ERASMUS UNIVERSITY ROTTERDAM
ERASMUS SCHOOL OF ECONOMICS

MASTER THESIS

Econometrics & Management Science

Quantitative Finance

Climate Change and Mortgage Delinquency

Quantifying the Influence of Extreme Weather Events

Name student: Kiki Hajer

Student ID number: 476072

Supervisor: Zhou, C.

Second assessor: Khismatullina, M.

Date final version: April 29, 2024

Abstract

In this research, the impact of temperature and precipitation extremes on mortgage delinquency rates are investigated for nine U.S. states for the period 2008 to 2022. The trends of extremes are estimated using extreme value techniques in a heteroscedastic extremes framework. To quantify the impact of temperature and precipitation extremes, these trends are used as covariates in a fixed effects regression model. In the regression analysis of the impact of extreme weather on mortgage delinquency rates, extreme temperature showed a consistently positive and significant impact on both short-term (30-89 days) and long-term (90+ days) delinquencies during the summer period, and a significantly positive impact on short-term delinquencies during the winter period. In contrast, precipitation only had a significant positive effect on long-term delinquencies during the summer. The results underscore the significant and nuanced impacts of climatic factors on financial stability, with extreme weather events influencing mortgage delinquencies differently across states and over time. This underscores the urgency for strategic climate resilience and financial adaptation measures within mortgage and housing policies to effectively mitigate the negative impacts of climate extremes.

Contents

1 Introduction

For the past decades, climate change has had an increasing effect on the frequency and severity of extreme weather events, such as hurricanes, floods, and wildfires, but also a rise in global temperature and precipitation. According to NASA, the global temperature is currently rising at a rate of over 0.20°C per decade and is expected to rise further. Furthermore, the worldwide increase in total annual precipitation over the last century is also raising concerns. Global precipitation has been increasing at an average rate of 1.016 millimeters per decade since the beginning of the 20th century. For the United States, this rate is even bigger, observed at 5.08 millimeters per decade (Environmental Protection Agency, 2022). These escalating extreme weather events have a significant impact on the financial system. Indirectly by disrupting economic activities, and directly by causing damage to properties and infrastructure. Therefore, it is essential to understand the connection between climate change and the financial system, especially taking the accelerating pace of climate change into account.

One of the aspects of the financial market that is particularly hard-hit by the effects of climate change, is real estate. It is highly susceptible to the impacts of climate change, due to its inherent immobility. Therefore, evaluating the effects of climate change on housing and mortgage markets is of particular concern in the context of climate-related financial risks. This research aims to better understand the effect of temperature and precipitation extremes on both short-term and long-term mortgage delinquency rates.

For this research we used monthly data on mortgage delinquency rates for 30 to 89 days delinquency as well as more than 90 days delinquency. This data stretches from January 2008 to December 2022 and was obtained from the Consumer Financial Protection Bureau. For the weather data we used daily data on average temperature and precipitation for the same time period. This data was extracted from the National Oceanic and Atmospheric Administration (NOAA). All data was obtained for nine southeastern U.S. states, namely Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina and Tennessee. This region is particularly prone to extreme weather events, especially high temperatures and heavy precipitation. To handle seasonality in the weather data, we split the data into a summer and a winter period. Furthermore, we perform a declustering procedure to remove temporal dependence in our dataset.

We use the heteroscedastic framework of Einmahl et al. (2022) to obtain a space-time trend of extremes in our weather data, and test for a constant frequency of extremes. By aggregating these trends of extremes into monthly values, we incorporate them as covariates in a regression model designed to quantify their impact on mortgage delinquency rates. Our empirical framework examines the influence of weather extremes on both short-term (30-89 days) and long-term (90+ days) mortgage delinquencies, taking into account seasonal variations and controlling for key economic factors like the House Price Index and unemployment rates. Additionally, we include state-by-year and month fixed effects in our regression model to isolate the specific influence of temperature and precipitation.

Our results indicate that extreme temperatures, particularly during the summer, significantly increase both short-term and long-term mortgage delinquency rates. Additionally, we find that during the winter, extreme temperatures also have a significant and positive effect on short-term delinquency rates. This relationship likely stems from increased economic strain due to higher utility bills, reduced agricultural productivity, and heat-related disruptions to employment, which are especially acute in regions dependent on climate-sensitive sectors. Similarly, our findings reveal that extreme precipitation significantly affects long-term delinquencies during the summer. This effect is pronounced in areas frequently hit by severe weather events such as hurricanes, which can lead to substantial property damage and prolonged economic disruptions. The contrast between the seasonal impacts suggests that while some regions may benefit from increased winter precipitation through enhanced agricultural yields and water availability, the overall negative economic impact of extreme weather events, underscores a critical vulnerability. These insights highlight the need for adaptive economic policies and infrastructural resilience to mitigate the financial instabilities introduced by weather extremes. Our results not only resonate with the existing literature on the financial consequences of climate change but also highlight the complex dynamics between distinct weather extremes and economic outcomes.

The body of literature that studies the relationship between climate change and mortgage delinquency rates is growing. However, the impact of precipitation extremes on mortgage delinquency rates has not been previously explored. Our research contributes to the existing literature by investigating this relationship, using a heteroscedastic framework to obtain the space-time trend of extremes. Additionally, our findings on the influence of temperature extremes on short-term mortgage delinquency rates are consistent with previous studies. These findings not only support the growing consensus in this field of research, but also distinctly illustrate the profound influence of extreme weather events on the economic stability of the housing market. Through this extended analysis, our study casts new light on the complex dynamics between extreme weather events and economic outcomes. It underscores the need for a deeper understanding of these factors, which is crucial for policymakers and financial institutions aiming to mitigate the risks associated with climate change.

The remainder of this paper will be structured as follows. First, we will discuss previous relevant literature in Section 2. Subsequently, in Section 3 the data that is used in this paper will be specified. In Section 4, all used methods will be introduced and explained. Section 5 will report the results, which will then be discussed in Section 6. Finally, the research will be summarized and concluded in Section 7.

2 Literature review

2.1 Extreme weather impact on mortgage delinquency

In the past years, climate change has emerged as an increasingly prominent topic in the scientific literature. This rise in attention coincides with an increase in the frequency of natural disasters, which is expected to persist due to climate change (IPCC, 2021). While there are a lot of ways in which climate change is affecting our lives, many researches studied the impact of climate change on the financial system and the accompanying risk. Reports from the European Central Bank emphasized the threats that climate change risks and natural disasters could pose for the stability of the financial system (ECB, 2020, 2021). In addition to natural disasters, Dell et al. (2014) identify extreme temperature and precipitation as risk factors that can affect the economy. Therefore, our research aims to investigate specific effects of temperature and precipitation extremes.

In the context of climate-related financial risks, mortgages are of particular concern. This is because their collateral, which consists of immovable assets, is fully exposed to physical risks (Calabrese et al., 2021). Several studies have identified a significant influence of natural disasters on mortgage delinquencies. The literature shows the impact of different type of climate events, such as hurricanes (Rossi, 2021) or wildfires (Issler et al., 2021). Focusing on temperature and precipitation, Calabrese et al. (2021) studied the impact of extreme weather events on mortgage risks in Florida and found a statistically significant impact of heavy rains on mortgage default in areas with large exposure to flood risks. Deng et al. (2021) investigated the impact of high temperature on mortgage default in the United States and discovered that one additional high temperature day in each month over the past year is associated with a 3.2% increase in the probability of 30-day delinquency. However, they did not observe a significant result for low temperature. Subsequently, Deng et al. (2023) further researched this topic and found that the probability to default on underwater homes as a consequence of high temperature is even higher. Specifically, when homes are underwater, one additional high temperature day in a month increases the default rate by 6.9%.

To clarify how temperature extremes can affect mortgage delinquency rates, Deng et al. (2021) propose three different mechanisms. The first mechanism is what they call rational belief updating. This entails that exposure to high temperatures could change an individual's view on climate change risks, leading them to perceive more risk. Consequently, this could cause them to update their beliefs and change their behaviour, ultimately triggering mortgage default. This increased likelihood of default is caused by a decline in utility associated with living in their current home and location. The second explanation they propose is that of income liquidity. When agricultural and other outdoor workers experience higher temperatures, they could face climate induced income loss or even job losses. Consequently, they may be more likely to default on their mortgage due to liquidity constraints. Naturally, this effect is most pronounced in states with a high proportion of outdoor labor. The third and final explanation they propose is called a psychological-behavioural effect. They discovered that when people are exposed to high temperatures for a longer period of time, they are more likely to experience irregular decision patterns, potentially leading to reckless financial choices such as mortgage defaults. They find the first mechanism to be the most pronounced, with the other two being complementary explanations. This shows how temperature extremes can potentially increase mortgage delinquency. While multiple studies have investigated and established the connection between temperature extremes and mortgage delinquency, research on the connection between precipitation extremes and mortgage delinquency is limited. With precipitation increasing due to climate change, this could also pose problems for the financial system and mortgage delinquency. The mechanisms Deng et al. (2021) propose regarding the impacts of extreme temperatures on mortgage delinquency could potentially also hold for precipitation extremes. Moreover, heavy precipitation could lead to an increased flooding risk, which can lead to decreased property values, increased insurance costs and ultimately property damage. This is of particular concern for the southeastern states of the U.S., which are most subject to rain.

