with a 1.8 percentage point decrease in loan growth, as reported in column 4.

Fifth, we use *Raw Loan Volume*, defined as the total loan amount in a county without scaling by acres operated in the county, as the dependent variable. *Forecast Anomalies* still has a significantly negative effect, as shown in column 5. *Raw Loan Volume* decreases by $128.20, or 3.0% from the mean when the county anticipates climate anomalies.

Sixth, while forecasted climate anomalies have a significant effect on financing, we further examine whether the effect is attributable to uncertainty regarding these forecasts. Toward this end, we include *Large Forecast Temp Dispersion* and *Large Forecast Precip Dispersion* in our baseline regression. *Large Forecast Temp* (*Precip*) *Dispersion* is an indicator that equals 1 if the difference between the 80th and 20th percentiles of the 1-month lead forecast temperature (precipitation) for a county-year-month is above the 90th percentile of all sample years of the county-month.[17] The idea is to capture large uncertainties of forecast climate conditions. As shown in column 6, these large forecast uncertainties have no significant impact on financing. Meanwhile, the baseline results regarding *Forecast Anomalies* and *Actual Anomalies* remain unperturbed by the inclusion of these additional variables.

[17] The NOAA derives estimates of temperature and precipitation at 2, 5, 10, 20, 30, 40, 50, 60, 70, 80, 90, 95, and 98 percentile levels based on the tercile probability anomalies in the Seasonal Climate Outlook.

Seventh, we run a placebo test. Particularly, we use *Small Business Loan* as the dependent variable and re-estimate equation (1). *Small Business Loan* is defined as the amount of small business loans in the county-year scaled by acres operated in the county-year. This exercise is meant to examine whether anticipated climate anomalies also affect financing of sectors that are less sensitive to climate conditions. As reported in column 7, projected climate anomalies have a negative relationship with small business financing, but the effect is not statistically significant.

Eighth, we control for government subsidies as they can affect producers' needs for liquidity. *Subsidies* is total farm subsidies paid to recipients in the county divided by acres operated in the county. As shown in column 8, the effect of *Forecast Anomalies* on *Loan Volume* remains negative and statistically significant. The economic magnitude is also similar to the baseline.

Ninth, we consider the possibility that our estimates are distorted by a bad controls problem because we include time-varying county control variables. The concern is that the economic impact of forecasted climate anomalies may include agricultural loan volume along with other outcomes. By controlling for those other outcomes, we reduce the opportunity for agricultural loan volume to be explained by forecasted anomalies, resulting in a downward bias in our coefficients. As shown in column 9, however, the baseline coefficient estimate changes only modestly (from -0.514 to -0.562) after we exclude county-year controls.

3.4. Loans from Farm Credit System (FCS) Institutions

As the other primary lender of agricultural loans, FCS institutions hold 41% of total farm debt, second only to commercial banks, which hold 42% of total farm debt. FCS institutions are federally chartered, borrower-owned, and have a mandate to serve agriculture-related borrowers only. FCS institutions make loans to creditworthy farmers and do not serve as a lender of last

resort. In this section, we further examine whether the loan reduction in anticipation of climate risk we observe among loans from commercial banks also occurs in FCS loans.

We use *FCS Loan Volume* as the dependent variable. Because *FCS Loan Volume* is observed at the institution-year-quarter level (*i-y-q*), we stack all the county-year-month (*c-y-m*) observations of an institution's territory counties in related months. While smaller FCS institutions may have business in one state, the territories of larger FCS institutions can span several states. As some territory counties are subject to climate anomalies while many others are not, the aggregate effect on loan volume at the institution level could be muted. To enhance the power of our tests, we focus on FCS institutions with most territories either forecasted to be hit or not hit by climate anomalies at a given time. We exclude observations if the standard deviation of *Forecast Anomalies* across an FCS institution's territory counties is above the median of the year-month.

We control for the following lender characteristics. *FCS Assets* is the total assets of the FCS institution. *FCS Leverage* equals the FCS institution's total debt divided by total assets. *FCS Profitability* is the FCS institution's net income divided by total assets. We also control for lender, year-month, and county-month fixed effects. We conduct OLS regressions to estimate the following relationship. Each observation is a territory county-year-month (*c-y-m*).

$$FCS\ Loan\ Volume_{iyq} = \alpha_i + \gamma_{cm} + \theta_{ym} + \beta_1 Forecast\ Anomalies_{cym} + \beta_2 Actual\ Anomalies_{cym} + \boldsymbol{\delta} \cdot \boldsymbol{X} + \varepsilon_{cym} \quad (4)$$

We report the results in Table 3. Loan volume issued by FCS institutions is significantly lower when climate anomalies are forecasted in its territory counties. Specifically, for an average FCS lender in the sample, the loan volume decreases by 76 cents per acre, or a 2.7% decrease from the mean. This magnitude is slightly larger than what we observed among commercial banks. The

negative effect of *Actual Anomalies*, as before for commercial banks, is not as strong as that of *Forecast Anomalies*. The significant effects among both commercial banks and FCS lenders confirm that the reduction of credit in anticipation of climate risk is common across the two main lender types in the agriculture sector.

4. Credit Demand and Supply

4.1. Federal Reserve Agricultural Credit Surveys

The results so far show a negative equilibrium relation between forecasted climate anomalies and agricultural credit origination. In this section, we determine whether this finding reflects a reduction in credit demand, credit supply, or both. Both agriculture producers and financiers may respond to the risk of projected climate anomalies and therefore cut credit demand and supply, respectively.

The Federal Reserve District Surveys of Agricultural Credit Conditions provide data on demand and supply conditions of agricultural loans at the Federal Reserve district level at the quarterly frequency. We use *Loan Demand* and *Loan Supply*, as introduced in Section 2, to analyze the demand and supply conditions, respectively. As discussed above, bankers specializing in agricultural loans are the survey respondents. They observe the demand and supply conditions separately before the two sides meet to form an equilibrium. Thus, *Loan Demand* and *Loan Supply* are direct measures of credit demand and supply, distinct from our primary dependent variable, *Loan Volume*, which captures equilibrium credit volume. To check the consistency of our baseline results, we also use *Loan Renewals* as a dependent variable to proxy for the quantity of credit origination.

There are twelve Federal Reserve districts in the U.S. Seven of them (Chicago, Dallas, Kansas City, Minneapolis, Richmond, San Francisco, and St. Louis) are involved in the Survey.

Each district covers hundreds of counties spanning a variety of climate divisions. Similar to how we evaluate credit origination by FCS institutions, we consider that some counties in a district are subject to climate anomalies while many others are not. To enhance the power of our tests, we focus on districts with most territories either forecasted to be hit or not hit by climate anomalies at a given time. Toward this end, we exclude a district if the standard deviation of *Forecast Anomalies* across its territory counties is above the median of the year-month. We conduct OLS regressions to estimate the following relation. Each observation is a county-year-month (*d-y-m*).

$$Credit\ Condtions_{dyq} = \alpha_{ym} + \gamma_{cm} + \beta_1 Forecast\ Anomalies_{cym} + \beta_2 Actual\ Anomalies_{cym} + \boldsymbol{\delta} \cdot \boldsymbol{X} + \varepsilon_{cym} \quad (5)$$

α_{ym} and γ_{cm} are year-month and county-month fixed effects, respectively. $\boldsymbol{X}$ is a vector of county-year control variables. We cluster standard errors by district-year-quarter.

Table 4 reports the results. Columns 1, 2, and 3 show the effects of climate anomalies on loan renewals, loan demand, and loan supply, respectively. Consistent with the baseline results, forecasted climate anomalies have a statistically significant and negative relation with loan renewals. The effect is also economically significant. When climate anomalies are forecasted to hit a territory county, *Loan Renewals* (a diffusion index based at 100) decreases by 3.53, which is a 3.3% drop from the mean, per Table 1. Actual anomalies have a negative but statistically insignificant effect on loan renewals. Producers appear to be less willing to fund their operations in anticipation of climate risk than to fund remedial needs when actual climate extremes hit.

We also find that district-level *Loan Demand* significantly declines when a county in the district is projected to have climate anomalies. The district-level *Loan Demand* (again, a diffusion index based at 100) drops by 3.25, or a 3.3% decline from the mean when a county in the district

is subject to forecasted climate anomalies. *Loan Supply*, however, increases by 2.64, which is a 2.2% increase from the mean, when a county anticipates climate anomalies. Banks appear willing to provide funding even though borrowers are not willing to take the risk. These results suggest that forecasted climate anomalies dampen credit origination mainly because of a decline in credit demand.

4.2. Credit Supply Shocks – Two Settings

We exploit two different settings to further examine whether the negative effect of climate anomalies on credit origination is driven by a reduction in demand or supply. Both approaches represent positive shocks to the supply of local credit. If our baseline results are driven by credit supply, then the negative relation we establish between forecasted climate anomalies and agricultural loan volume should attenuate when credit supply expands. The first approach takes advantage of the Interstate Banking and Branching Efficiency Act (IBBEA) of 1994. The IBBEA allowed bank holding companies to enter other states without state permission. However, states had the authority to impose a variety of restrictions on this activity. Different states erected some or all of these restrictions and adjusted them over the early years of our sample. As such, local areas experienced staggered changes in openness to outside banks due to these state-level regulations. As a state relaxes branching restrictions for outside banks, the availability of credit expands (Rice and Strahan, 2010). Meanwhile, these regulatory changes are not directly related to local producers' credit demand. Thus, this setting helps isolate the role of credit supply in the decline of credit origination in anticipation of climate risks. We estimate the following regression equation.

$$
\begin{aligned}
Loan\ Volume_{cy} \quad & (6)\\
&= \alpha_{ym} + \gamma_{cm} + \theta_{sym} + \beta_1 Forecast\ Anomalies_{cym}\\
&+ \beta_2 Forecast\ Anomalies_{cym} \times Branching\ Restrictions\ Index_{sym}\\
&+ \beta_3 Actual\ Anomalies_{cym}\\
&+ \beta_4 Actual\ Anomalies_{cym} \times Branching\ Restrictions\ Index_{sym} + \boldsymbol{\delta}\\
&\cdot \boldsymbol{X} + \varepsilon_{cym}
\end{aligned}
$$

Branching Restrictions Index varies at the state-year-month level (*s*-*y*-*m*). We control for state-year-month fixed effects, θ_{sym}, as state political and economic environment could affect deregulation as well as credit conditions simultaneously. We expect β_2 to be negative and significant if greater funding availability (low *BRI*) can mitigate the negative effect of climate risk on credit origination.

Column 1 of Table 5 reports the results. The coefficient on *Forecast Anomalies* continues to be negative and significant, as in our baseline results. The coefficient on the interaction, *Forecast Anomalies* × *Branching Restriction Index*, is not statistically significant. Thus, we see no attenuation in the negative relation between forecasted anomalies and credit origination whether a county is more open to outside banks or not. This non-result casts doubt on the possibility that our main findings are driven by a reduction in credit supply.

The second approach takes advantage of the U.S. shale boom. Driven by technological developments in horizontal drilling and hydraulic fracturing (fracking), the shale revolution brought large wealth windfalls to landowners in counties with shale formations. Banks with branch presence in those counties also experienced large inflows of deposits and consequently provided more credit to non-boom counties compared with banks with no exposure to the shale boom (Gilje, Loutskina, and Strahan, 2016). Credit demand in non-boom counties is unlikely to be affected by

the shale boom. Hence, by comparing the relation between forecasted anomalies and credit origination in non-boom counties between banks with high exposure to the shale boom and banks with less exposure, we can shed light on the role of credit supply. An advantage of this approach is that it avoids confounding effects of cash windfalls to farmers derived from the mineral rights on their land. Indeed, Thakor (2023) documents that farmers owning mineral rights in boom counties enjoy relaxed credit constraints from these windfalls. We estimate the following regression, where each observation is a bank-county-year-month (*b-c-y-m*).

$$
\begin{aligned}
&Bank\ Loan\ Volume_{bcy} \qquad (7)\\
&= \alpha_{bym} + \gamma_{bcm} + \beta_1 Forecast\ Anomalies_{cym}\\
&+ \beta_2 Forecast\ Anomalies_{cym}\\
&\times Share\ of\ Branches\ in\ Boom\ Counties_{by}\\
&+ \beta_3 Actual\ Anomalies_{cym}\\
&+ \beta_4 Actual\ Anomalies_{cym} \times Share\ of\ Branches\ in\ Boom\ Counties_{by}\\
&+ \boldsymbol{\delta} \cdot \boldsymbol{X} + \varepsilon_{bcym}
\end{aligned}
$$

Bank Loan Volume is the annual amount (in $) of farm loans in a county issued by a bank divided by acres operated in the county. *Share of Branches in Boom Counties* is measured at the bank-year level (*b-y*). We expect β_2 to be positive and significant if greater funding availability (high *Share of Branches in Boom Counties*) mitigates the negative relation between climate risk and credit origination.

Column 2 of Table 5 reports the results. The coefficient on *Forecast Anomalies* indicates that bank loan volume declines significantly – the point estimate of -0.0227 corresponds to a 4% decrease from the median – when climate anomalies are forecasted to hit a county. However, banks with greater exposure to the shale boom do not adjust their lending volume. The coefficient on the

interaction, *Forecast Anomalies* × *Share of Branches in Boom Counties*, is negative and insignificant. The results suggest that the decline of credit in anticipation of climate risks is unlikely driven by unavailability of funds. However, lending volume increases among banks with higher shares of branches in boom counties when actual anomalies materialize. This result echoes our earlier findings for loan supply based on Federal Reserve District Surveys. If anything, banks are more willing to lend to farmers facing climate anomalies. Taken together, the non-results based on the IBBEA and the U.S. shale boom indicate that a greater supply of credit does not mitigate the negative relation between forecasted climate anomalies and credit origination. Therefore, our main results more likely reflect a reduction in demand for credit.

5. Crop Productivity

5.1. Forecasted Climate Anomalies and Food Production

The results so far show significantly negative responses of financing to projected climate anomalies resulting from reduced demand for credit. Next, we ask whether projected anomalies have consequences for farmers' production decisions. We observe the acres planted of each crop in a county-year and use it to measure the extensive margin of investment (*Acres Planted*). We regress this variable on *Forecast Anomalies* and *Actual Anomalies*, controlling for county characteristics and crop-year-month and crop-county-month fixed effects. Table 6, Column 1 reports the results. Projected climate risks have a statistically significant and negative effect on acres planted. However, the economic magnitude is modest. *Acres Planted* decreases by 0.2% (0.6%) from the mean (median). *Actual Anomalies* also has a negative effect on *Acres Planted*, but it is not statistically significant.