Even though literature on the effects of precipitation on mortgage delinquency rates is lacking, the negative impact of heavy precipitation on the financial system has been established (OECD, 2021). Furthermore, Cathcart et al. (2023) studied the impact of high temperature and heavy precipitation on the default probability of small and micro firms and found a significant relationship for both variables. Specifically, they found that a 2.46 millimeters increase in the average precipitation on wet days increases the probability of default by 0.324%. This finding indicates that heavy precipitation could potentially impact mortgage delinquency as well. Therefore, our research will further investigate the impact of both extreme temperature and precipitation on mortgage delinquency to advance our understanding of these climate-related financial risks.

2.2 Extreme Value Theory

Given our focus on the frequency of extreme events, it is essential to delve into the fundamentals of Extreme Value Theory. This theory models the probability of extreme occurrences effectively. It delves into the tail of a probability distribution, concentrating on regions close to the maximum values, where drawing conclusions becomes challenging due to the scarcity of data. Extreme Value Theory was first introduced by Fisher and Tippett (1928) and Tippett (1925) and has been extended and applied broadly on multiple areas since then.

Einmahl et al. (2016) extend classical Extreme Value Theory to datasets where observations are not uniformly disributed, by introducing a theoretical framework that allows for time-varying frequency of extreme observations, also referred to as heteroscedastic extremes. They introduce a model accommodating this variability through a positive scedasis function. This function helps model potential changes in the tail of a distribution function continuously over time, offering a way to examine changes in extreme event frequencies. Furthermore, they introduce a test statistic for evaluating the constancy of these frequencies. Their approach applies to the analysis of heteroscedastic extremes without assuming a specific parametric model and requires only a single observation at each time point for analysis.

Subsequent research by Einmahl et al. (2022) has further developed and implemented the approach for investigating heteroscedastic extremes, by incorporating spatial and temporal dimensions into the analysis of extreme events. This extension allows for a nuanced examination of how extreme weather events, like rainfall, are interconnected across different locations and how their frequencies and intensities evolve over time. Additionally, they introduce a test statistic to assess whether the frequency of extreme events remains constant over both time and space. They apply their methods to analyze the space-time trends in extreme rainfall events across North-Western Germany. We will use this space-time framework to identify the trend of extremes in our temperature and precipitation data.

2.3 Fixed effects

In panel regression, it is common in the literature to add fixed effects to the regression model. Fixed effects control for unobservable characteristics that are unique to each cross-sectional unit and are constant over time. These could include individual-specific attributes or other invariant features within entities such as firms, countries, or states. By controlling for these fixed, unobserved traits, the models are able to focus on estimating the effect of the variables that change over time within those units. This approach helps to mitigate the issue of omitted variable bias, which occurs when the omitted characteristics are correlated with both the dependent and independent variables. Consequently, including fixed effects in panel regressions allows for more precise estimation of causal relationships, as it isolates the impact of the independent variables from the influence of the constant unobserved heterogeneity. However, when determining which fixed effects to include, it is crucial to consider the potential pitfall of overfitting and multicollinearity. Overfitting occurs when too many fixed effects tailor a model too closely to the sample, reducing its predictive power. It often happens when the number of fixed effects is close to the number of observations. Multicollinearity from multiple fixed effects can inflate standard errors, obscuring the significance and impact of predictors.

Previous literature has used many different combinations of fixed effects. For example, Deng et al. (2021) use three two-way fixed effects, specifically, county-by-year, county-by-month and year-by-month fixed effects. Similarly, Aguilar-Gomez et al. (2022) use municipality-by-year, municipality-by-quarter and year-by-quarter fixed effects. Others decided to include less fixed effects, such as Jacob et al. (2007) who use jurisdiction-by-year and month fixed effects in their regression, Cathcart et al. (2023) use firm and industry-by-year fixed effects, Cathcart et al. (2020) use country and industry fixed effects and Addoum et al. (2020) use industry-by-year and establishment-by-quarter fixed effects.

In our research, we included state-by-year and month fixed effects in the panel regression. The inclusion of state-by-year fixed effects allows to control for unobserved, time-varying factors that are unique to each state and could influence delinquency rates, such as state-specific economic trends, policy changes, and other local developments that occur on an annual basis. By incorporating month fixed effects, we account for common seasonal patterns that affect all states similarly, such as seasonal employment fluctuations, holiday effects, and general economic cycles. This fixed effects structure is chosen to capture the broad temporal and seasonal variations that could confound the impact of weather conditions on mortgage delinquencies, without overfitting the model with more granular interactions.

3 Data

Our analysis is based on data from nine U.S. states, specifically Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, and Tennessee.

3.1 Mortgage delinquency rates

For our analytical framework, we make use of monthly mortgage delinquency rates, differentiating amongst delinquencies spanning 30 to 89 days and those exceeding 90 days. Borrowers who fall into the former category have missed one or two mortgage payments. This rate is a measure of early stage delinquencies and can be an early indicator of the mortgage market's overall health. Borrowers that are over 90 days delinquent have missed three or more mortgage payments. This rate measures more severe economic distress. Our dataset contains observations from January 2008 to December 2022, resulting in a total of 180 months. This data was obtained from the Consumer Financial Protection Bureau. Panel A in Table 1 displays the overall mean and standard deviations of mortgage delinquency rates in our dataset. We observe that the average delinquency rate for 30-89 days is 3.27%, with a standard deviation of 1.31%, while the mean for 90+ days is 2.19%, with a slightly higher standard deviation of 1.54%. These numbers indicate that while the mortgage delinquency rate is higher for the 30-89 days category, there is more variability in the 90+ days category.

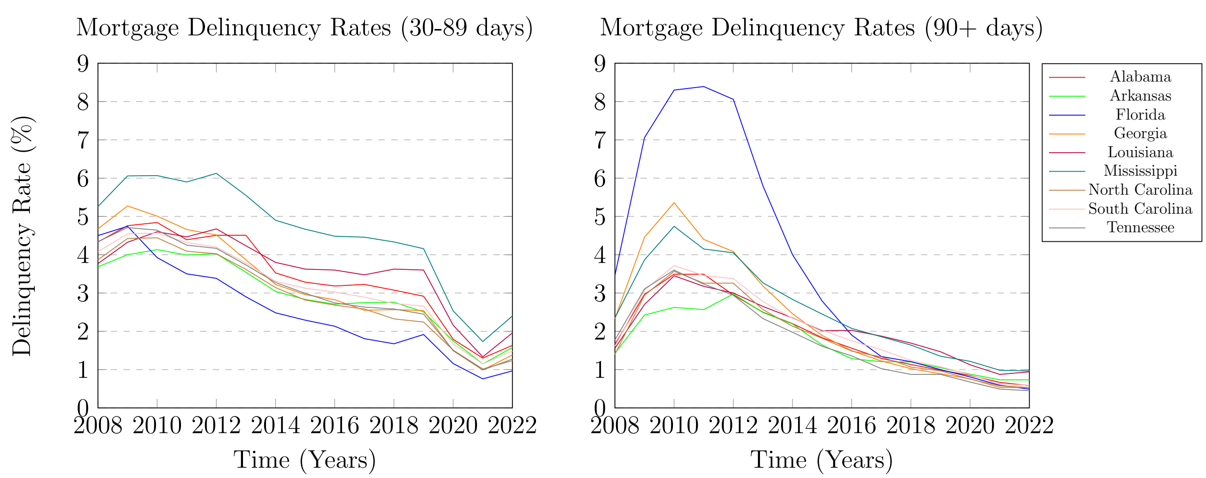


Figure 1: Mortgage Delinquency Rates per State over Time

Figure 1 shows the yearly mortgage delinquency rates over time per state, for 30 to 89 days delinquency as well as more than 90 days delinquency. We observe an overall decrease over time for each state for the 30 to 89 days delinquency rates. This trend may be attributed to multiple factors, such as overall improvements in economic conditions or implementation of policies aimed at preventing delinquencies. Remarkably, Mississippi consistently maintains a higher average 30 to 89 days mortgage delinquency rate compared to the other states.

Considering the graph for the 90+ days mortgage delinquency rates, we see an increase for each state between 2008 and 2010. This was in all probability a consequence of the 2008 housing crisis, which led to widespread economic distress, job losses and dropping property values, leaving all homeowners struggling to meet their mortgage obligations. However, this increase is particularly high for Florida, resulting in a spike of over 8%, reflecting that Florida was particularly hard-hit by the housing crisis.

Table 1: Overall descriptive statistics

Variables	**Mean**	**St. dev.**
Panel A: Delinquency rates (in %)		
30-89 days	3.27	1.31
90+ days	2.19	1.54
Panel B: Weather variables		
Temperature (in °C)	18.55	8.65
Precipitation (in mm)	3.79	11.36
Panel C: Control variables		
Unemployment rate (in %)	3.27	1.31
House Price Index	2.19	1.54

Note: Statistics of delinquency rates and control variables were calculated using monthly data. Weather statistics were calculated using daily data.