Next, we use *Production Input* to measure the intensive margin of investment. *Production Input* equals total production expenses in the county-year divided by acres operated in the county-

year. Production expenses include purchases of feed, seeds, livestock, fertilizer, other agriculture chemicals, and petroleum products, as well as hired labor. These items are primary expenses for agriculture production. Table 6, Column 2 reports the results. We find that *Forecast Anomalies* has a negative and significant impact on the intensive margin of investment. *Production Input* drops by $4.2 per acre in anticipation of upcoming climate anomalies, or a 1% decrease from the mean. For an average county with ~300,000 acres operated, these effects translate to an economically significant $1.26 million decline in farm spending. Importantly, these "contingent" effects arrive even before actual climate shocks bring any actual damage. The results also show that investment intensity increases when climate anomalies eventually hit the local area. One possible explanation is that producers need extra investment to mitigate damages caused by anomalies. Another possibility is that operating costs are higher under harsh climate conditions. For example, Park, Pankratz, and Behrer (2021) show that high temperatures significantly increase workplace injuries. Hence, there are additional safety costs to reducing hazards in extreme conditions.

Finally, we examine producers' diversification of their investments in anticipation of climate risks. We construct *Crop Concentration*, the Herfindahl index of the acres harvested of all the crops in a county-year. Although acres planted is a good measure of investment *ex ante*, these data are not available for all crops. Acres harvested is available for almost all crops and is a good proxy for acres planted. As reported in Table 6, Column 3, forecasted and actual climate anomalies do not have significant effects on the diversification decision. Our conjecture is that, unlike investment opportunities in financial markets, potential choices of crops to plant in an area are limited. Thus, producers may not have much flexibility to diversify the crops they plant in response to forecasted anomalies.

5.2. Forecasted Climate Anomalies, Credit, and Agricultural Productivity

Agricultural financing declines in anticipation of climate anomalies. We extend the analysis by testing whether this relation has consequences for agricultural productivity. The classic literature on the finance-growth nexus generally finds that finance promotes productivity and growth (Jayaratne and Strahan, 1996; and Butler and Cornaggia, 2011). If financing declines in anticipation of climate anomalies, will productivity fall as a result? Answering this question is challenging because financing and productivity are jointly determined. Credit can be particularly useful for supporting underperforming producers. If these producers are inherently less efficient, then OLS regressions may underestimate the true relation between credit and productivity. Alternatively, creditors may lend greater amounts to more productive producers, e.g., because these producers can provide more collateral for loans. In this case, OLS regressions would overestimate the true effect.

Our setting provides a unique opportunity to circumvent these endogenous selection concerns. We use *Forecast Anomalies* as an instrumental variable for *Loan Volume*. Based on our findings above, the relevance condition is satisfied. Regarding the exclusion condition, projected climate anomalies should affect productivity only through their impact on financing, given that we control for actual climate conditions (through *Actual Anomalies*) and agricultural inputs (through *Acres Operated* for fixed costs and *Production Input* for variable costs). We define the dependent variable, *Productivity*, as the dollar amount of a county's farm output per acre operated. We estimate the following relationship with two-stage least square (2SLS) regressions:

$$Loan\ Volume_{cy} = \alpha_{ym} + \gamma_{cm} + \beta_1 Forecast\ Anomalies_{cym} + \boldsymbol{\delta} \cdot \boldsymbol{Z} + \varepsilon_{cym} \quad (8a)$$

$$Productivity_{cy} = \tau_{ym} + \mu_{cm} + \beta_2 Loan\ \widehat{Volume}_{cy} + \boldsymbol{\theta} \cdot \boldsymbol{Z} + \epsilon_{cym} \quad (8b)$$

We report the results in Table 7. Column (1) shows results from a naïve OLS regression. The relation between *Loan Volume* and *Productivity* is insignificant both statistically and economically. Column (4) shows the results of the 2SLS regression approach. Here, the effect is statistically significant, and the economic magnitude is more pronounced. A one-standard deviation (1σ) increase in *Loan Volume* explains an increase of *Productivity* equal to 17% of its mean. The first-stage *F* statistic in column (2) is over 106, easily satisfying the Stock and Yogo threshold of 16, which limits the potential bias to at most 10% (Stock and Yogo, 2005). Comparing columns (1) and (4) reveals that OLS underestimates the true relation between loan volume and productivity. As explained above, OLS could mask the true effect if loans are targeted toward improving underperforming producers. This explanation is plausible because banks are encouraged to support underserved communities under the Community Reinvestment Act. Importantly, the results suggest that a decline in financing due to anticipated climate anomalies results in real output losses, significantly hindering agricultural productivity. This effect implies a threat to food security. Anticipated climate anomalies motivate farmers to borrow less and produce less food.

6. The Role of Hedging

Our results so far show that anticipation of climate anomalies hinders finance and productivity. Next, we examine the role of hedging in this relationship. Crop insurance is the primary risk management tool used by agricultural producers (Cornaggia, 2013). Crop insurance affects producers' capital-labor allocation decisions (Berger et al., 2023) and encourages irrigation (Deryugina and Konar, 2017). Depending on the types of insurance policies, producers can purchase protection against yield losses or revenue losses. Moreover, producers can choose between catastrophe (CAT) plans and buyup plans for different levels of protection. CAT plans

provide protection against catastrophic events only. That is, they only cover yield or revenue shortages that are beyond 50% of the benchmark yield or revenue (i.e., a deductible of 50%). Buyup plans provide more protection than CAT, and buyers can choose a range of coverage levels from 50% to 85% (i.e., a deductible of 15% - 50%). With insurance protection, producers and creditors should be less concerned about yield and/or revenue losses caused by climate anomalies. As a result, they may be more willing to finance farm operations with debt.

Insurers set closing dates for producers to purchase insurance. These closing dates are usually a couple of months before the planting season for the product concerned. Therefore, insurance is unlikely endogenous to aggregate financing for the year, at least with respect to financing that occurs during the growing cycle of the product concerned. To test whether risk management has a moderating effect on the negative relation between forecasted anomalies and agricultural credit, we conduct OLS regressions to estimate the equation below.

$$
\begin{aligned}
Loan\ Volume_{cy} &= \alpha_{ym} + \gamma_{cm} \\
&+ \beta_1 Forecast\ Anomalies_{cym} \times High\ Insruance\ Protection_{cy} \\
&+ \beta_2 Forecast\ Anomalies_{cym} \times Low\ Insruance\ Protection_{cy} \\
&+ \beta_3 Actual\ Anomalies_{cym} \times High\ Insruance\ Protection_{cy} \\
&+ \beta_4 Actual\ Anomalies_{cym} \times Low\ Insruance\ Protection_{cy} \\
&+ \beta_5 High\ Insruance\ Protection_{cy} + \boldsymbol{\delta} \cdot \boldsymbol{X} + \varepsilon_{cym}
\end{aligned}
\tag{9}
$$

We use four unique sets of variables for *High* (*Low*) *Insurance Protection* as follows. First, we check the overall effect of insurance protection. We construct two dummy variables. *High Insured Liability* (*Low Insured Liability*) equals 1 if the total insured liability amount per acre in the county-year is above (below or equal to) the county's median over the sample period. We

interact *Forecast Anomalies* with *High Insured Liability* and *Low Insured Liability*, respectively. If insurance helps alleviate the negative impact of projected climate anomalies on financing, then we expect *Forecast Anomalies* × *High Insured Liability* to have a larger (less negative) coefficient than *Forecast Anomalies* × *Low Insured Liability*. This is indeed the case, as shown by the first pair of whiskers in Figure 6 (also see Table 8, column 1). In county-years with high insured liability, financing is 2.2% lower than the mean when climate anomalies are forecasted. In contrast, in county-years with low insured liability, financing is 3.0% lower than the mean when climate anomalies are forecasted. However, the overlap of the whiskers indicates that the difference is not statistically significant.

Second, we examine the extensive margin of insurance based on acres insured. Specifically, we define two dummy variables. *High Insured Acreage* (*Low Insured Acreage*) equals 1 if the number of insured acres as a proportion of total acres operated in the county-year is above (below or equal to) the median of all sample years of the county. As presented by the second pair of whiskers in Figure 6 (also see Table 8, column 2), in county-years with high insured acreage, financing is 1.9% lower than the mean when climate anomalies are forecasted. In county-years with low insured acreage, financing is more sensitive to forecast climate anomalies, decreasing by 3.4% from the mean when climate anomalies are forecasted. The difference is statistically distinguishable, as the two whiskers do not overlap.

Third, we examine the intensive margin, exploiting the higher coverage levels provided by buyup plans relative to CAT plans. We define two dummy variables. *High Buyup Ratio* (*Low Buyup Ratio*) equals 1 if the ratio of acres insured by buyup policies over total acres insured in the county-year is above (below or equal to) the median of all sample years of the county. Consistent with insurance alleviating concerns of climate risk, the negative impact of *Forecast Anomalies* is

less pronounced in county-years with high buyup ratios than in county-years with low buyup ratios, as illustrated by the third pair of whiskers in Figure 6 (also see Table 8, column 3). Based on the point estimates, switching to a high buyup ratio regime offsets 55% of the negative effect of projected climate anomalies on financing. This difference is statistically significant.

Fourth and finally, we examine the intensive margin based directly on coverage levels (i.e., one minus the percentage of deductibles). We define two dummy variables. *High Coverage Level* (*Low Coverage Level*) equals 1 if the average coverage level in a county-year weighted by insured acres is above (below or equal to) the median of all sample years of the county. As the last pair of whiskers in Figure 6 show (also see Table 8, column 4), financing in county-years with high coverage levels responds less negatively to projected climate anomalies than in county-years with low coverage levels. Based on the point estimates, switching to a high coverage level regime offsets a statistically and economically significant 46% of the negative effect of projected climate anomalies on financing.

Overall, the results suggest that risk management can help producers and creditors maintain financing activities in the face of climate risk. The mitigating effects of insurance work through both the extensive and intensive margins. Our results complement Ghosh and Vats (2022), who show that farmers in India exhibit greater demand for credit when their incomes are ensured.

7. Conclusion

We study the relation between climate risk, credit, and agricultural productivity in the United States. We find that credit origination declines when climate anomalies are expected in the near-term. This result is robust across lender types – credit from both commercial banks and Farm Credit Services institutions dries up. Survey evidence indicates the reduction in credit derives from a reduction in demand rather than supply. Consistent with this explanation, we find no evidence

that positive supply shocks to local credit mitigate the negative relation between climate risk and credit origination. We trace the effects of reduced credit to agricultural productivity. We find that forecasted anomalies explain reductions in agricultural inputs. Forecasted anomalies also explain lower lending volume which, in turn, explains lower agricultural productivity.

These results indicate that climate anomalies have implications for food security through a finance channel – part of the reason climate risk threatens food production is because it reduces credit that facilitates agricultural productivity. However, we find that risk management instruments (crop insurance) mitigate the negative relation between climate risk and credit origination. These results are important because, as Fisher et al. (2012) and Deschênes and Green (2012) show, the potential economic impact of climate change on U.S. agriculture is large and negative. Overall, we show that capital markets and financial instruments have an important role to play in the relationship between climate risk and food security.

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Table A.1. Variable Definitions
This table reports variable names, definitions, and data sources used to construct the variables.

Variable	Definition (Data Source)
Loan Volume	Amount of loans (in $) issued to farms in the county-year divided by acres operated in the county-year. (CRA filings maintained by the FFIEC)
Forecast High Temp	For the 1-month lead forecast targeting a county-year-month, the indicator equals 1 if the forecast probability of above-normal temperature is above the 90th percentile of all sample years of this county-month. (NOAA)
Forecast Low Temp	For the 1 month-lead forecast targeting a county-year-month, the indicator equals 1 if the forecast probability of below-normal temperature is above the 90th percentile of all sample years of this county-month. (NOAA)
Forecast High Precip	For the 1 month-lead forecast targeting a county-year-month, the indicator equals 1 if the forecast probability of above-normal precipitation is above the 90th percentile of all sample years of this county-month. (NOAA)
Forecast Low Precip	For the 1 month-lead forecast targeting a county-year-month, the indicator equals 1 if the forecast probability of below-normal precipitation is above the 90th percentile of all sample years of this county-month. (NOAA)
Actual High Temp	For a county-year-month, the indicator equals 1 if the average temperature is above normal, i.e., in the top tercile of the past 30 years of this county-month. (NOAA)
Actual Low Temp	For a county-year-month, the indicator equals 1 if the average temperature is below normal, i.e., in the bottom tercile of the past 30 years of this county-month. (NOAA)
Actual High Precip	For a county-year-month, the indicator equals 1 if the precipitation is above normal, i.e., in the top tercile of the past 30 years of this county-month. (NOAA)
Actual Low Precip	For a county-year-month, the indicator equals 1 if the precipitation is below normal, i.e., in the bottom tercile of the past 30 years of this county-month. (NOAA)
Forecast Anomalies	Indicator equaling 1 if Forecast High Temp, Forecast Low Temp, Forecast High Precip, or Forecast Low Precip equals 1. (NOAA)
Actual Anomalies	Indicator equaling 1 if Actual High Temp, Actual Low Temp, Actual High Precip, or Actual Low Precip equals 1. (NOAA)
Small Business Loan	Amount of small business loans (in $) in the county-year divided by acres operated in the county-year. In bank-county level regressions, it is defined for each individual bank. (CRA filings maintained by the FFIEC)
Deposits	Total deposits (in thousand $) in the county-year divided by acres operated in the county-year. In bank-county level regressions, it is defined for each individual bank. (Summary of Deposits data maintained by the FDIC)
Area Operated	Total area (in thousand acres) operated by farms in the county-year. (USDA)
Farm Employment	Farm employment per thousand acres operated in the county-year. (BEA)
Farm Size	Average area (in thousand acres) per farm in the county-year. (BEA)
Farm Value	Average asset value (in thousand $) per farm in the county-year. (BEA)
Per Capital Income	Per capital personal income (in thousand $) in the county-year. (Census Bureau)