3.2 Weather

Daily weather data for the aforementioned nine states were obtained from the National Oceanic and Atmospheric Administration (NOAA). As weather data is only available per weather station, we decided to obtain records from five weather stations within each state, balancing time limitations with the necessity to ensure adequate data representation. This weather dataset encompasses the key meteorological variables used for this research, which are average temperature and precipitation. Temperature values were converted from Fahrenheit to Celsius and precipitation values were transformed from inches to millimeters. Figure

2 displays the locations of the weather station areas that were obtained for this research, ensuring a broad spread across each state.

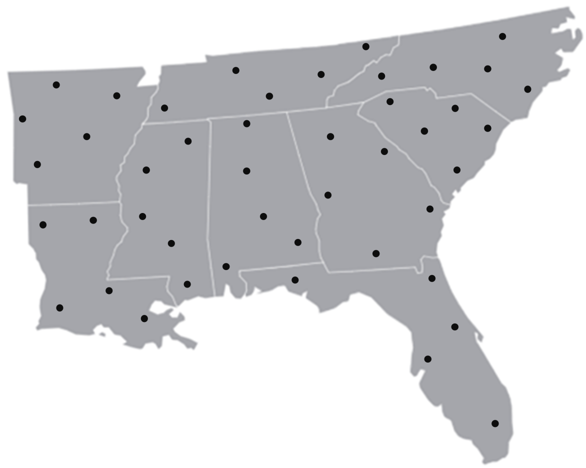


Figure 2: Map of the weather station locations

Furthermore, the dataset contained two types of missing values. Firstly, within the precipitation data, several dates contained a T value, signifying a small amount of precipitation that will wet a rain gauge but is less than the 0.01 inch measuring limit. As this research specifically focuses on precipitation extremes, days containing the T values, indicating very low precipitation, are set to zero. Secondly, the dataset contained some values marked as M, indicating missing statistics. Data for an element can be missing if the primary sensor for that weather element is inoperable or malfunctioning and any collocated backup sensor is also inoperable or malfunctioning. We dealt with these missing values by computing the mean of the corresponding date from the two preceding years and the two subsequent years. Subsequently, the missing value was substituted with this computed mean. In the case of any of these four dates being unavailable, the corresponding data point was simply omitted from the calculation.

Panel B in Table 1 reports overall descriptive statistics for both our weather variables, calculated from daily data. We observe an average mean temperature of 18.55°C with a standard deviation of 8.65°C. The average daily precipitation amount is 3.79 mm with a standard deviation of 11.36 mm, indicating high variability. This finding is not unusual, as there are numerous days with little to no precipitation, alongside days that experience significantly high rainfall amounts.

3.2.1 Seasonality

Seasonality commonly shows in meteorological variables such as temperature and precipitation. Figure 3 displays boxplots depicting the seasonality of daily data for precipitation and temperature in Alabama, respectively.

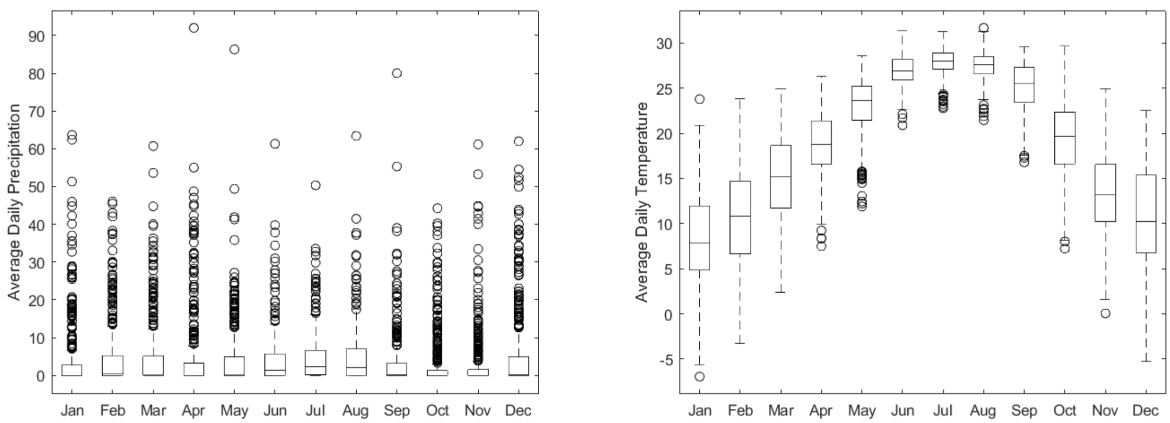


Figure 3: Seasonality boxplots of average daily precipitation and temperature in Alabama

The boxplot for temperature clearly shows a seasonal pattern, with higher average temperature during the summer months than during the winter months. Somewhat less clearly, average precipitation exhibits a similar seasonal pattern. Given that our data display seasonal patterns, we anticipate that their extremes will follow a similar trend. The black circles, representing the outliers, confirm the presence of this pattern. To address this seasonality in our data, we will divide the data into summer and winter periods, following Einmahl et al. (2022). Excluding transitional months April and October, we define the summer period as May to September and the winter period as November to March.

3.2.2 Descriptive statistics

Table 2 shows the descriptive statistics of the daily temperature data for each state and the summer and winter period separately. The dataset exhibits spatial consistency across the states during the summer season. However, during the winter season, Florida's average temperature is notably higher than that of the other states. Furthermore, we can observe the seasonal pattern here as well. Specifically, the temperature during the summer months exceeds that of the winter months in terms of the mean, 95th percentile, and maximum value.

Table 2: Descriptive statistics for temperature in °C

	Alabama	**Arkansas**	**Florida**	**Georgia**	**Louisiana**	**Mississippi**	**North Carolina**	**South Carolina**	**Tennessee**
Summer									
Mean	26.08	24.33	27.60	26.17	27.23	25.86	24.36	25.61	24.40
St. dev.	2.88	4.61	1.70	2.76	2.67	3.43	3.33	3.04	3.43
95th percentile	29.56	30.06	29.78	29.50	30.56	29.72	28.61	29.44	28.72
Max.	31.67	36.00	31.50	31.61	32.78	32.50	31.06	31.50	32.11
Winter									
Mean	11.62	7.18	17.96	12.19	13.42	11.50	8.83	10.81	7.65
St. dev.	5.62	6.26	4.31	5.24	5.56	5.77	5.52	5.34	5.76
95th percentile	20.67	17.56	23.89	20.78	22.11	20.94	18.39	19.67	17.06
Max.	24.94	23.00	26.78	25.78	26.06	25.06	24.17	24.33	22.61

Note: All statistics are calculated using daily data from five weather stations per state, resulting in a total of 11475 observations (2295 days $\times$ 5 stations) for each state in the summer period and 11345 observations in the winter period

Similarly, Table 3 presents the descriptive statistics for daily precipitation data across each state, for summer and winter periods separately. The spatial coherence across the states is evident for both the summer and winter periods. Again, seasonal patterns are observable, with the mean, 95th percentile, and maximum values being higher for the summer period compared to the winter period.

3.2.3 Declustering of extremes

Besides seasonality, meteorological variables also tend to exhibit temporal dependence, meaning that extreme events could be clustered over time. Therefore, we will follow Einmahl et al. (2022) and employ their declustering procedure in order to remove the temporal dependence. The idea is to remove some observations in order to create gaps between consecutive extreme observations, which will be explained in more detail in the next paragraph.

The declustering procedure is performed for both variables and each state separately.

Table 3: Descriptive statistics for precipitation in mm

	Alabama	Arkansas	Florida	Georgia	Louisiana	Mississippi	North Carolina	South Carolina	Tennessee
Summer									
Mean	4.14	3.45	6.15	3.72	4.59	4.20	4.20	4.20	3.51
St. dev.	7.14	7.13	7.81	6.39	8.67	7.69	7.90	7.69	6.22
95th percentile	17.83	17.96	21.05	16.10	21.27	18.29	18.43	19.50	15.18
Max.	86.31	71.32	107.75	84.43	90.98	77.06	87.93	100.69	98.65
Winter									
Mean	4.15	3.10	2.44	3.29	3.76	4.19	3.05	2.90	3.99
St. dev.	8.79	7.94	5.07	7.37	8.43	8.71	6.81	6.83	7.67
95th percentile	22.97	17.89	12.71	19.05	21.80	23.22	16.57	17.08	21.29
Max.	63.65	95.91	52.83	67.61	77.93	68.02	77.27	66.55	63.09

Note: All statistics are calculated using daily data from five weather stations per state, resulting in a total of 11475 observations (2295 days $\times$ 5 stations) for each state in the summer period and 11345 observations in the winter period

First, we will calculate the maxima for each point in time $i = 1, \dots, n$ across all five weather stations. Second, we will order these maxima from high to low. When the date of the second largest maximum is within two days of the largest maximum, this specific date is removed from the dataset across all stations. Otherwise, both dates are kept in the dataset. This process is methodically applied to each subsequent pair of maxima, sequentially eliminating temporally related data. After the declustering procedure, we have a serially independent dataset for both variables and each state, with the number of observations for each state, variable and period summarized in Table 4.

Table 4: Number of observations for each state after declustering

	Alabama	Arkansas	Florida	Georgia	Louisiana	Mississippi	North Carolina	South Carolina	Tennessee
Precipitation									
Summer	9370	8200	10745	9590	9290	9015	9690	9315	9400
Winter	8170	7590	8820	8110	7950	7980	8255	7760	8975
Temperature									
Summer	9370	10025	8755	9465	9220	9285	10055	9820	10015
Winter	10625	10850	10070	10710	10695	10725	10875	10730	10740

Note: The declustering procedure is performed on each state, period and variable

4 Methodology

This section explains the methods used to perform our research and consists of two main parts. First, we will use Extreme Value Theory and the heteroscedastic extremes framework of Einmahl et al. (2022), Einmahl et al. (2016) to extract a trend of extremes from the weather data. Subsequently, we will use these trends as covariates in our regression to quantify the effect of extreme temperature and extreme precipitation on mortgage delinquency rates. For the latter part, our approach follows that of other studies relevant to our objectives, which include Cathcart et al. (2023), Dell et al. (2014), Deng et al. (2021), and Jacob et al. (2007).

4.1 Space-time framework

We will introduce our methods by first introducing the Peak-Over-Threshold method where observations are assumed to be independent and identically distributed (i.i.d.). Then, relaxing this assumption and by allowing for spatial dependence, we will estimate and test the frequency of extremes for both our variables applying the method developed by Einmahl et al. (2022).

4.1.1 Peak-Over-Threshold

Suppose that we have univariate $(X_1, X_2, \ldots, X_n)$, which we treat as an i.i.d. sample, where n denotes the number of observations, with corresponding identical distribution functions $F(x) = P\{X \leq x\}$. The Peak-Over-Threshold (POT) method is useful for assessing the risk of extreme events, where the idea is to consider only the extreme observations in the data. Therefore, we let $X_{1:n} \leq X_{2:n} \leq \ldots \leq X_{n:n}$ be the order statistics of $(X_1, X_2, \ldots, X_n)$. Then, for an intermediate sequence $k = k(n)$, that is, a sequence that satisfies

$$\lim_{n\to\infty} k = \infty \text{ and } \lim_{n\to\infty} \frac{k}{n} = 0, \tag{1}$$

we select the extreme value threshold as the upper order statistic $X_{n-k:n}$, where k represents the number of observations that exceed the threshold in the sample. Following Einmahl et al. (2022), we will use pseudo maximum likelihood estimation to estimate the extreme value parameters (γ, σ).

Now, we can define the set $\{Y_1, \ldots, Y_k\}$ as $\{X_i - X_{n-k:n} | X_i \geq X_{n-k:n}\}$, which denotes the set of exceedances above the threshold $X_{n-k:n}$, with distribution function $F_k(x) = P\left(X - X_{n-k:n} \leq x | X > X_{n-k:n}\right)$. Pickands III (1975) proved that if F_k is in the maximum domain of attraction of the Generalized Extreme Value (GEV) distribution G_γ, that is, $F_k \in \mathcal{D}(G_\gamma)$, then the distribution function F_k is approximately a Generalized Pareto (GP) distribution with the same shape parameter γ. For $\sigma > 0$, we can define the continuous distribution function of the GP distribution as

$$Z_\gamma(x;\gamma;\sigma) = \begin{cases} 1 - \left(1 + \frac{\gamma x}{\sigma}\right)^{-\frac{1}{\gamma}} & \text{for } \gamma \neq 0 \\ 1 - \exp\left(-\frac{x}{\sigma}\right) & \text{for } \gamma = 0 \end{cases} \tag{2}$$

where $x \geq 0$ if $\gamma \geq 0$, and $0 \geq x \geq -\frac{\sigma}{\gamma}$ if $\gamma < 0$.

For the estimation of γ and σ, Pseudo Maximum Likelihood Estimation is applied. The log-likelihood function derived from equation (2) is denoted by

$$L(\gamma, \sigma | Y_1, \ldots, Y_k) = -k \log \sigma - \left(1 + \frac{1}{\gamma}\right) \sum_{j=1}^{k} \log\left(1 + \frac{\gamma}{\sigma} Y_j\right) \tag{3}$$

Generally, $\hat{\gamma}$ and $\hat{\sigma}$ are maximum likelihood estimates if they maximize $L(\gamma, \sigma | Y_1, \ldots, Y_k)$, which means solving the score equations

$$\begin{cases} \frac{\partial}{\partial \gamma} L(\gamma, \sigma | Y_1, \ldots, Y_k) & = 0 \\ \frac{\partial}{\partial \sigma} L(\gamma, \sigma | Y_1, \ldots, Y_k) & = 0 \end{cases} \tag{4}$$

The score equations can be numerically solved for γ and σ. From Einmahl et al. (2022) we know that, under the required conditions, with $\gamma > -\frac{1}{2}$, there exists a unique sequence of estimators $(\hat{\gamma}, \hat{\sigma})$ that maximizes equation (3) and tend to the true unknown extreme value parameters.

Evidently, selecting an appropriate threshold is crucial as it involves a trade-off between variance and bias. Setting the threshold too low might lead to biased estimates by including ordinary data points that are not genuinely extreme. Conversely, setting the threshold too high can cause parameter estimates to be based on too few data points, increasing uncertainty and reducing the reliability of statistical conclusions. Following Einmahl et al. (2022), the pseudo maximum likelihood estimators $(\hat{\gamma}, \hat{\sigma})$ as a function of k will be used to identify a plateau of stability to determine our threshold.

However, since observations can differ in their distribution over time and space, the next section will introduce a model that takes spatially dependent observations into account. Note that the declustering procedure explained in Section 3.2.3 ensures that the observations are independent across time.

4.1.2 Space-time trend

We follow the framework of Einmahl et al. (2022) who extended previous methodology to the situation that includes spatially dependent observations. This allows us to model spatial trends and examine the spatial coherence for temporal trends. We will apply this framework to our nine different states, denoted by v, separately. Let $(X_{i,1}, X_{i,2}, \ldots, X_{i,m})$, with $i = 1, 2, \ldots, n$, be independent random vectors where n denotes the number of observations and m the number of weather stations.

Let $F_{i,j}$ be the continuous distribution function of $X_{i,j}$, for all $i = 1, \ldots, n$ and $j = 1, \ldots, m$. Then, for some continuous distribution function F_0 in the maximum domain of attraction of an extreme value distribution, we get

$$\lim_{x \uparrow x^*} \frac{1 - F_{i,j}(x)}{1 - F_0(x)} = c\left(\frac{i}{n}, j\right) \in (0, \infty) \tag{5}$$

which holds for $i = 1, \ldots, n$ and $j = 1, \ldots, m$. The scedasis function $c\left(\frac{i}{n}, j\right)$ is a positive continuous function. To ensure that the scedasis function c is uniquely defined, we impose the condition

$$\sum_{j=1}^{m} \frac{1}{m} \int_0^1 c(u, j) du = 1 \tag{6}$$

For the estimation of the scedasis function $c\left(\frac{i}{n}, j\right)$, we will use a kernel density estimation (KDE) method. This method allows for a flexible approach to model the scedasis function without assuming a specific parametric form. Let G be a continuous kernel function defined on $[-1, 1]$, such that $\int_{-1}^{1} G(s) ds = 1$, and set $G(s) = 0$ for $|s| > 1$. Let $h := h_n > 0$ be a bandwidth such that $h \to 0$ and $kh \to \infty$ when $n \to \infty$. Additionally, following Einmahl et al. (2022), we define the common threshold to be a high empirical quantile of the combined observations of all weather stations, which is defined as $N := n \times m$. Using the pooled observations for the estimation of the extreme value index improves estimation accuracy. Then, the scedasis function c can be estimated non-parametrically by

$$\hat{c}(s, j) = \frac{1}{kh} \sum_{i=1}^{n} \mathbb{1}_{\{X_i > X_{N-k:N}\}} G\left(\frac{s - \frac{i}{n}}{h}\right) \tag{7}$$

Similar to the application in Einmahl et al. (2016), we will use the biweight kernel $G(x) = 15(1 - x^2)^2/16$ as our kernel function. The scedasis function $c\left(\frac{i}{n}, j\right)$ can be interpreted as the relative frequency of extreme events at time i and station j, where $c \equiv 1$ represents homoscedastic extremes, which corresponds to a constant frequency of extreme events. While the scedasis function $c\left(\frac{i}{n}, j\right)$ is valuable for exploratory analysis due to its straightforward interpretability, we need the integrated scedasis for formal testing. The integrated scedasis for station j is given by $C_j(s)$ and defined as

$$C_j(s) = \frac{1}{m}\int_0^s c(u, j)du \text{ for } s \in [0, 1] \tag{8}$$

Combining equation (8) with the imposed condition in (6) translates to imposing the condition

$$\sum_{j=1}^{m} C_j(1) = 1 \tag{9}$$

We assumed that F_0 is in the maximum domain of attraction of G_γ, that is, $F_0 \in \mathcal{D}(G_\gamma)$, with $\gamma \in \mathbb{R}$. Thus, we have that $F_{i,j} \in \mathcal{D}(G_\gamma)$ for all $i = 1, \ldots, n$ and $j = 1, \ldots, m$. Consequently, γ is the common extreme value index, and is therefore assumed to be constant over time and space, within each state.