Table A.1. Continued

Variable	Definition (Data Source)
Educated Population	Percentage of population aged 25 years and over with high school education or higher in the county-year. (Census Bureau)
Population Density	Population per acre in the county-year. (Census Bureau and USDA)
Loans <= 250K	Total amount of loans (in $) with individual amounts of $250,000 or less issued to farms in the county-year divided by acres operated in the county-year. (CRA filings maintained by the FFIEC)
Loan Volume Growth	Growth rate of Loan Volume from last county-year to the current county-year. (CRA filings maintained by the FFIEC)
Small Bus. Loan Growth	Growth rate of Small Business Loan from last county-year to the current county-year. (CRA filings maintained by the FFIEC)
Deposit Growth	Growth rate of Deposits from last county-year to the current county-year. (Summary of Deposits data maintained by the FDIC)
Raw Loan Volume	Total farm loans (in $) to farms with revenue of $1 million or less in the county-year without scaling by acres operated in the county-year. (CRA filings maintained by the FFIEC)
Large Forecast Temp Dispersion	Indicator equaling 1 if the difference between the 80th and 20th percentiles of the 1-month lead forecast temperature is above the 90th percentile of all sample years of this county-month. (NOAA)
Large Forecast Precip Dispersion	Indicator equaling 1 if the difference between the 80th and 20th percentiles of the 1-month lead forecast precipitation is above the 90th percentile of all sample years of this county-month. (NOAA)
Subsidies	Total farm subsidies paid to recipients in the county-year divided by acres operated in the county-year. (Farm Payment Files maintained by the USDA)
FCS Loan Volume	Amount of agriculture production and intermediate loans (in $) issued by a Farm Credit System institution in a year-quarter divided by acres operated in its territory counties. (U.S. Farm Credit Administration)
FCS Assets	Logarithm of an FCS institution's total assets in a year-quarter
FCS Leverage	An FCS institutions' total assets divided by its total assets in a year-quarter
FCS Profitability	An FCS institutions' net income divided by its total assets in a year-quarter
Loan Renewals	Bankers responded to the survey question about loan renewals or extensions by indicating whether conditions during the current quarter were higher than, lower than, or the same as in the year-earlier period. Fed district-year-quarter values are computed by subtracting the percent of bankers that responded "lower" from the percent that responded "higher" and adding 100. (Federal Reserve District Surveys of Agricultural Credit Conditions)
Loan Demand	Bankers responded to the survey question about demand for loans by indicating whether conditions during the current quarter were higher than, lower than, or the same as in the year-earlier period. Fed district-year-quarter values are computed by subtracting the percent of bankers that responded "lower" from the percent that responded "higher" and adding 100. (Federal Reserve District Surveys of Agricultural Credit Conditions)

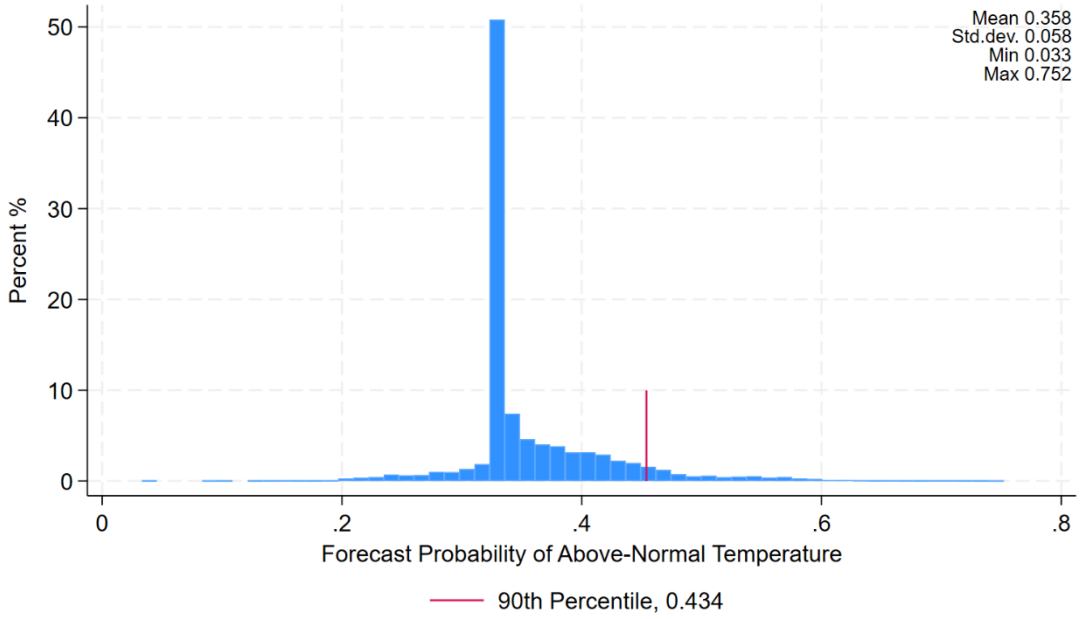
Table A.1. Continued

Variable	Definition (Data Source)
Loan Supply	Bankers responded to the survey question about loan fund availability by indicating whether conditions during the current quarter were higher than, lower than, or the same as in the year-earlier period. Fed district-year-quarter values are computed by subtracting the percent of bankers that responded "lower" from the percent that responded "higher" and adding 100. (Federal Reserve District Surveys of Agricultural Credit Conditions)
Branching Restrictions Index	Index set to zero for states that are most open to branching by out-of-state banks. We add one to the index when a state adds any of the four barriers allowed by the Interstate Banking and Branching Efficiency Act of 1994. Specifically, we add one to the index: if a state imposes a minimum age of 3 or more years on target institutions of interstate acquirers; if a state does not permit de novo interstate branching; if a state does not permit the acquisition of individual branches by an out-of-state bank; and if a state imposes a deposit cap less than 30%. The index ranges from zero to four. (Rice and Strahan, 2010)
Bank Loan Volume	Amount of loans (in $) to farms in a county-year issued by a bank divided by acres operated in the county-year. (CRA filings maintained by the FFIEC and USDA)
Share of Branches in Boom Counties	The fraction of branches owned by a bank that are located in a shale-boom county. A county is considered as a shale-boom county if the county is in the top quartile of all county-years with shale well activity. (Shale Well Data from WRDS)
Acres Planted	Number of acres planted for a crop-county-year. (USDA)
Production Input	Total farm production expense (in $) divided by acres operated in a county-year. (U.S. BEA)
Crop Concentration	Herfindahl-Hirschman index of acres grown of different crops in a county-year. (USDA)
Productivity	Total farm output (in $) divided by acres operated in the county-year. Output equals farms' cash receipts adjusted for changes in inventory. (U.S. BEA and USDA)
High (Low) Insured Liability	Indicator equaling 1 if the total insured liability amount per acre of the county-year is above (below or equal to) the 50th percentile of all sample years of the county. (Risk Management Agency of the USDA)
High (Low) Insured Acreage	Indicator equaling 1 if the ratio of acres insured over acres operated in the county-year is above (below or equal to) the 50th percentile of all sample years of the county. (Risk Management Agency of the USDA)
High (Low) Buyup Ratio	Indicator equaling 1 if the ratio of acres insured by buyup policies over total acres insured in the county-year is above (below or equal to) the 50th percentile of all sample years of the county. (Risk Management Agency of the USDA)
High (Low) Coverage Level	Indicator equaling 1 if the insured acres-weighted coverage level (equivalent to one minus % of deductible) in the county-year is above (below or equal to) the 50th percentile of all sample years of the county. (Risk Management Agency of the USDA)

Figure 1. Histograms of Forecast Probabilities of Climate Anomalies

Panel A (B, C, D) shows the histogram of forecast probabilities of above-normal temperature (below-normal temperature, above-normal precipitation, below-normal precipitation) for county-year-months in the sample. Climatological norms are the average temperature or precipitation in a county-month in the most recent 30 years. Vertical red lines indicate 90th percentiles of the distributions. Data are from the National Oceanic and Atmospheric Administration (NOAA).

Panel A – Forecast Probability of Above-Normal Temperature



Panel B – Forecast Probability of Below-Normal Temperature

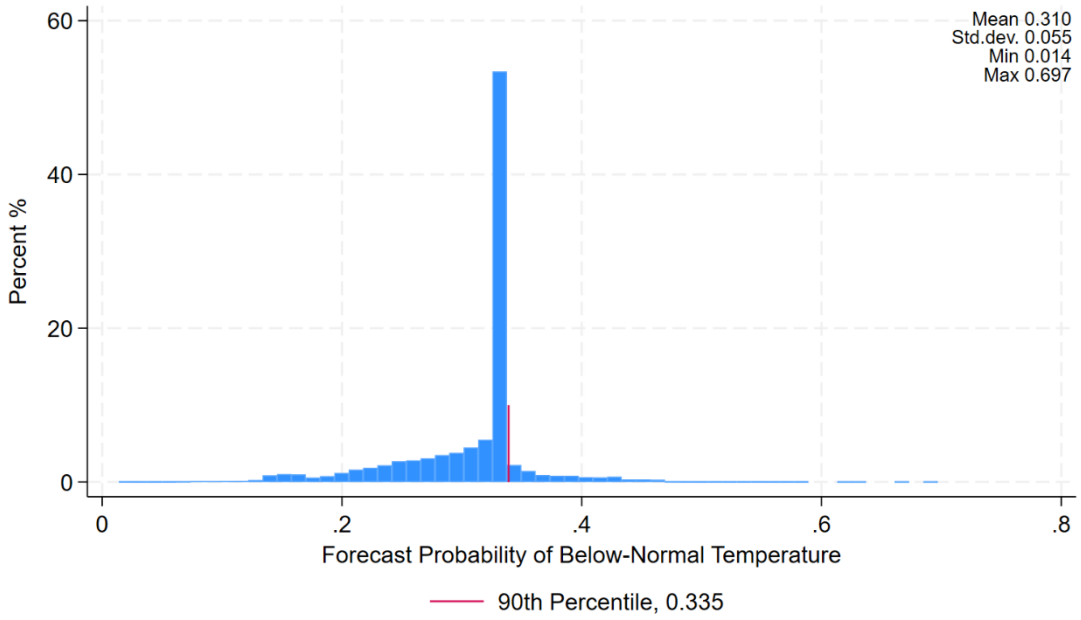
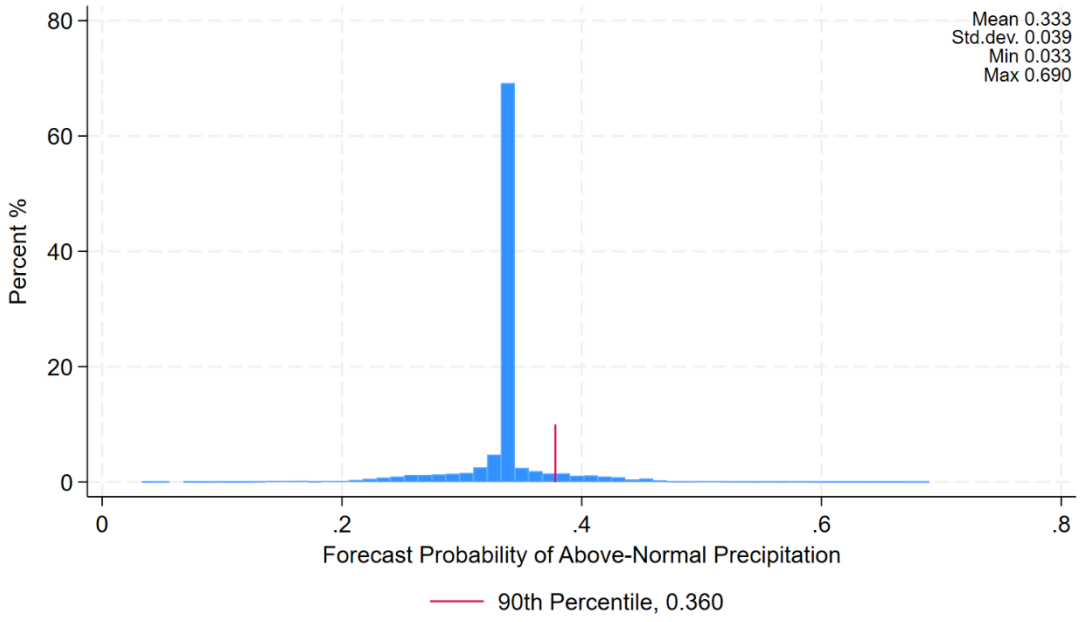


Figure 1. Continued

Panel C – Forecast Probability of Above-Normal Precipitation



Panel D – Forecast Probability of Below-Normal Precipitation

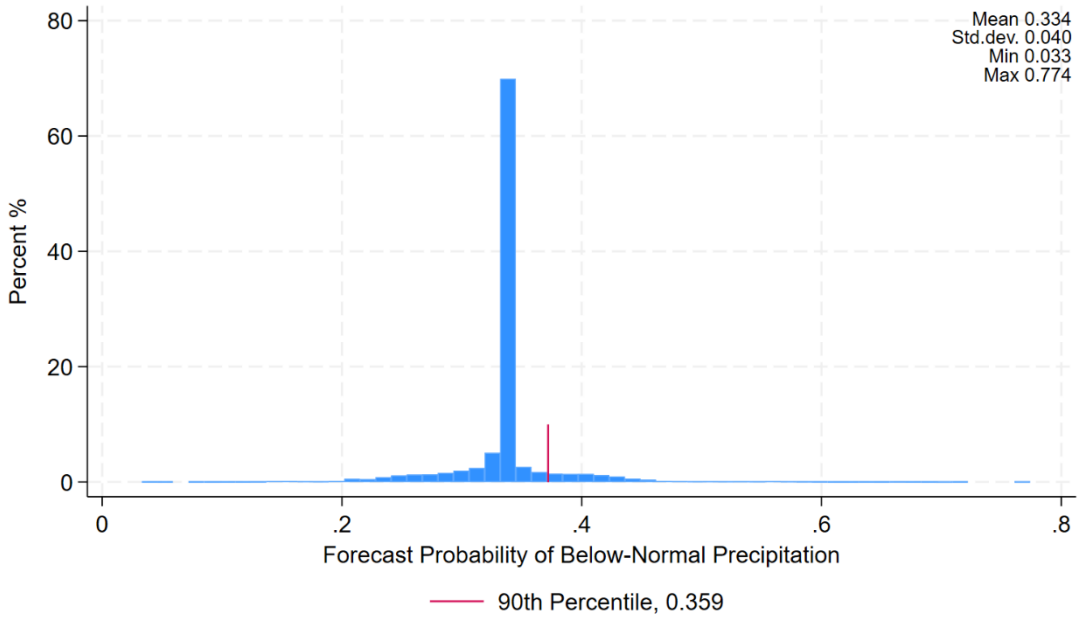
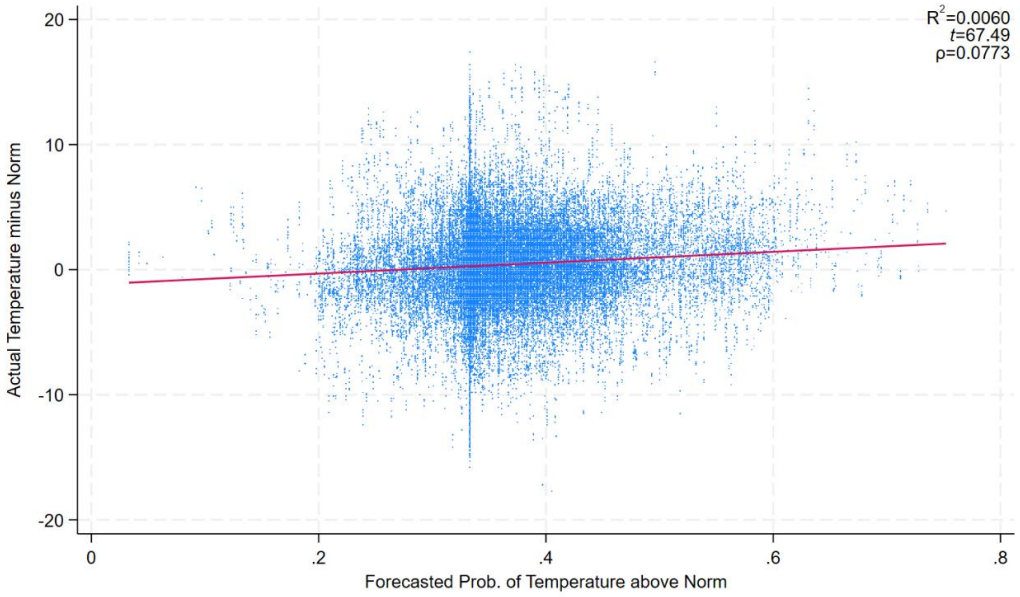