The function C_j can be estimated by the number of exceedances over a certain high threshold at station j. Because we want to test for a trend in frequency of extremes across space, we need to use the same threshold for all weather stations within each state. Let $X_{N-k:N}$ be the $(N-k)$-th order statistic of the observations $\{X_{i,j}\}$ for $i = 1, \ldots, n$ and $j = 1, \ldots, m$. Then, for an intermediate sequence k, i.e., $k = k(n) \to \infty$ and $k(n)/n \to 0$ as $n \to \infty$, we define the integrated scedasis estimator as

$$\hat{C}_j(s) := \frac{1}{k}\sum_{i=1}^{\lfloor ns \rfloor} \mathbb{1}_{\{X_{i,j} > X_{N-k:N}\}} \tag{10}$$

We can now test for a trend in frequency of extremes across space. Specifically, we will test whether $C_j(1) = \frac{1}{m}$ for all $j = 1, \ldots, m$. Mathematically, this looks like

$$H_0 : C_j(1) = \frac{1}{m} \text{ for all } j = 1, \ldots, m \tag{11}$$

$$H_a : C_j(1) \neq \frac{1}{m} \text{ for some } j = 1, \ldots, m \tag{12}$$

Define $M = I_m - \frac{1}{m}\mathbb{1}_m\mathbb{1}_m'$ with I_m the $m \times m$ identity matrix and $\mathbb{1}_m$ the m-unit vector. Einmahl et al. (2022) show that under the null, it holds that $D = \sqrt{k}\left(\hat{C}_1(1) - \frac{1}{m}, \ldots, \hat{C}_m(1) - \frac{1}{m}\right)'$ is asymptotically, m-variate normally distributed with zero mean vector and the covariance matrix denoted by $M\Sigma M'$, where Σ denotes a symmetric matrix whose entries are given by

$$\sigma_{j_1,j_2} = \frac{1}{m}\int_0^1 R_{j_1,j_2}\big(c(u,j_1), c(u,j_2)\big)du \tag{13}$$

for all j_1 and j_2 for which holds that $j_1 \neq j_2$. Here, R_{j_1,j_2} is defined as the tail copula of j_1 and j_2. We assume that Σ is invertible, it then follows that $\text{rank}(M\Sigma M') = \text{rank}(M) = m - 1$. Therefore, we will focus on the first $m-1$ elements of D, indicated by D_{m-1}, with an asymptotic covariance matrix denoted by $(M\Sigma M')_{m-1}$. Specifically, this notation indicates a restricted matrix consisting of the first $m-1$ rows and columns. Following Einmahl et al. (2022), the estimator of Σ, $\hat{\Sigma} = (\hat{\sigma}_{j_1,j_2})_{1\leq j_1,j_2\leq m}$, is done using the empirical counterpart of equation (13), which, for $j_1 \neq j_2$, is shown by

$$\hat{\sigma}_{j_1,j_2} = \frac{1}{k}\sum_{i=1}^{n} \mathbb{1}_{\left\{X_{i,j_1} > X_{N-k:N}, X_{i,j_2} > X_{N-k:N}\right\}} \tag{14}$$

Finally, the test statistic is defined as

$$T_1 = D_{m-1}'\left(\left(M\hat{\Sigma}M'\right)_{m-1}\right)^{-1} D_{m-1} \tag{15}$$

From Einmahl et al. (2022) we get the joint asymptotic properties under the null. Assuming that the required conditions are satisfied, then as $n \to \infty$, we get

$$T_1 \xrightarrow{d} \chi^2_{m-1} \tag{16}$$

Subsequently, we will test whether the scedasis function $c\left(\frac{i}{n}, j\right)$ for each station is constant over time. Mathematically, this means testing

$$H_0 : C_j(s) = sC_j(1) \tag{17}$$

$$H_a : C_j(s) \neq sC_j(1) \tag{18}$$

Here, rejecting the null means that the frequency of extremes is not constant for a specific station over the considered time period. Einmahl et al. (2022) propose a Kolomogorov-Smirnov test statistic based on the process $\sqrt{k}\left(\hat{C}_j(s) - s\hat{C}_j(1)\right)/\sqrt{\hat{C}_j(1)}$ for $0 \leq s \leq 1$. Under the null, we get that

$$\left\{\sqrt{k\hat{C}_j(1)}\left(\frac{\hat{C}_j(s)}{\hat{C}_j(1)} - s\right)\right\}_{0\leq s\leq 1} \xrightarrow{d} \{B(s)\}_{0\leq s\leq 1} \tag{19}$$

with B a standard Brownian bridge. Then, we define the Kolmogorov-Smirnov test statistic as

$$T_2 := \sup_{0\leq s\leq 1} \left|\hat{C}_j(s) - s\hat{C}_j(1)\right| \frac{1}{\sqrt{\hat{C}_j(1)}} \tag{20}$$

Assuming all the required conditions are satisfied, then, as $T \to \infty$,

$$\sqrt{k}T_2 \xrightarrow{d} \sup_{0\leq s\leq 1} |B(s)| \tag{21}$$

is the asymptotic distribution of the test statistic under the null.

4.2 Regression model

Our regression model aims to quantify the effect of temperature and precipitation extremes on mortgage delinquency rates. There are nine states, denoted as $v = 1, \ldots, 9$. Our regression model is defined by the following equation:

$$R^{d,p}_{v,t} = \beta_0 + \beta_1 P_{v,(t-1,t-10)} + \beta_2 T_{v,(t-1,t-10)} + \rho X_{v,t} + \mu_{v,y} + \delta_{l_p} + \varepsilon_{v,t} \tag{22}$$

where v denotes a state and t denotes the time in months. The dependent variables are gathered in $R^{d,p}_{v,t}$, which represent the mortgage delinquency rates, with $d = \{30\text{-}89, 90+\}$ the distinction between 30-89 days delinquency or 90+ days delinquency, and $p = \{\text{summer}, \text{winter}\}$ the distinction between the summer and winter period. For each state v, there are 5 stations and estimates $\hat{C}_{j,v}(s)$ for $0 \leq s \leq 1$, $j = 1, \ldots, 5$ and $v = 1, \ldots, 9$. In order to obtain the monthly integrated scedasis for our precipitation variable, we calculate $P_{v,t}$ as the monthly integral of scedasis function c, that is, $P_{v,t} = \sum_{j=1}^{5} \hat{C}_{j,v}(b_t) - \hat{C}_{j,v}(b_{t-1})$. Here, b_t corresponds with the end of month t. Specifically, in equation (22), $P_{v,(t-1,t-10)}$ is calculated as $\frac{1}{10} \sum_{q=1}^{10} P_{v,t-q}$, which is the average over the preceding ten months. We calculate $T_{v,t}$ analogously. We decided to include both the temperature and precipitation extremes in this manner following Deng et al. (2021), who showed that the effect of extreme weather is strongest in the last twelve months. However, given the seasonality in our weather data, we excluded two months from our analysis. Consequently, we will apply their insights to the preceding ten months instead. Finally, $X_{v,t}$ contains other control variables, specifically House Price Index and unemployment rate. The decision on which and how many control variables to include is a trade-off between "bad controls" and "over-controlling" (Angrist & Pischke, 2009). Note that the regression will be performed for the summer period and winter period separately.

Additionally, in order to isolate the effect of high temperature and heavy precipitation on mortgage delinquency rates, we included two different fixed effects, which are used to account for unobserved omitted variables. Specifically, $\mu_{v,y}$ contains the state-by-year fixed effects and δ_{l_p} represents month fixed effects, where a specific month is denoted by $l_{\text{summer}} = \{\text{May, June, July, August, September}\}$, $l_{\text{winter}} = \{\text{January, February, March, November, December}\}$ and a specific year by $y = \{2008, 2009, \ldots, 2021, 2022\}$. State-by-year fixed effects capture long-term trends specific to each state, primarily accounting for state-specific economic changes that might impact residents' ability to pay their mortgages. These effects also account for the cross-sectional differences between states that cannot be captured in the regression, due to the loss of information when the scedasis functions from individual weather stations are aggregated into a state-level frequency of extremes. Furthermore, month fixed effects capture common seasonal patterns that affect all states similarly. This fixed effects structure is chosen to capture the broad temporal and seasonal variations that could influence the impact of weather conditions on mortgage delinquencies, without overfitting the model.

Finally, as we investigate the effect of weather conditions on mortgage delinquency rates, it is important to account for the potential autocorrelation in our data, both spatially and temporally. This is because weather conditions and mortgage performance are likely to be spatially and temporally correlated. To handle this, we cluster all standard errors at the year-month level. Using two-way clustered standard errors provides greater robustness compared to standard errors clustered only at the state level or adjusted for spatial correlations (Addoum et al., 2020). Moreover, standard errors clustered at the state level here could potentially lead to small cluster bias.