Figure 2. Forecasted Probabilities of Anomalies and Actual Climate Conditions
This figure shows scatter plots and fitted linear relationships between realized and forecasted deviations from normal climate conditions. Panels A (B, C, D) shows *Actual Temperature minus Norm* (*Actual Temperature minus Norm*, *Actual Precipitation minus Norm*, *Actual Precipitation minus Norm*) on the y-axis and *Forecasted Probability of Temperature above Norm* (*Forecasted Probability of Temperature below Norm*, *Forecasted Probability of Temperature above Norm*, and *Forecasted Probability of Temperature below Norm*) on the x-axis for our main sample of county-year-months. Data are from the National Oceanic and Atmospheric Administration (NOAA).

Panel A – Actual Temperature Deviation from Normal versus Forecasted Prob. of Above Normal Temp.



Panel B – Actual Temperature Deviation from Normal versus Forecasted Prob. of Below Normal Temp.

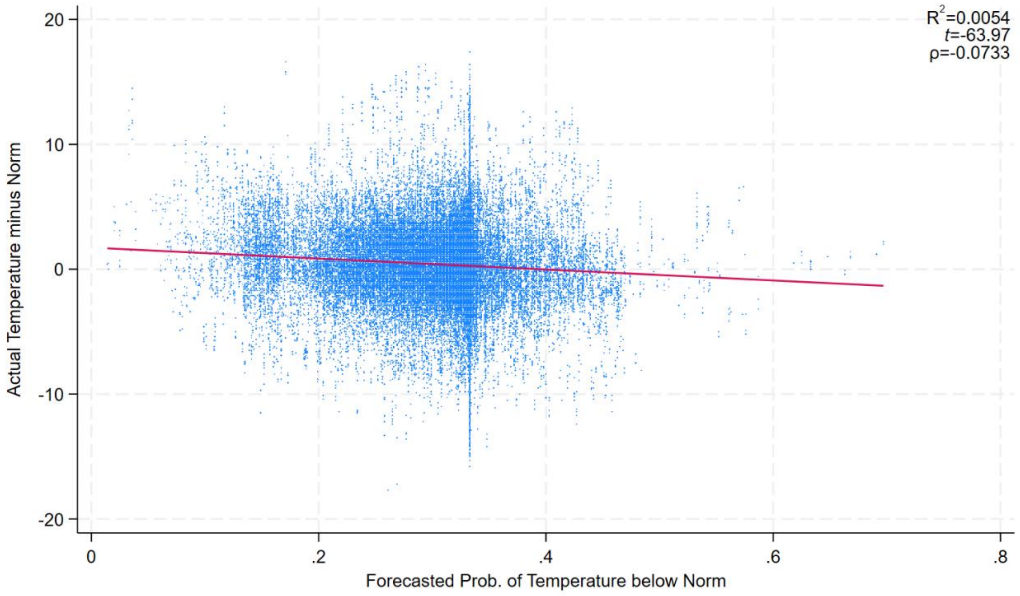
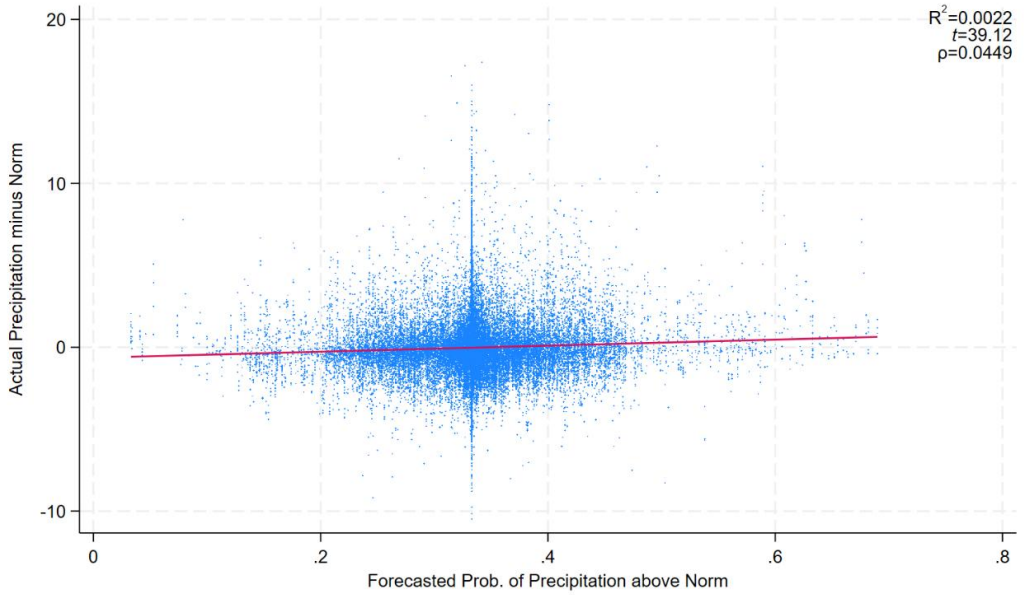


Figure 2. Continued

Panel C – Actual Precipitation Deviation from Normal versus Forecasted Prob. of Above Normal Precip.



Panel D – Actual Precipitation Deviation from Normal versus Forecasted Prob. of Below Normal Precip.

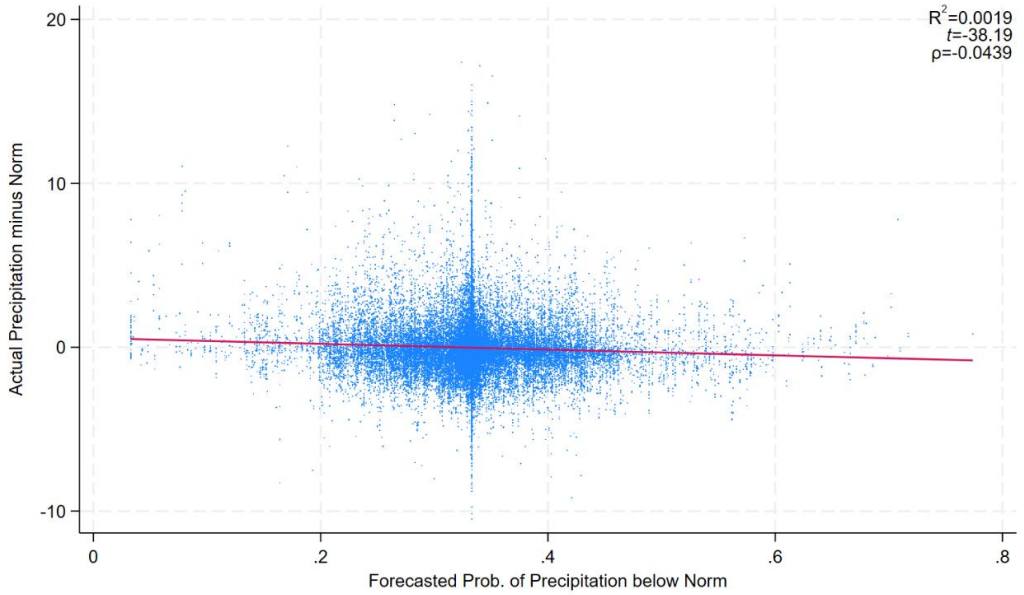
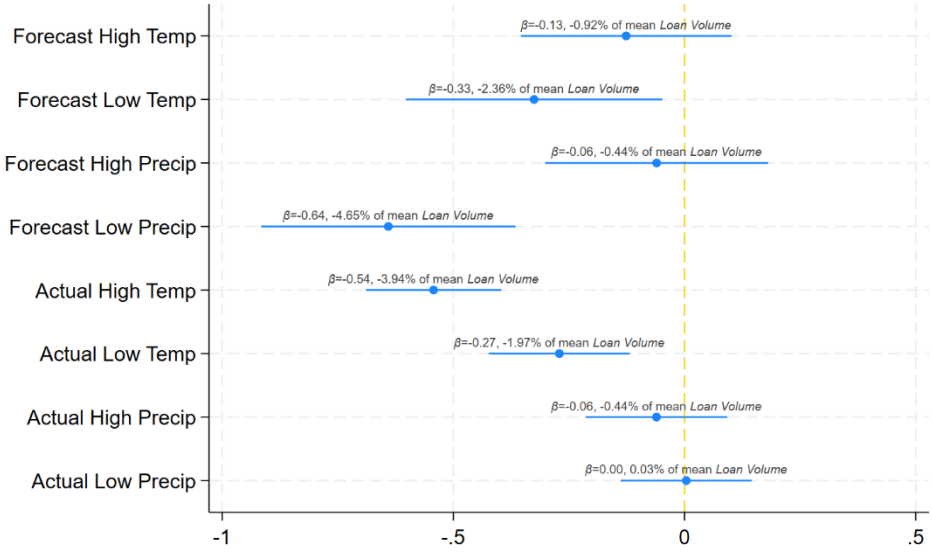


Figure 3. Forecast Anomalies and Credit Origination across Crops
This figure plots coefficient estimates and 90% confidence intervals for variables from equation (2) for subsamples of the data. We split the sample of county-year observations based on the main crops in U.S. counties. Panel A (B, C, D) uses the subsample of counties where hay (corn and soybean; wheat, sorghum, and sunflower; cotton and peanuts) is the main crop. The dependent variable is *Loan Volume* and the key explanatory variables are forecasted and actual climate conditions: *Forecast High Temp*, *Forecast Low Temp*, *Forecast High Precip*, *Forecast Low Precip*, *Actual High Temp*, *Actual Low Temp*, *Actual High Precip*, and *Actual Low Precip*. The regressions include control variables, including *Small Business Loan*, *Deposits*, *Acres Operated*, *Farm Employment*, *Farm Size*, *Farm Value*, *Per Capita Income*, *Educated Population*, *Population Density*, year-month fixed effects, and county-month fixed effects. Variable definitions are in Table A.1.

Panel A – Hay



Panel B – Corn and Soybean

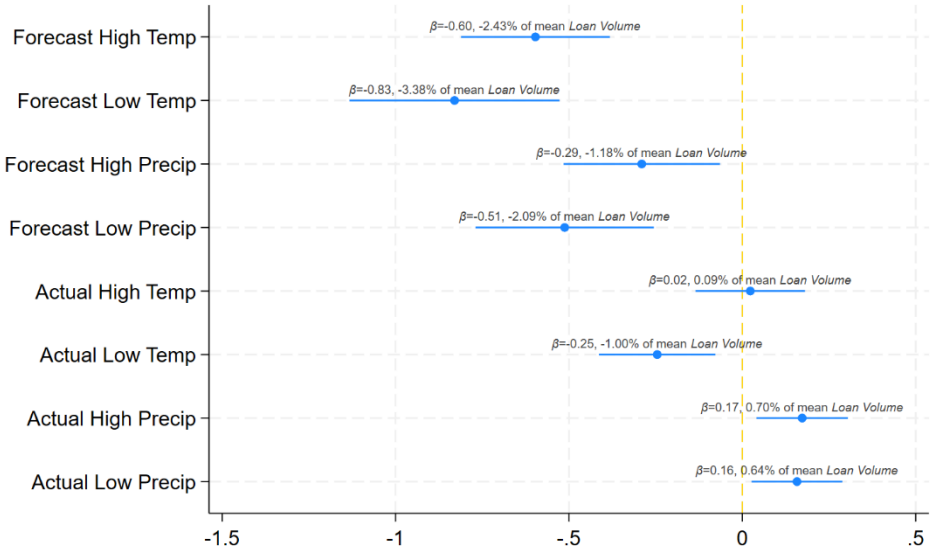
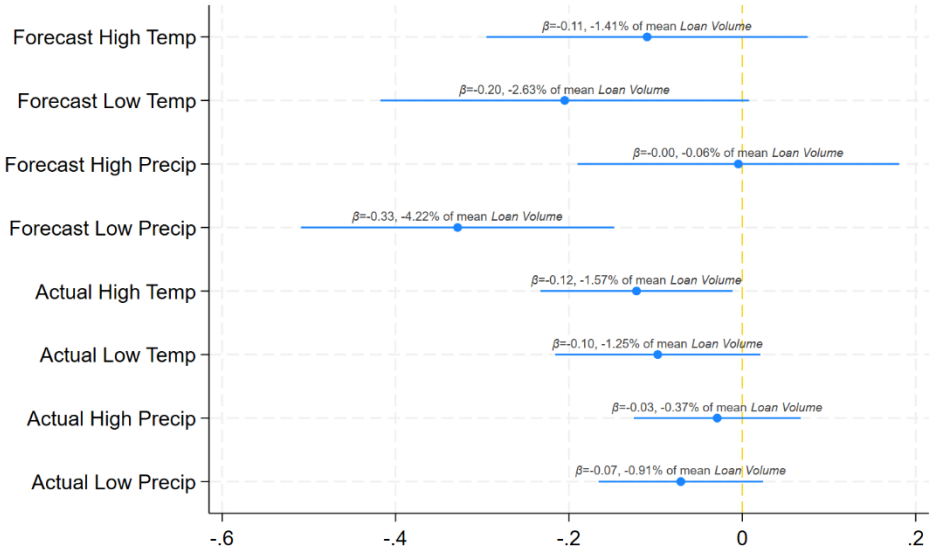


Figure 3. Continued

Panel C – Wheat, Sorghum, and Sunflower



Panel D – Cotton and Peanuts

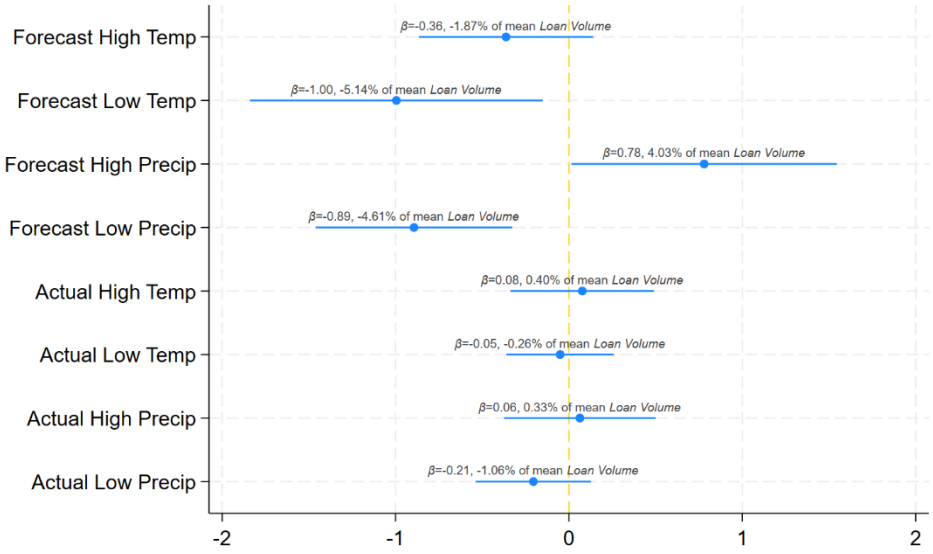


Figure 4. Forecast Anomalies and Credit Origination across Calendar Months
This figure plots coefficient estimates and 90% confidence intervals for *Forecast Anomalies* from equation (1). Each regression is based on a subsample of the data split by calendar month. The dependent variable is *Loan Volume*. Each regression includes *Actual Anomalies* as an explanatory variable, as well as control variables, including *Small Business Loan*, *Deposits*, *Acres Operated*, *Farm Employment*, *Farm Size*, *Farm Value*, *Per Capita Income*, *Educated Population*, *Population Density*, year-month fixed effects, and county-month fixed effects. Variable definitions are in Table A.1.

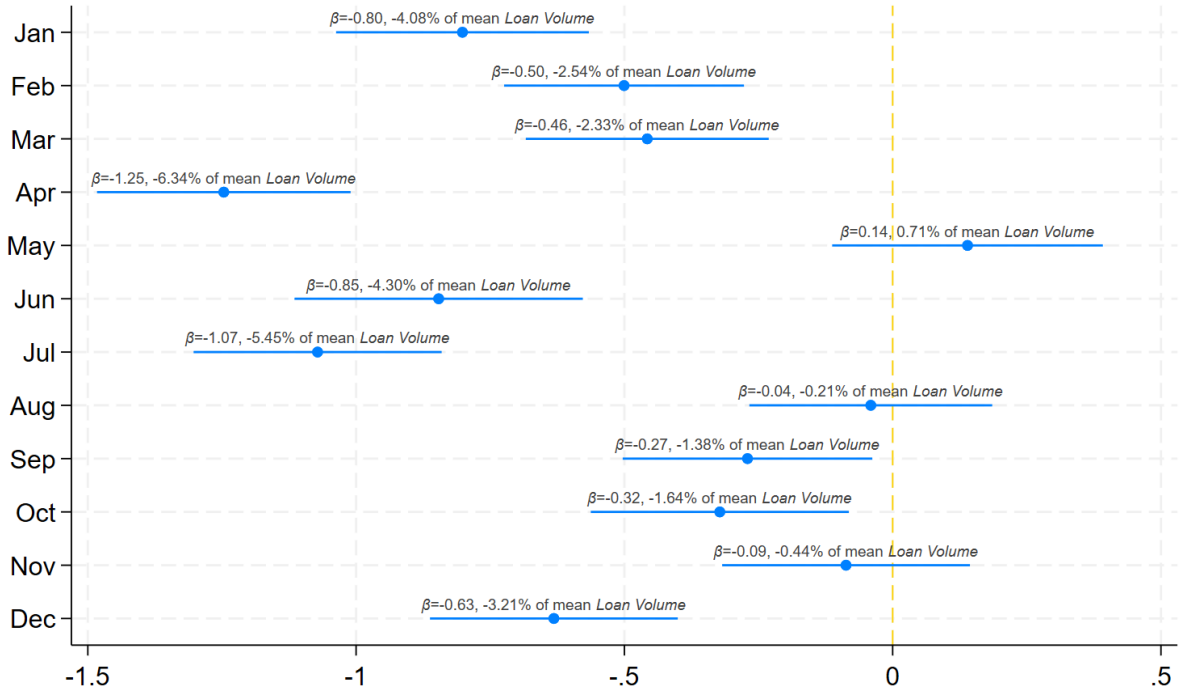
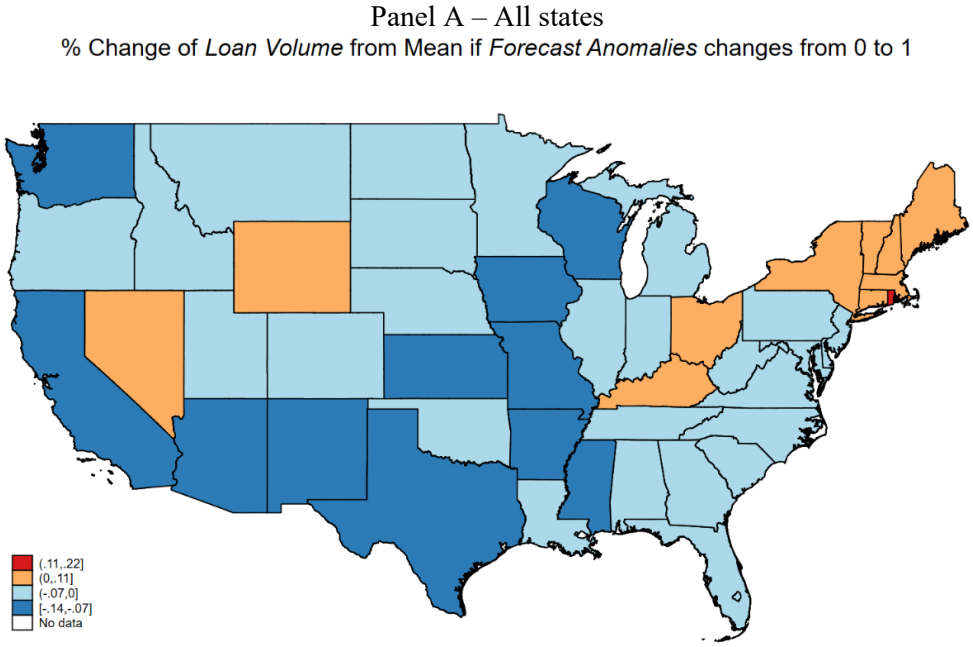


Figure 5. Forecast Anomalies and Credit Origination across States
This figure shows coefficient estimates for *Forecast Anomalies* from equation (1). Each regression is based on a subsample of the data split by U.S. state. The dependent variable is *Loan Volume*. Each regression includes *Actual Anomalies* as an explanatory variable, as well as control variables, including *Small Business Loan*, *Deposits*, *Acres Operated*, *Farm Employment*, *Farm Size*, *Farm Value*, *Per Capita Income*, *Educated Population*, *Population Density*, year-month fixed effects, and county-month fixed effects. Variable definitions are in Table A.1. Panel A shows estimates for every state; Panel B only reports estimates that are statistically significant at 10% or lower.

Panel A – All states



Panel B – States with statistically significant coefficients (10% statistical significance or lower)

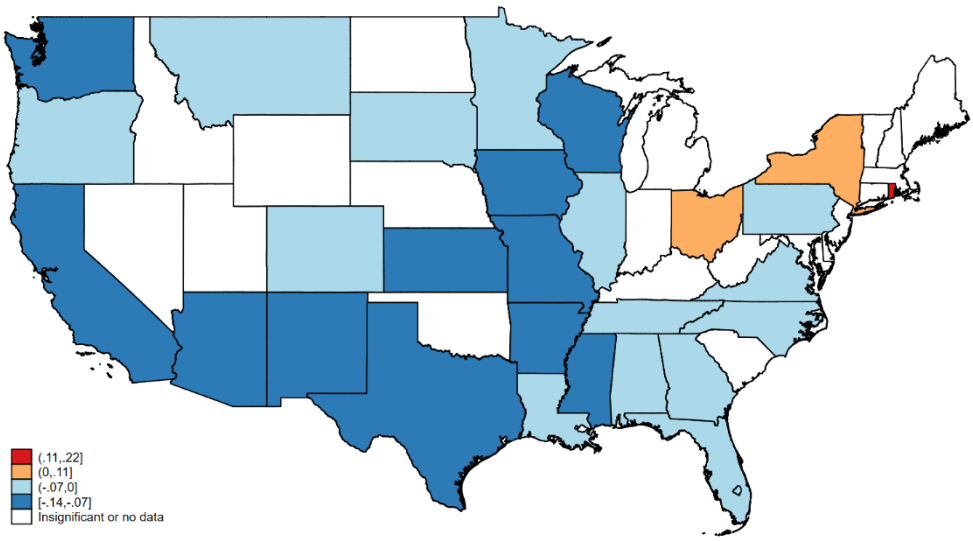


Figure 6. Credit and Forecast Anomalies in the Presence of Crop Insurance
This figure plots coefficient estimates and 90% confidence intervals for *Forecast Anomalies* interacted with insurance indicators from equation (9). The insurance indicators include *High Insurance Liability*, *Low Insurance Liability*, *High Insurance Acreage*, *Low Insurance Acreage*, *High Buyup Ratio*, *Low Buyup Ratio*, *High Coverage Level*, and *Low Coverage Level*. The dependent variable is *Loan Volume*. The regression includes *Actual Anomalies* as an explanatory variable, as well as control variables, including *Small Business Loan*, *Deposits*, *Acres Operated*, *Farm Employment*, *Farm Size*, *Farm Value*, *Per Capita Income*, *Educated Population*, *Population Density*, year-month fixed effects, and county-month fixed effects. Variable definitions are in Table A.1.

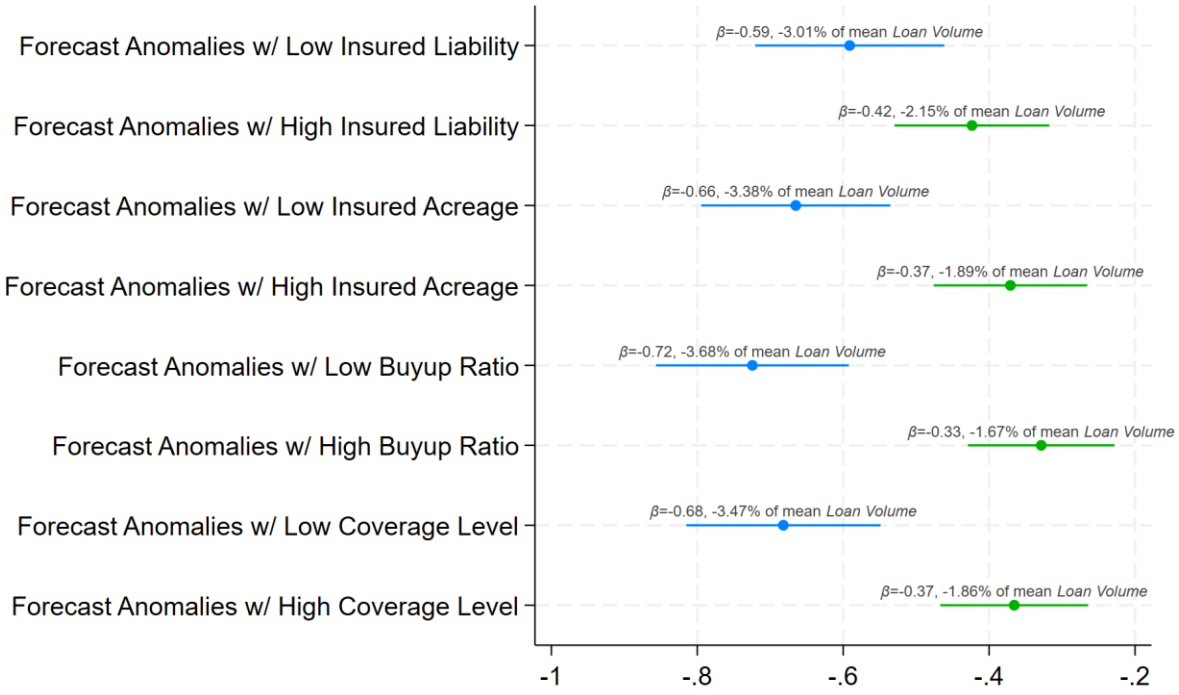


Table 1. Summary Statistics
This table reports the summary statistics of the main variables. Variables are defined in Table A1.