4.3 Robustness

To enhance the robustness of our analysis, we will explore variations in the number of lags included in the regression for both the extreme temperature and extreme precipitation variable. This approach allows us to assess the sensitivity of our results to different lag specifications, investigating whether our findings are not driven by a specific temporal configuration. This robustness test contributes to the reliability and generalizability of our findings, ensuring that the patterns observed are not contingent on specific methodological choices but hold under alternative specifications, thereby enhancing the credibility of our research outcomes.

5 Results

The results are applied on each state separately, using the pooled observations of all five weather stations per state.

5.1 Precipitation

We will use Pseudo Maximum Likelihood Estimation to estimate shape and scale parameters $(\hat{\gamma}, \hat{\sigma})$ using pooled observations $N = n \times w$ for each state v. We interpret $\hat{\gamma}$ as the extreme value index, which in this framework is common over space and time, within each state.

First, we will find a value k to select a proper threshold $X_{N-k:N}$ using stability plots. These plots display the maximum likelihood estimate $\hat{\gamma}$ as a function of k. Figure 4 shows the stability plots for daily precipitation in Alabama, for the summer and winter period respectively.

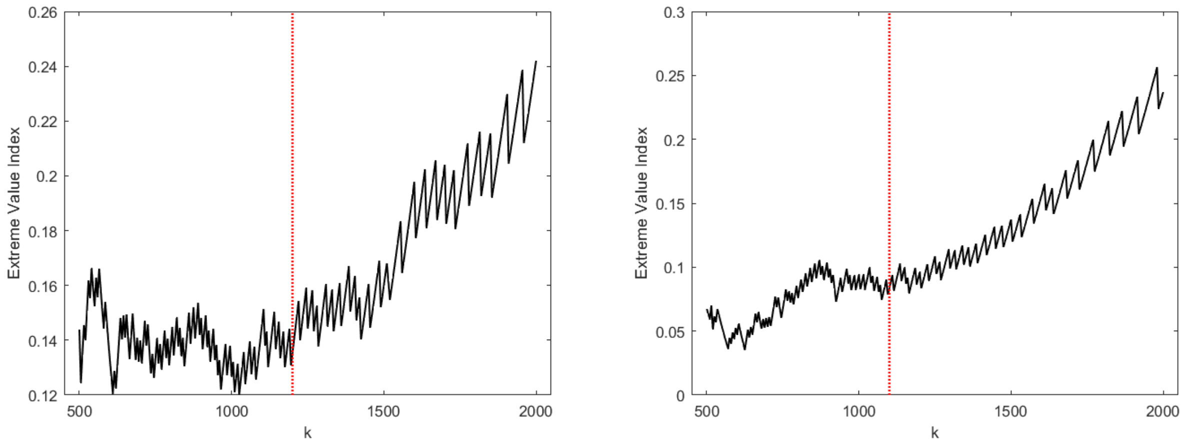


Figure 4: Stability plots of average daily precipitation in Alabama for the summer and winter period

Our goal is to choose the largest possible value for k, while avoiding the inclusion of non-tail observations that could introduce bias. For the summer period we identify a plateau of stability around $k = 1200$, after which we observe a steep increase. This is similar for the winter period, where we identify an increase in Extreme Value Index for k bigger than 1100, hence we set $k = 1100$. The stability plots for the other states are displayed in the Appendix.

After we set appropriate thresholds for each state and period, we estimate the parameters $(\hat{\gamma}, \hat{\sigma})$ using Pseudo Maximum Likelihood Estimation. The results are presented in Table 5.

For both the summer and winter period, we observe a positive shape parameter for each state. In the summer, shape parameter estimates range from 0.08 to 0.21, indicating variability in the tail heaviness of the precipitation distributions across states. The scale parameter estimates vary more broadly, from 12.76 to 18.45, reflecting differences in the intensity of precipitation events. During winter, the shape parameter estimates show a wider range, from 0.04 to 0.29, suggesting a bigger difference in the distribution tails between states, with Florida experiencing more extreme precipitation events. The scale parameter estimates for winter also exhibit variability, from 10.50 to 17.01, indicating regional differences in precipitation intensity. Furthermore, it is noticeable that the shape parameter is higher in summer

Table 5: MLE parameter estimates $(\hat{\gamma}, \hat{\sigma})$ for average daily precipitation

	Alabama	**Arkansas**	**Florida**	**Georgia**	**Louisiana**	**Mississippi**	**North Carolina**	**South Carolina**	**Tennessee**
Summer									
Shape $\hat{\gamma}$	0.14	0.08	0.16	0.15	0.18	0.12	0.21	0.11	0.14
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)
Scale $\hat{\sigma}$	15.80	16.94	18.45	13.75	17.63	16.50	14.96	15.89	12.76
	(0.72)	(0.80)	(0.84)	(0.60)	(0.81)	(0.77)	(0.74)	(0.77)	(0.59)
Winter									
Shape $\hat{\gamma}$	0.08	0.21	0.29	0.04	0.16	0.08	0.04	0.04	0.04
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Scale $\hat{\sigma}$	17.01	11.91	10.50	15.57	15.82	16.28	12.63	12.87	13.23
	(0.80)	(0.58)	(0.60)	(0.76)	(0.78)	(0.74)	(0.62)	(0.63)	(0.62)

Note: Standard errors are reported in the brackets

than in winter for most states. This suggests that the distribution of extreme precipitation events during the summer has a heavier tail compared to winter. This implies that, during summer, there is a higher likelihood of observing very large extreme precipitation events.

Next, we estimate the integrated scedasis $\hat{C}_j(s)$ for $j = 1, ..., m$ for each station, enabling us to test for a trend in frequency of extremes across space within each state. That is, testing the null that $H_0 : C_j(1) = \frac{1}{m}$ for all $j = 1, \dots, m$. The results of the test statistics and the corresponding p-values are reported in Table 6.

The p-values stay above 0.05 for most states in both the summer and winter period, suggesting that we cannot reject the null hypothesis for those instances. However, for Georgia and Louisiana we can reject the null in the summer period at a 5% significance level and for South Carolina at a 10% significance level. In the winter period we can reject the null for Arkansas, Florida, Georgia and Tennessee at a 5% significance level, indicating that the precipitation extremes across space within these states are not constant.

Now, we test for a trend over time for each scedasis function, which we have for each station j. That is, we tested the null that $H_0 : C_j(s) = sC_j(1)$. The p-values of the test

Table 6: Test statistics and corresponding p-values for T_1 for daily average precipitation

	Alabama	**Arkansas**	**Florida**	**Georgia**	**Louisiana**	**Mississippi**	**North Carolina**	**South Carolina**	**Tennessee**
Summer									
T_1	4.78	7.47	0.77	9.67	40.38	6.07	6.98	8.69	1.49
p-value	0.3103	0.1131	0.9431	0.0464	0.0000	0.1941	0.1368	0.0692	0.8287
Winter									
T_1	3.03	44.74	34.71	17.91	5.14	2.13	1.79	3.16	9.86
p-value	0.5536	0.0000	0.0000	0.0013	0.2735	0.7110	0.7752	0.5312	0.0428

statistics are displayed in Table 7. The rows represent the states for both periods and the columns represent the weather stations.

Table 7: p-values for T_2 for daily average precipitation

	Station 1	**Station 2**	**Station 3**	**Station 4**	**Station 5**
Summer					
Alabama	0.4879	0.8395	0.5916	0.2567	0.6008
Arkansas	0.0136**	0.2822	0.0519*	0.1123	0.2933
Florida	0.1440	0.4440	0.6401	0.0543*	0.2277
Georgia	0.6541	0.2608	0.7884	0.3236	0.3209
Louisiana	0.0481**	0.0943*	0.4533	0.1460	0.6609
Mississippi	0.2041	0.2058	0.9458	0.3990	0.6363
North Carolina	0.5516	0.7873	0.8404	0.3866	0.1429
South Carolina	0.7847	0.8449	0.7041	0.6708	0.4375
Tennessee	0.3845	0.3126	0.6045	0.7921	0.8422
Winter					
Alabama	0.9959	0.6505	0.9751	0.5335	0.9073
Arkansas	0.7725	0.2681	0.1599	0.4805	0.5088
Florida	0.1090	0.0006***	0.4089	0.7089	0.6352
Georgia	0.7701	0.2154	0.6326	0.2701	0.0193**
Louisiana	0.6112	0.4520	0.5819	0.5906	0.3520
Mississippi	0.1564	0.4375	0.8728	0.3028	0.2507
North Carolina	0.2402	0.0047***	0.4620	0.0986*	0.8087
South Carolina	0.0673*	0.5615	0.2287	0.4007	0.5790
Tennessee	0.1114	0.1015	0.5017	0.2704	0.4347

Note: p-values depend on k which varies across the states. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

For most weather stations we observe a high p-value in both the summer and winter period. For those instances the results do not provide sufficient evidence to reject the null hypothesis of constant frequency of extremes over time. However, there are a few stations that do return significant results, indicating that we can reject the null hypothesis and conclude that a trend exists in the frequency of extremes at these locations.