	(1) N	(2) Mean	(3) S.D.	(4) P10	(5) Median	(6) P90
Loan Volume	588,604	19.669	26.672	0.946	10.168	48.399
Forecast Anomalies	588,604	0.309	0.462	0.000	0.000	1.000
Actual Anomalies	588,604	0.886	0.318	0.000	1.000	1.000
Forecast High Temp	588,604	0.120	0.325	0.000	0.000	1.000
Forecast Low Temp	588,604	0.065	0.246	0.000	0.000	0.000
Forecast High Precip	588,604	0.088	0.284	0.000	0.000	0.000
Forecast Low Precip	588,604	0.087	0.281	0.000	0.000	0.000
Actual High Temp	588,604	0.401	0.490	0.000	0.000	1.000
Actual Low Temp	588,604	0.265	0.441	0.000	0.000	1.000
Actual High Precip	588,604	0.321	0.467	0.000	0.000	1.000
Actual Low Precip	588,604	0.347	0.476	0.000	0.000	1.000
Small Business Loan	588,604	458.877	1,794.387	0.899	33.848	697.135
Deposits	588,604	33.052	164.341	0.186	1.954	26.468
Area Operated	588,604	300.339	335.581	43.302	195.115	627.735
Farm Employment	588,604	5.700	5.737	0.856	4.389	10.990
Farm Size	588,604	0.586	0.947	0.108	0.259	1.334
Farm Value	588,604	747.769	577.103	269.598	560.521	1,446.525
Per Capital Income	588,604	30.774	9.040	21.040	29.114	42.451
Educated Population	588,604	80.605	8.808	68.400	82.200	90.600
Population Density	588,604	132.771	299.817	4.435	42.138	295.656
FCS Loan Volume	200,906	28.730	35.717	0.583	13.301	90.157
Loan Renewals	124,064	105.853	17.781	83.000	106.000	130.000
Loan Demand	123,468	97.472	18.468	71.000	100.000	119.000
Loan Supply	129,726	118.078	15.884	98.980	117.000	141.670
Branching Restrictions Index	588,604	2.320	1.435	0.000	3.000	4.000
Share of Branches in Boom Counties	3,152,793	0.004	0.018	0.000	0.000	0.009
Acres Planted	1,333,968	35,783.0	48,029.0	1,400.0	13,500.0	106,000.0
Production Input	588,604	429.263	457.978	75.694	293.951	894.458
Crop Concentration	144,132	0.268	0.135	0.138	0.241	0.441
Productivity	588,604	456.175	536.108	58.761	286.142	1,014.234

Table 2. Climate Anomalies and Financing: Baseline

This table reports coefficient estimates from equation (1) in column (1), and equation (2) in column (2). The dependent variable in both columns is *Loan Volume*. Column 1 uses *Forecast Anomalies* and *Actual Anomalies* as key explanatory variables. Column 2 uses *Forecast High Temp*, *Forecast Low Temp*, *Forecast High Precip*, *Forecast Low Precip*, *Actual High Temp*, *Actual Low Temp*, *Actual High Precip*, and *Actual Low Precip* as key explanatory variables. Control variables include *Small Business Loan*, *Deposits*, *Acres Operated*, *Farm Employment*, *Farm Size*, *Farm Value*, *Per Capita Income*, *Educated Population*, and *Population Density*. Variable definitions are in Table A.1. County-year level variables such as *Loan Volume* are stacked for the corresponding county-year-months. Standard errors clustered by county-year are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 2. Continued

	(1)	(2)
Forecast Anomalies	-0.514***	
	(0.0504)	
Actual Anomalies	-0.0501	
	(0.0560)	
Forecast High Temp		-0.351***
		(0.0732)
Forecast Low Temp		-0.727***
		(0.0975)
Forecast High Precip		-0.219***
		(0.0808)
Forecast Low Precip		-0.635***
		(0.0860)
Actual High Temp		-0.176***
		(0.0482)
Actual Low Temp		-0.149***
		(0.0488)
Actual High Precip		0.00137
		(0.0471)
Actual Low Precip		0.0540
		(0.0439)
Small Business Loan	0.00542***	0.00542***
	(0.000279)	(0.000278)
Deposits	0.00124	0.00124
	(0.00346)	(0.00346)
Acres Operated	-0.0129***	-0.0129***
	(0.00127)	(0.00127)
Farm Employment	0.801***	0.802***
	(0.111)	(0.111)
Farm Size	-0.876***	-0.887***
	(0.172)	(0.173)
Farm Value	0.00117***	0.00118***
	(0.000263)	(0.000263)
Per Capita Income	0.0944***	0.0957***
	(0.0185)	(0.0185)
Educated Population	-0.0220	-0.0221
	(0.0306)	(0.0306)
Population Density	-0.0166***	-0.0165***
	(0.00630)	(0.00630)
Year-Month fixed effects	Yes	Yes
County-Month fixed effects	Yes	Yes
N	588,604	588,604
R-sqr	0.788	0.788

Table 3. Climate Anomalies and Financing by Farm Credit System (FCS) Institutions

This table reports coefficient estimates from regression equation (4). The dependent variable is *FCS Loan Volume*. Column 1 uses *Forecast Anomalies* and *Actual Anomalies* as key explanatory variables. Column 2 uses *Forecast High Temp*, *Forecast Low Temp*, *Forecast High Precip*, *Forecast Low Precip*, *Actual High Temp*, *Actual Low Temp*, *Actual High Precip*, and *Actual Low Precip* as key explanatory variables. County control variables include *Small Business Loan*, *Deposits*, *Acres Operated*, *Farm Employment*, *Farm Size*, *Farm Value*, *Per Capita Income*, *Educated Population*, and *Population Density*. Lender control variables include *FCS Assets*, *FCS Leverage*, and *FCS Profitability*. Variable definitions are in Table A.1. Lender-year-quarter level variables such as *FCS Loan Volume* are stacked for the corresponding county-year-months. Standard errors clustered by lender-year-quarter are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. To focus on lenders with most territories either hit or not hit by climate anomalies at a given time, we exclude a lender if the standard deviation of *Forecast Anomalies* across its territory counties is above the median of the year-month.

	(1)	(2)
Forecast Anomalies	-0.762**	
	(0.339)	
Actual Anomalies	-0.00255	
	(0.287)	
Forecast High Temp		-0.963**
		(0.474)
Forecast Low Temp		0.223
		(0.544)
Forecast High Precip		-0.963**
		(0.452)
Forecast Low Precip		-0.367
		(0.628)
Actual High Temp		-0.516
		(0.368)
Actual Low Temp		-0.244
		(0.359)
Actual High Precip		-0.168
		(0.233)
Actual Low Precip		0.134
		(0.252)
County-Year Controls	Yes	Yes
Lender-Year-Quarter Controls	Yes	Yes
Lender fixed effects	Yes	Yes
Year-Month fixed effects	Yes	Yes
County-Month fixed effects	Yes	Yes
N	200,906	200,906
R-sqr	0.96	0.96

Table 4. Climate Anomalies and Credit Demand and Supply

This table reports coefficient estimates from regression equation (5). Columns 1, 2, and 3 use *Loan Renewals*, *Loan Demand*, and *Loan Supply*, respectively, as the dependent variable. These measures reflect credit conditions reported by the Fed's Agriculture Credit Survey. These variables are measured at the district-year-quarter level and are stacked for the corresponding county-year-month. Explanatory variables include *Forecast Anomalies* and *Actual Anomalies* for each county-year-month, as well as county controls including *Small Business Loan*, *Deposits*, *Acres Operated*, *Farm Employment*, *Farm Size*, *Farm Value*, *Per Capita Income*, *Educated Population*, and *Population Density*. Standard errors clustered by district-year-quarter are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. To focus on Federal Reserve districts with most territories either forecasted to be hit or not hit by climate anomalies at a given time, we exclude a district if the standard deviation of *Forecast Anomalies* across its territory counties is above the median of the year-month.

	(1) Loan Renewals	(2) Loan Demand	(3) Loan Supply
Forecast Anomalies	-3.531***	-3.246**	2.644**
	(1.217)	(1.397)	(1.293)
Actual Anomalies	-0.256	-0.310	-0.218
	(0.489)	(0.468)	(0.413)
County-Year controls	Yes	Yes	Yes
Year-Month fixed effects	Yes	Yes	Yes
County-Month fixed effects	Yes	Yes	Yes
N	123,766	123,170	129,726
R-sqr	0.805	0.811	0.823

Table 5. Climate Anomalies and Financing with Credit Supply Shocks

Column 1 reports coefficient estimates from regression equation (6). The dependent variable is *Loan Volume.* Key explanatory variables are *Forecast Anomalies* and *Actual Anomalies*, as well as their interactions with *Branching Restrictions Index.* The index is set to zero for states that are most open to branching by out-of-state banks. We add one to the index when a state adds any of the four barriers allowed by the Interstate Banking and Branching Efficiency Act of 1994. Specifically, we add one to the index: if a state imposes a minimum age of 3 or more years on target institutions of interstate acquirers; if a state does not permit de novo interstate branching; if a state does not permit the acquisition of individual branches by an out-of-state bank; and if a state imposes a deposit cap less than 30%. The index ranges from zero to four. County-year level variables such as *Loan Volume* are stacked for the corresponding county-year-months. Standard errors clustered by county-year are reported in parentheses. Column 2 reports coefficient estimates from regression equation (7). The dependent variable is a bank-county-year's *Bank Loan Volume*. Key explanatory variables include *Forecast Anomalies* and *Actual Anomalies* for each county-year-month, as well as their interactions with *Share of Branches in Boom Counties*. *Share of Branches in Boom Counties* is defined as the fraction of branches owned by a bank that are located in a shale-boom county. A county is considered as a shale-boom county if the county is in the top quartile of all county-years with shale well activity. County control variables include *Small Business Loan*, *Deposits*, *Acres Operated*, *Farm Employment*, *Farm Size*, *Farm Value*, *Per Capita Income*, *Educated Population*, and *Population Density*. Variable definitions are in Table A.1. Bank-county-year level variables such as *Loan Volume* are stacked for the corresponding bank-county-year-months. Standard errors clustered by bank-year and county-year are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Column 2 excludes counties that have any shale well activities.

	(1)	(2)
Forecast Anomalies	-0.390**	-0.0227*
	(0.177)	(0.0121)
Forecast Anomalies × Branching Restrictions Index	0.0662	
	(0.0594)	
Forecast Anomalies × Share of Branches in Boom Counties		-0.774
		(0.716)
Actual Anomalies	0.200	-0.00683
	(0.136)	(0.00952)
Actual Anomalies × Branching Restrictions Index	-0.0268	
	(0.0475)	
Actual Anomalies × Share of Branches in Boom Counties		0.774**
		(0.378)
County-Year Controls	Yes	Yes
Year-Month fixed effects	Yes	
County-Month fixed effects	Yes	
State-Year-Month fixed effects	Yes	
Bank-Year-Month fixed effects		Yes
Bank-County-Month fixed effects		Yes
N	588,484	3,152,793
R-sqr	0.81	0.85

Table 6. Climate Anomalies and Crop Production

This table reports coefficient estimates from regressions with *Acres Planted*, *Production Input*, and *Crop Concentration*, respectively, as dependent variables. Key explanatory variables include *Forecast Anomalies* and *Actual Anomalies*. County control variables include *Small Business Loan*, *Deposits*, *Acres Operated*, *Farm Employment*, *Farm Size*, *Farm Value*, *Per Capita Income*, *Educated Population*, and *Population Density*. Variable definitions are in Table A.1. County-year level variables are stacked for the corresponding county-year-months. Standard errors clustered by county-year are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)
	Acres Planted	Production Input	Crop Concentration
Forecast Anomalies	-75.36***	-4.204***	-0.000292
	(22.75)	(0.485)	(0.000614)
Actual Anomalies	-17.87	2.034***	0.000108
	(24.81)	(0.502)	(0.000795)
County-Year Controls	Yes	Yes	Yes
Year-Month Fixed Effects		Yes	Yes
County-Month Fixed Effects		Yes	Yes
Crop-Year-Month fixed effects	Yes		
Crop-County-Month fixed effects	Yes		
N	1,333,968	588,604	144,132
R-sqr	0.971	0.94	0.768

Table 7. Financing and Agricultural Productivity: Instrumental Variable Regression

This table reports coefficient estimates from equations (8a) and (8b). Column 1 is an OLS regression with *Productivity* as the dependent variable and *Loan Volume* as the key explanatory variables. Columns 2 and 4 are the first and second stages, respectively, of the 2SLS regression. *Loan Volume* is the dependent variable in column 2 and *Forecast Anomalies* is the instrumental variable. Column 3 reports the first stage regression without control variables. *Productivity* is the dependent variable in column 4 and instrumented *Loan Volume* is the key explanatory variable. Column 5 reports a reduced form regression with *Productivity* as the dependent variable and *Forecast Anomalies* as the key explanatory variable. Control variables include *Actual Anomalies* and county variables including *Small Business Loan*, *Deposits*, *Acres Operated*, *Farm Employment*, *Farm Size*, *Farm Value*, *Per Capita Income*, *Educated Population*, and *Population Density*. Variable definitions are in Table A.1. County-year level variables such as *Loan Volume* are stacked for the corresponding county-year-months. Standard errors clustered by county-year are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1) OLS	(2) 1st Stage	(3) 1st Stage w/o Controls	(4) 2nd Stage	(5) Reduced Form
Loan Volume	0.0628			2.954***	
	(0.0641)			(0.776)	
Forecast Anomalies		-0.522***	-0.564***		-1.542***
		(0.0506)	(0.0531)		(0.379)
Actual Anomalies	-1.683***	-0.0460		-1.570***	-1.706***
	(0.401)	(0.0560)		(0.432)	(0.401)
Production Input Per Acre	1.004***	-0.00201**		1.010***	1.004***
	(0.00946)	(0.000809)		(0.00972)	(0.00947)
Small Business Loan	-0.00309	0.00544***		-0.0188***	-0.00275
	(0.00198)	(0.000279)		(0.00465)	(0.00195)
Deposits	0.00245	0.00155		-0.00215	0.00243
	(0.0274)	(0.00347)		(0.0290)	(0.0274)
Acres Operated	-0.113***	-0.0136***		-0.0736***	-0.114***
	(0.0135)	(0.00130)		(0.0174)	(0.0135)
Farm Employment Per Acre	-5.042***	0.865***		-7.536***	-4.980***
	(1.053)	(0.112)		(1.256)	(1.054)
Farm Size	5.878***	-0.751***		8.026***	5.809***
	(1.804)	(0.178)		(1.901)	(1.804)
Farm Value	0.0219***	0.00130***		0.0181***	0.0219***
	(0.00215)	(0.000265)		(0.00251)	(0.00215)
Per Capita Income	3.718***	0.0857***		3.468***	3.721***
	(0.181)	(0.0187)		(0.199)	(0.181)
Educated Population	-2.098***	-0.0236		-2.030***	-2.100***
	(0.205)	(0.0306)		(0.223)	(0.205)
Population Density	-0.295***	-0.0157**		-0.249***	-0.295***
	(0.0433)	(0.00632)		(0.0501)	(0.0433)
Year-Month FE	Yes	Yes	Yes	Yes	Yes
County-Month FE	Yes	Yes	Yes	Yes	Yes
N	588,604	588,604	588,604	588,604	588,604
R-sqr	0.97	0.79	0.77	0.59	0.97
First-Stage F Statistic		106.3			