Finally, we will aggregate the scedasis functions of all five weather stations w within each state v, forming a state-level frequency of extremes that will be used in the regression later. The test above reveals that for many stations we could not detect a trend in the frequency of extremes, leading us to infer a similar absence of a temporal trend at the state-level frequency of extremes. The relevance of including the frequency of precipitation extremes might be called into question, given that a significant temporal trend is absent at most stations. Nevertheless, the occurrence of significant trends at individual stations in various states suggests that the possibility for a temporal trend in the state-level frequency of extremes remains a reasonable consideration.

5.2 Temperature

Now, we will perform the same analysis on our temperature variable. First, using Pseudo Maximum Likelihood Estimation to obtain estimates for our shape and scale parameters $(\hat{\gamma}, \hat{\sigma})$ using pooled observations $N = n \times w$ for each state v. We interpret $\hat{\gamma}$ as the extreme value index, which in this framework is common over space and time within each state.

In order to obtain the parameter estimates, we will use stability plots to choose a value k for the threshold $X_{N-k:N}$ for each state v. These plots display the parameter estimate $\hat{\gamma}$ as a function of k. Figure 5 presents the stability plots for daily average temperature in Alabama, for the summer and winter period respectively.

The stair-shaped form of the graphs is caused by the temperature data which contains many tied values, making it harder to identify a plateau of stability. However, for the summer period we notice a downward sloping trend, where the values after each drop between $900 \leq k \leq 1200$ are relatively stable around -0.2. Our goal is to choose the largest possible value for k, while avoiding the inclusion of non-tail observations that could introduce bias. Therefore, we set $k = 1200$ for the summer period. Similarly, for the winter period we see an

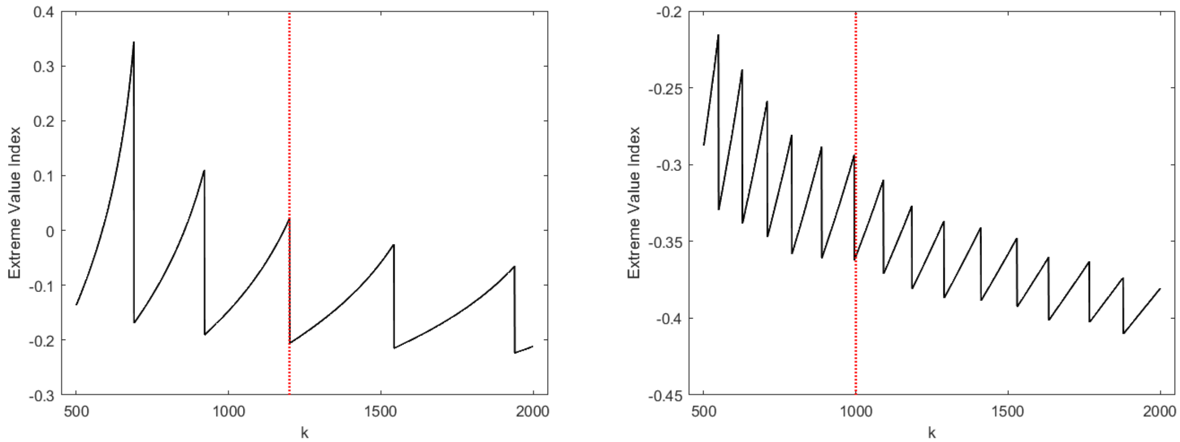


Figure 5: Stability plots of average daily precipitation in Alabama for the summer and winter period

overall downward trend. Between $800 \leq k \leq 1000$ we again observe stable values after each drop, at approximately -0.35. Following the same reasoning as before, we set $k = 1000$. The stability plots for the other states are displayed in the Appendix.

After we set appropriate thresholds for each state and period, we estimate the parameters $(\hat{\gamma}, \hat{\sigma})$ using Pseudo Maximum Likelihood Estimation. The results are presented in Table 8.

Table 8: MLE parameter estimates $(\hat{\gamma}, \hat{\sigma})$ for average daily temperature

	Alabama	***Arkansas***	***Florida***	***Georgia***	***Louisiana***	***Mississippi***	***North Carolina***	***South Carolina***	***Tennessee***
Summer									
Shape $\hat{\gamma}$	-0.02	-0.17	-0.24	-0.23	-0.12	-0.20	-0.30	-0.25	-0.19
	(0.01)	(0.06)	(0.04)	(0.12)	(0.04)	(0.03)	(0.04)	(0.03)	(0.06)
Scale $\hat{\sigma}$	0.68	1.76	0.89	1.14	1.10	1.05	1.54	1.26	1.43
	(0.21)	(0.20)	(0.05)	(0.22)	(0.07)	(0.06)	(0.11)	(0.07)	(0.16)
Winter									
Shape $\hat{\gamma}$	-0.36	-0.39	-0.31	-0.25	-0.34	-0.46	-0.32	-0.39	-0.38
	(0.03)	(0.03)	(0.05)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Scale $\hat{\sigma}$	2.58	3.59	1.71	2.12	2.07	2.90	3.29	2.93	3.58
	(0.18)	(0.20)	(0.17)	(0.15)	(0.17)	(0.19)	(0.19)	(0.19)	(0.18)

Note: Standard errors are reported in the brackets

All states show negative shape parameter estimates for summer, ranging from -0.02 to

-0.30, indicating that the temperature distributions have lighter tails on the right side, which suggests fewer and less severe hot temperature extremes than would be expected in a heavy-tailed distribution like the generalized extreme value distribution. The scale parameter varies among states, where higher values suggest a greater dispersion of temperatures around the mean. Similar to summer, the estimates of the shape parameter for the winter period are negative across all states, ranging more narrowly from -0.25 to -0.46. These values suggest lighter tails for winter temperature distributions as well, but the magnitude of the shape parameters is generally larger in winter than in summer, implying even fewer or less severe cold temperature extremes.

Next, we estimate the integrated scedasis $\hat{C}_j(s)$ for $j = 1, ..., m$ for each station. Subsequently, we test for a trend in frequency of extremes across space, that is, testing the null that $H_0 : C_j(1) = \frac{1}{m}$ for all $j = 1, \ldots, m$. The results of the test statistics and the corresponding p-values are reported in Table 9.

Table 9: Test statistics and corresponding p-values for T_1 for daily average temperature

	Alabama	**Arkansas**	**Florida**	**Georgia**	**Louisiana**	**Mississippi**	**North Carolina**	**South Carolina**	**Tennessee**
Summer									
T_1	31.36	12.48	35.74	8.86	14.41	4.26	26.30	13.52	49.82
p-value	0.0000	0.0141	0.0000	0.0647	0.0061	0.3714	0.0000	0.0009	0.0000
Winter									
T_1	13.05	15.11	51.22	34.22	13.04	7.35	32.61	17.37	11.70
p-value	0.0110	0.0045	0.0000	0.0000	0.0111	0.1186	0.0000	0.0016	0.0198

For the summer period, Alabama, Arkansas, Florida, Louisiana, North Carolina, South Carolina, and Tennessee show significant p-values at a 5% significance level and for Georgia at a 10% significance level, indicating strong evidence against the null hypothesis. This suggests a difference exists in extreme temperature frequencies across stations within these states. For the winter period, we observe significant p-values for all states except Mississippi, indicating strong evidence against the null, suggesting a difference in the frequency of extreme temperature across stations. This points to significant spatial variability in the occurrence of extreme temperature events during both summer and winter.

Subsequently, we will test for a temporal trend for each weather station j separately, by testing the null $H_0 : C_j(s) = sC_j(1)$. The results are displayed in Table 10.

Table 10: p-values for T_2 for daily average temperature

	Station 1	**Station 2**	**Station 3**	**Station 4**	**Station 5**
Summer					
Alabama	0.0000***	0.0000***	0.0002***	0.0002***	0.0144**
Arkansas	0.0000***	0.0001***	0.0000***	0.0000***	0.0000***
Florida	0.0493**	0.0006***	0.0000***	0.1512	0.0000***
Georgia	0.0280**	0.0170**	0.0002***	0.0097***	0.0000***
Louisiana	0.0040***	0.0000***	0.0000***	0.0002***	0.0007***
Mississippi	0.0000***	0.0007***	0.0000***	0.0000***	0.0010***
North Carolina	NaN	0.0218**	0.1925	0.0002***	0.1162
South Carolina	0.0023***	0.0022***	0.0041***	0.0000***	0.0022***
Tennessee	0.0871*	0.0019***	0.0003***	0.0067***	0.0004***
Winter					
Alabama	0.0006***	0.0000***	0.0024***	0.0000***	0.0000***
Arkansas	0.0428**	0.0606*	0.0222**	0.0301**	0.0391**
Florida	0.0003***	0.0000***	0.0000***	0.0000***	0.0000***
Georgia	0.0007***	0.0000***	0.0000***	0.0000***	0.0000***
Louisiana	0.0000***	0.0002***	0.1237	0.0000***	0.0234**
Mississippi	0.0050***	0.0000***	0.0000***	0.0000***	0.0024***
North Carolina	0.0003***	0.0000***	0.0001***	0.0013***	0.0007***
South Carolina	0.0000***	0.0000***	0.0001***	0.0016***	0.0001***
Tennessee	0.0000***	0.0000***	0.0000***	0.0359**	0.0000***

Note: p-values depend on k which varies across the states. NaN values indicate that the test statistic could not be calculated because no data points exceeded the threshold set for extreme values. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

In contrast to the precipitation variable, the analysis of temperature extremes reveals mostly significant outcomes, indicating a trend in frequency of temperature extremes over time for the majority of weather stations. During the summer period, only a single station in Florida and two in North Carolina yielded insignificant results. For one station in North Carolina the test statistic and corresponding p-value were unobtainable, due to the absence of data points that exceeded the predefined threshold. Furthermore, the winter period shows only one insignificant result, from a weather station in Louisiana, denoting the lack of a substantial temporal trend in the frequency of extreme temperature events. All other stations report significant results at the 5% or 1% significance level.