Table 8. Climate Anomalies and Financing: The Role of Risk Management

This table reports coefficient estimates from equation (9) with *Loan Volume* as the dependent variable. Key explanatory variables are *Forecast Anomalies* interacted with insurance indicators. The insurance indicators include *High Insurance Liability*, *Low Insurance Liability*, *High Insurance Acreage*, *Low Insurance Acreage*, *High Buyup Ratio*, *Low Buyup Ratio*, *High Coverage Level*, and *Low Coverage Level*. County control variables include *Small Business Loan*, *Deposits*, *Acres Operated*, *Farm Employment*, *Farm Size*, *Farm Value*, *Per Capita Income*, *Educated Population*, and *Population Density*. Variable definitions are in Table A.1. County-year level variables such as *Loan Volume* are stacked for the corresponding county-year-months. Standard errors clustered by county-year are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)
Forecast Anomalies × Low Insured Liability	-0.591***			
	(0.0788)			
Forecast Anomalies × High Insured Liability	-0.424***			
	(0.0645)			
High Insured Liability	0.689***			
	(0.197)			
Forecast Anomalies × Low Insured Acreage		-0.665***		
		(0.0788)		
Forecast Anomalies × High Insured Acreage		-0.371***		
		(0.0640)		
High Insured Acreage		0.767***		
		(0.171)		
Forecast Anomalies × Low Buyup Ratio			-0.724***	
			(0.0803)	
Forecast Anomalies × High Buyup Ratio			-0.329***	
			(0.0611)	
High Buyup Ratio			0.0191	
			(0.183)	
Forecast Anomalies × Low Coverage Level				-0.682***
				(0.0810)
Forecast Anomalies × High Coverage Level				-0.366***
				(0.0616)
High Coverage Level				-0.0938
				(0.180)
County-Year Controls	Yes	Yes	Yes	Yes
Year-Month fixed effects	Yes	Yes	Yes	Yes
County-Month fixed effects	Yes	Yes	Yes	Yes
N	588,604	588,604	588,604	588,604
R-sqr	0.79	0.79	0.79	0.79

Climate Risk, Credit, and Food Security

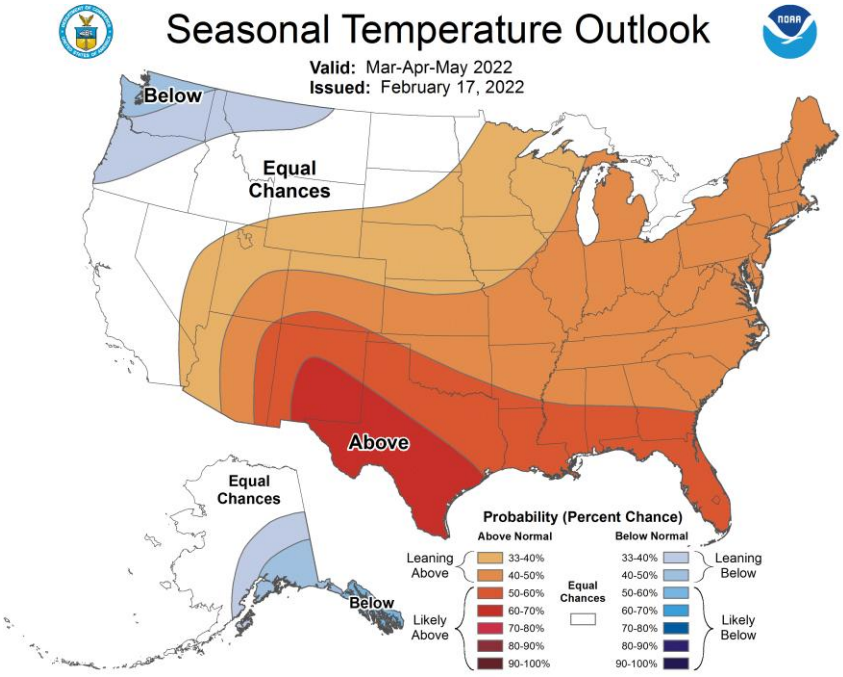
Internet Appendix

Figure IA.1. Seasonal Climate Outlook Examples

The figures show the National Oceanic and Atmospheric Administration's Seasonal Temperature Outlook and Seasonal Precipitation Outlook issued on February 17, 2022 for Mar-Apr-May of 2022. Shaded regions marked Above (Below) indicate forecast temperature or precipitation is in the top (bottom) tercile of its climatological distribution in the past 30 years. When the forecasters decide that one of the abnormal categories, say Above, is the most likely one, they assign probabilities which exceed 33.33% to that category. When either Above or Below is the most likely category, the probability of the middle category (Normal) remains at 33.33% for most situations. This means, for example, that when the probability of Above (Below) is 40%, the probability of Normal is 33.33%, and the probability of Below (Above) is 26.67% (= 100% - (40% + 33.33%)). When probability values of the favored category reach 70%, or higher, the probability of the opposite category is fixed at 3.3%, and the probability of the middle category is adjusted to values (less than 33.33%) which cause the sum of the three probabilities to equal 100%. When the middle category (Normal) is higher than 33.33%, the probabilities of the Above and Below categories decline by (equal) amounts required for the sum of the Above, Normal, Below probabilities to equal 100%. In regions where the forecasters have no forecast tools which favor the chance of either Above or Below, the chance of these two categories is defined to be 33.33% each, and the region is labeled Equal Chances. Degrees of shading are used to indicate different levels of probability above 33.33%.

Figure IA.1. Continued

Panel A – Seasonal Temperature Outlook Issued Feb. 2022 for March-May 2022



Panel A – Seasonal Precipitation Outlook Issued Feb. 2022 for March-May 2022

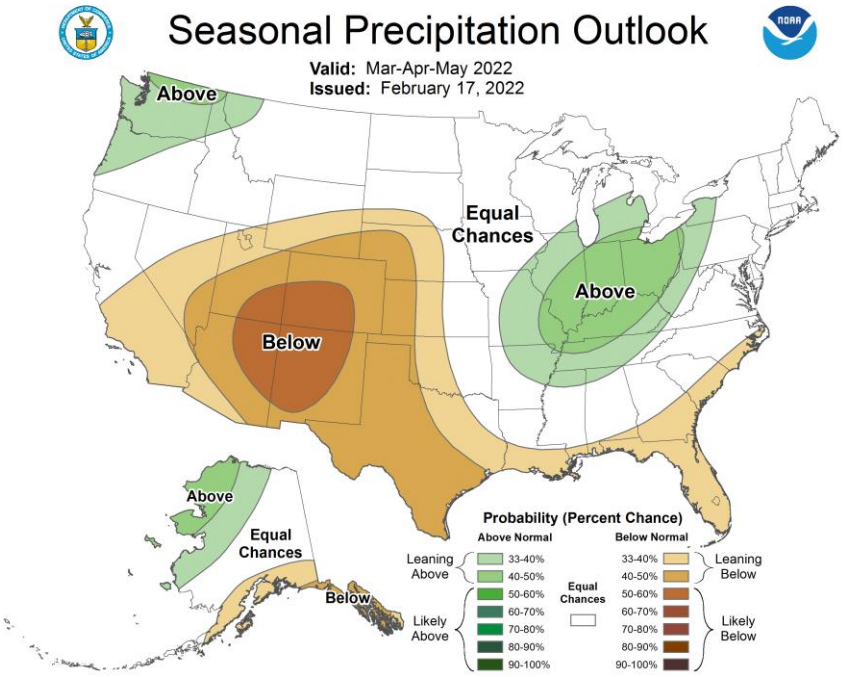
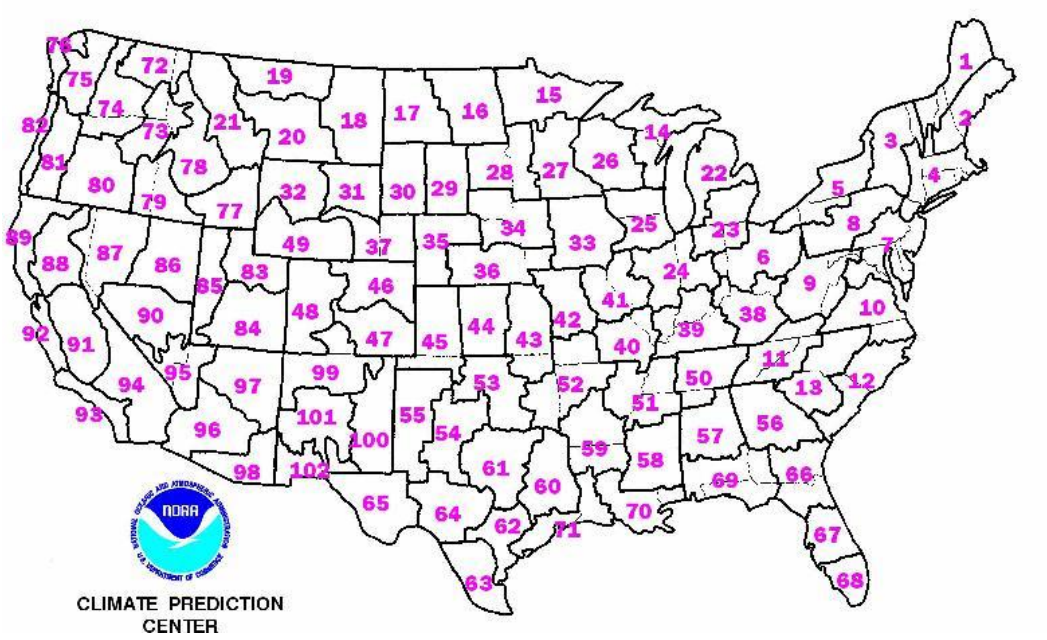
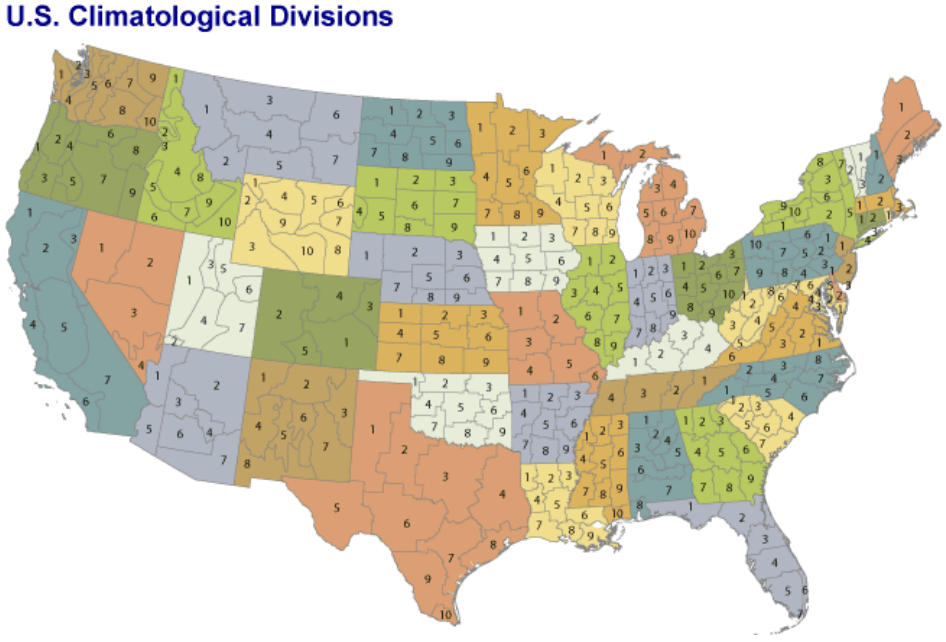


Figure IA.2. Forecast Divisions and Climate Divisions in the Continental U.S.
Panels A and B plot the 102 forecast divisions and 344 climate divisions, respectively, in the continental United States (CONUS). Forecast divisions and climate divisions are established by the National Oceanic and Atmospheric Administration (NOAA).

Panel A – Forecast Divisions[18]



Panel B – Climate Divisions[19]

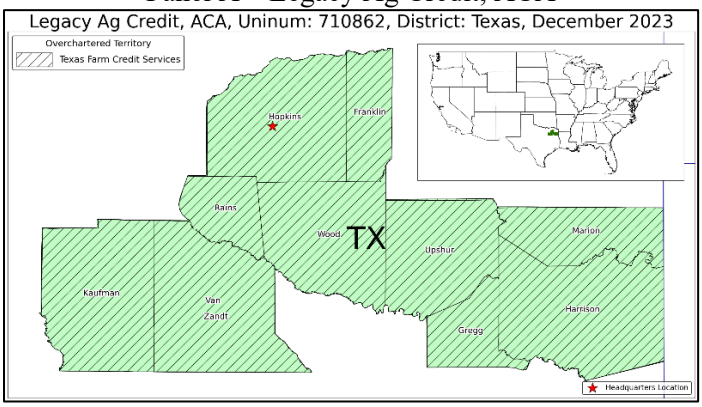


[18] URL accessed May 26, 2025: https://www.cpc.ncep.noaa.gov/products/predictions/long_range/poe_index.php?lead=1&var=t

[19] URL accessed May 2026, 2025: https://www.ncei.noaa.gov/access/monitoring/reference-maps/conus-climate-divisions

Figure IA.3. Examples of Territories Served by Farm Credit Service (FCS) Institutions
Panel A provides a map of the counties served by Legacy Ag Credit, ACA. Panel B provides a map of the counties served by AgSouth Farm Credit, ACA. Panel C provides a map of the counties served by Farm Credit Mid-America, ACA. FCS institutions' territory maps and descriptions are available from the Farm Credit Administration.

Panel A – Legacy Ag Credit, ACA



Panel B – AgSouth Farm Credit, ACA

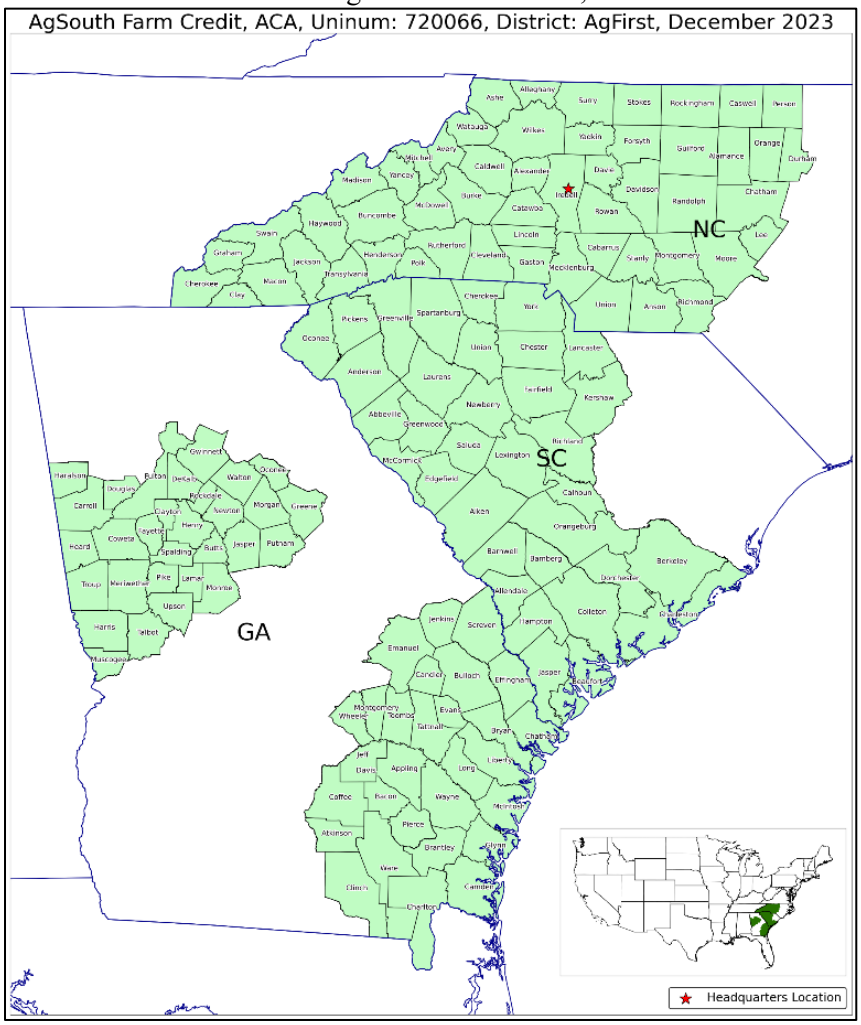


Figure IA.3. Continued

Panel C – Farm Credit Mid-America, ACA

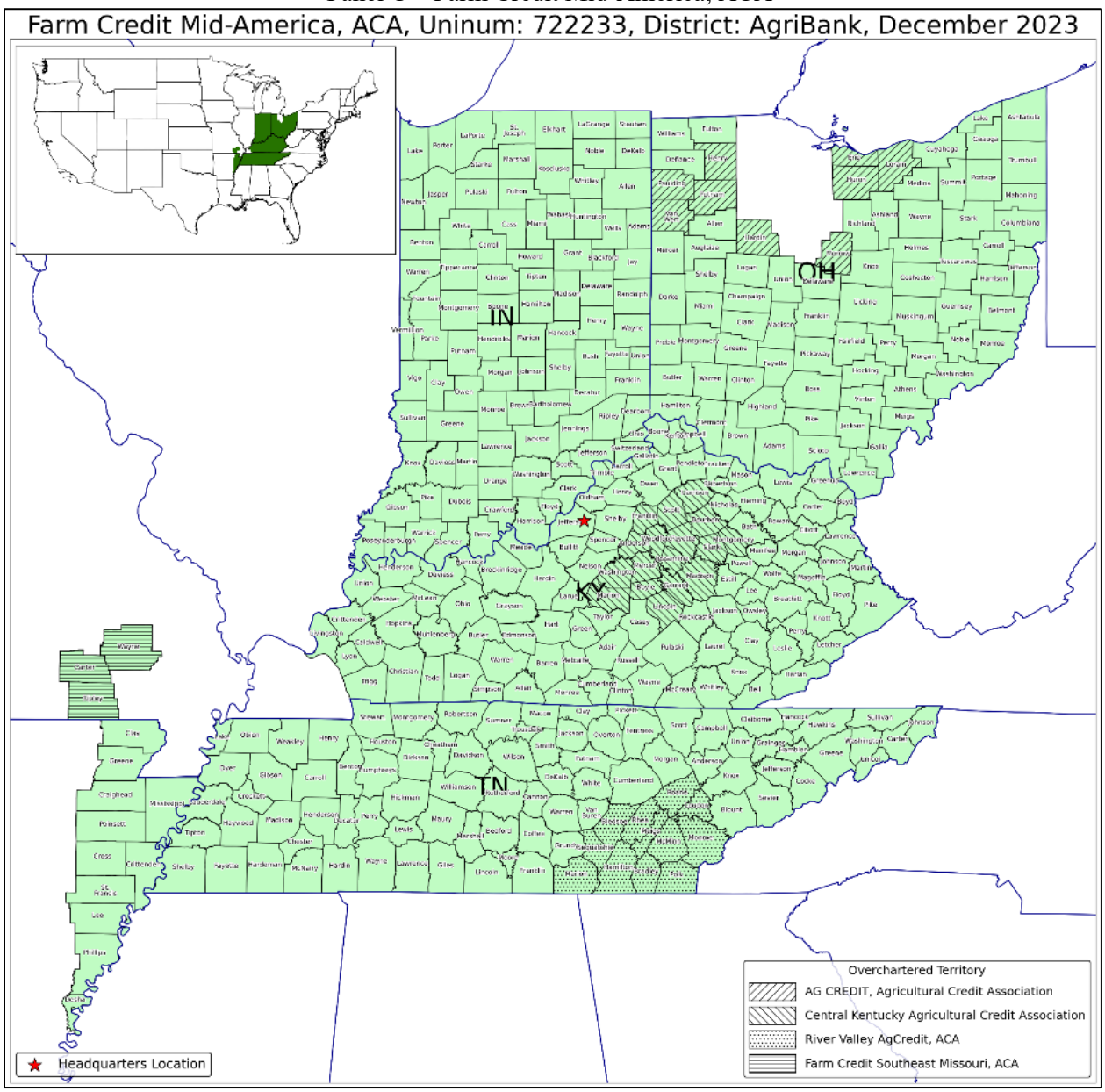


Figure IA.4. Pooled Regression of Credit Origination and Each Month's Forecast Anomalies
This figure plots coefficient estimates and 90% confidence intervals from the following regression:

$$Loan\ Volume_{cy} = \alpha_y + \gamma_c + \beta_1 Forecast\ Anomalies_{cyJan} + \beta_2 Forecast\ Anomalies_{cyFeb} + \cdots + \beta_{12} Forecast\ Anomalies_{cyDec} + \beta_{13} Actual\ Anomalies_{cyJan} + \beta_{14} Actual\ Anomalies_{cyFeb} + \cdots + \beta_{24} Actual\ Anomalies_{cyDec} + \boldsymbol{\delta} \cdot \boldsymbol{X} + \varepsilon_{cy}$$

The unit of observation is a county-year (*c-y*). In other words, a year's *Loan Volume* is regressed on separate variables of *Forecast Anomalies* and *Actual Anomalies* for each month from January to December of that year. α_y and γ_c are county and year fixed effects, respectively. $\boldsymbol{X}$ is the same set of county control variables as in equation (1). These include *Small Business Loan*, *Deposits*, *Acres Operated*, *Farm Employment*, *Farm Size*, *Farm Value*, *Per Capita Income*, *Educated Population*, and *Population Density*. Variable definitions are in Table A.1. Standard errors are clustered by county.

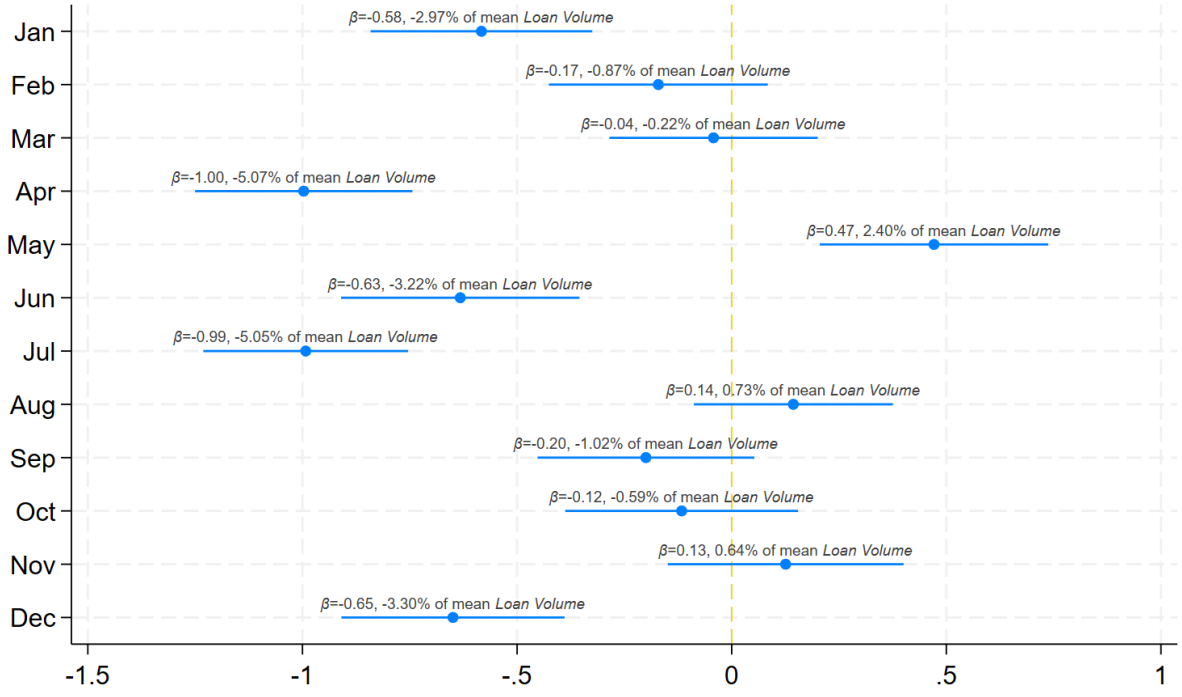


Table IA.1. Climate Anomalies and Financing: Alternative Approaches to Clustering Standard Errors

This table reports coefficient estimates from equation (1) in columns 1-3 and equation (2) in columns 4-6 with different ways of clustering standard errors. The dependent variable is *Loan Volume*. Columns 1-3 uses *Forecast Anomalies* and *Actual Anomalies* as key explanatory variables. Column 4-6 uses *Forecast High Temp*, *Forecast Low Temp*, *Forecast High Precip*, *Forecast Low Precip*, *Actual High Temp*, *Actual Low Temp*, *Actual High Precip*, and *Actual Low Precip* as key explanatory variables. Control variables include *Small Business Loan*, *Deposits*, *Acres Operated*, *Farm Employment*, *Farm Size*, *Farm Value*, *Per Capita Income*, *Educated Population*, and *Population Density*. Variable definitions are in Table A.1. County-year level variables such as *Loan Volume* are stacked for the corresponding county-year-months. Standard errors, reported in parentheses, are clustered by county in columns 1 and 4, by forecast division in columns 2 and 5, and by forecast division-year in columns 4 and 6. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Forecast Anomalies	-0.514***	-0.514***	-0.514***			
	(0.0574)	(0.121)	(0.103)			
Actual Anomalies	-0.0501	-0.0501	-0.0501			
	(0.0553)	(0.0976)	(0.0957)			
Forecast High Temp				-0.351***	-0.351***	-0.351**
				(0.0709)	(0.128)	(0.142)
Forecast Low Temp				-0.727***	-0.727***	-0.727***
				(0.105)	(0.198)	(0.200)
Forecast High Precip				-0.219***	-0.219	-0.219
				(0.0816)	(0.136)	(0.160)
Forecast Low Precip				-0.635***	-0.635***	-0.635***
				(0.103)	(0.226)	(0.172)
Actual High Temp				-0.176***	-0.176*	-0.176*
				(0.0507)	(0.103)	(0.0913)
Actual Low Temp				-0.149***	-0.149**	-0.149
				(0.0476)	(0.0725)	(0.0906)
Actual High Precip				0.00137	0.00137	0.00137
				(0.0448)	(0.0842)	(0.0814)
Actual Low Precip				0.0540	0.0540	0.0540
				(0.0422)	(0.0718)	(0.0765)
Year-Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
County-Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors cluster by	County	Division	Division-Year	County	Division	Division-Year
N	588,604	588,604	588,604	588,604	588,604	588,604
R-sqr	0.788	0.788	0.788	0.788	0.788	0.788

Table IA.2. Climate Anomalies and Financing: Robustness

This table reports coefficient estimates from alternative regression specifications. Key explanatory variables are *Forecast Anomalies* and *Actual Anomalies*. The dependent variables in columns 2, 3, 6, 8, and 9 are *Loan Volume*. Column 1 uses *Loans <= 250K* as the dependent variable. Column 2 uses 2-month lead forecasts of climate anomalies in place of 1-month lead forecasts used in the baseline as key explanatory variables. Column 3 defines *Forecast Anomalies* as equal to 1 if the projected probability of abnormal temperature or precipitation is in the top quartile (instead of the top decline used in the baseline) of all years for the county-month. Column 4 uses *Loan Volume Growth* as the dependent variable. Column 5 uses *Raw Loan Volume* as the dependent variable. Column 6 controls for *Large Forecast Temp Dispersion* and *Large Forecast Precip Dispersion*. Column 7 uses *Small Business Loan* as the dependent variable. Column 8 further controls for *Subsidies*. Column 9 does not include any time-varying county controls. County control variables include *Small Business Loan*, *Deposits*, *Acres Operated*, *Farm Employment*, *Farm Size*, *Farm Value*, *Per Capita Income*, *Educated Population*, and *Population Density*. Variable definitions are in Table A.1. County-year level variables are stacked for the corresponding county-year-months. Standard errors clustered by county-year are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Loans <= $250K	2 Month Lead Forecast	Anomaly Prob. in Top Quartile	Loan Volume Growth	Raw Loan Volume	Control for Forecast Uncertainty	Small Business Loan	Control for Subsidies	Exclude County-Year Controls
Forecast Anomalies	-0.241***	-0.452***	-0.451***	-0.0177**	-128.2***	-0.512***	-3.628	-0.505***	-0.562***
	(0.0325)	(0.0532)	(0.0461)	(0.00865)	(10.28)	(0.0505)	(2.667)	(0.0504)	(0.0529)
Actual Anomalies	-0.0293	-0.0571	-0.0477	-0.00893	-1.759	-0.0500	-0.0712	-0.0456	-0.0813
	(0.0374)	(0.0559)	(0.0560)	(0.00978)	(11.32)	(0.0560)	(2.707)	(0.0560)	(0.0581)
Large Forecast Temp Dispersion						0.120			
						(0.119)			
Large Forecast Precip Dispersion						-0.0193			
						(0.110)			
Subsidies								0.0454***	
								(0.0104)	
County-Year Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
Year-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	588,604	591,563	588,604	537,164	588,604	588,604	588,604	588,604	593,428
R-sqr	0.78	0.79	0.79	0.24	0.837	0.79	0.90	0.79	0.76