Finally, the scedasis functions of all five weather stations within each state will be aggregated into a state-level frequency of extremes that will be used in the regression later. From above test we concluded that most weather stations exhibit a temporal trend in the frequency of temperature extremes, indicating that the state-level frequency of extremes possibly depicts a similar temporal trend.

5.3 Regression results

Next, we will discuss the regression results that show the impact of extreme temperature and precipitation events on mortgage delinquency rates. Following the structure of the previous sections, we will differentiate between the summer and winter period for the regression as well.

5.3.1 Summer

Table 11 presents the regression results for both short-term (30-89 days) delinquency and long-term (90+ days) delinquency as dependent variables.

Table 11: Regression results for the summer period

	30-89 days	**90+ days**
Intercept	3.332*** (0.826)	1.315 (1.400)
Precipitation	-0.138 (0.385)	1.470** (0.708)
Temperature	0.232* (0.190)	0.575** (0.298)
Unemployment	0.064*** (0.016)	0.035** (0.013)
HPI	-0.002 (0.002)	-0.004 (0.003)
State-by-year FE	Yes	Yes
Month FE	Yes	Yes

Note: This table presents the effects of temperature and precipitation on the probability of 30-89 days or 90+ days delinquency. Precipitation and temperature are calculated as the average over the last ten months. All the estimates are based on equation (22). All standard errors are clustered at the year-month level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

The regression results for the short-term mortgage delinquency rates show that extreme temperature has a positive and significant influence on the delinquency rates, while the effect of precipitation is not significant. This suggests that temperature extremes can directly influence financial strain on households, leading to higher rates of delinquency. The lack of significance for extreme precipitation is not surprising, as we observed the high p-values in Table 7, indicating the absence of a temporal trend in the frequency of precipitation extremes.

The regression results for the long-term mortgage delinquency rates depict a different picture. Here, we observe a statistically significant value for both precipitation and temperature extremes at the 5% significance level. This indicates that both types of extreme weather conditions have a persistent impact on financial stability over a longer period during the summer. Such findings suggest that extreme weather not only affects immediate financial health but also has more sustained effects that could influence the economic resilience of households. This could be due to long-term damage to property, prolonged economic disruptions in weather-sensitive industries, or sustained increases in living and recovery costs.

Subsequently, we add both precipitation and temperature extremes separately to the regression model to examine their individual and interactive effects on mortgage delinquency rates. The results are displayed in Table 12.

When included without extreme temperature, extreme precipitation still does not return a significant coefficient for short-term delinquency rates, when the control variables are either included or excluded. However, extreme temperature shows a significant positive relationship with short-term delinquency when solely included in the model, but becomes insignificant again when included with the control variables. This significant result indicates a direct relationship between extreme temperature and short-term delinquency rates, which may be masked by the inclusion of control variables. This suggests that these economic control variables, which have strong and direct correlations with mortgage delinquency rates, might overshadow the effect of temperature under these specific conditions. This masking effect occurs because these economic variables capture significant variations in short-term delinquency rates that are closely tied to economic conditions, which might also be influenced indirectly by climate extremes. The results in Table 11 show that despite the precipitation variable being insignificant itself, its presence in the model appears to enhance the significance

Table 12: Alternative regression results for the summer period

30-89 days					
Intercept	3.380***	3.139***	4.047***	2.739***	3.083***
	(0.418)	(0.305)	(0.001)	(0.156)	(0.536)
Precipitation		-0.106	-0.418		
		(0.336)	(0.367)		
Temperature				0.345**	0.257
				(0.175)	(0.180)
Unemployment	0.067***		0.067***		0.063***
	(0.015)		(0.001)		(0.016)
HPI	-0.002*		-0.003*		-0.002
	(0.001)		(0.659)		(0.001)
90+ days					
Intercept	4.326***	0.986	3.085**	1.772***	3.971***
	(1.401)	(0.754)	(1.242)	(0.226)	(1.291)
Precipitation		1.251	0.778		
		(0.823)	(0.667)		
Temperature				0.410	0.308
				(0.259)	(0.240)
Unemployment	0.044***		0.044***		0.039***
	(0.015)		(0.015)		(0.013)
HPI	-0.007*		-0.006		-0.007*
	(0.004)		(0.004)		(0.004)

Note: This table presents the effects of temperature and precipitation on the probability of 30-89 days or 90+ days delinquency. Precipitation and temperature are calculated as the average over the last ten months. All the estimates are based on equation (22). All standard errors are clustered at the year-month level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

of temperature. This suggests that the interaction between temperature and precipitation, or the methodological balance they provide when analyzed together, plays a critical role in fully capturing the impact of weather variables on mortgage delinquencies. For long-term delinquency, extreme precipitation and temperature neither are consistently significant across different model setups and their predictive power heavily depends on the presence of each other and control variables. Therefore, we conclude that neither temperature nor precipitation are robust predictors of long-term mortgage delinquency rates on their own.

Finally, we perform the regression on each state separately, reported in Table 13. For short-term delinquency all states show no significant relationship between precipitation extremes and short-term delinquency, which is in line with the results from Table 11 and Table 12. For temperature extremes we observe a significant relationship only for Arkansas

Table 13: Regression results for each state for the summer period

	Alabama	**Arkansas**	**Florida**	**Georgia**	**Louisiana**	**Mississippi**	**North Carolina**	**South Carolina**	**Tennessee**
30-89 days									
Precipitation	-0.286	0.059	0.011	-0.373	0.661	-0.022	0.968	0.154	-1.066
	(0.671)	(0.486)	(0.707)	(0.670)	(0.803)	(1.352)	(0.749)	(1.057)	(0.735)
Temperature	-0.066	0.490***	0.332	0.196	0.383	0.135	0.623*	0.186	0.164
	(0.201)	(0.182)	(0.437)	(0.294)	(0.318)	(0.367)	(0.332)	(0.261)	(0.296)
90+ days									
Precipitation	2.073***	0.879***	4.090*	2.646**	1.527**	1.602	1.987**	0.831	1.881**
	(0.673)	(0.416)	(2.225)	(1.252)	(0.785)	(1.096)	(0.858)	(1.354)	(0.817)
Temperature	0.535***	0.669***	3.010**	0.588	0.482**	0.385	0.914*	0.251	0.398
	(0.190)	(0.182)	(1.285)	(0.511)	(0.218)	(0.333)	(0.495)	(0.515)	(0.263)

Note: This table presents the effects of temperature and precipitation on the probability of 30-89 days or 90+ days delinquency. Precipitation and temperature are calculated as the average over the last ten months. All the estimates are based on equation (22). All standard errors are clustered at the year-month level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

and North Carolina, indicating that higher frequencies of extreme temperature events are associated with increases in short-term mortgage delinquencies in these states. A possible explanation for this significant relationship may stem from the fact that both Arkansas and North Carolina have economies heavily dependent on agriculture. Extreme temperatures can dramatically affect crop yields and farming operations. For example, heat waves can stress crops, reduce yields, and increase operational costs. These agricultural stresses can translate into broader economic challenges, affecting employment and financial stability, thereby impacting the ability to meet financial obligations like mortgage payments.

The impact of precipitation extremes on long-term delinquency is significantly positive in all states except Mississippi and South Carolina. This indicates a strong positive relationship between extreme precipitation and long-term mortgage delinquency rates in these states. The states where the relationship is significant often experience more severe precipitation extremes, such as hurricanes and tropical storms, which are particularly common in Louisiana and Florida, as well as the states like Georgia and North Carolina. These events can cause substantial property damage and economic disruption, leading to higher mortgage delinquency rates. For temperature extremes we observe significantly positive coefficients for all states except Georgia, Mississippi, South Carolina and Tennessee. This finding suggests that extreme temperatures can have a prolonged impact on mortgage delinquency rates for these states. The states where temperature extremes have a significant impact on long-term mortgage delinquency rates likely exhibit a combination of higher economic vulnerability to temperature changes, lower resilience in housing and infrastructure, and less comprehensive adaptation strategies. Overall, there is a clear indication of regional variations in how weather extremes affect mortgage delinquency rates.

5.3.2 Winter

We will discuss the regression results obtained for the winter period. First, Table 14 displays our baseline regression results for both short-term and long-term delinquency rates as the dependent variables.

The results show that temperature extremes have a significantly positive effect on short-

Table 14: Regression results for the winter period

	30-89 days	**90+ days**
Intercept	4.013*** (0.946)	0.230 (1.464)
Precipitation	-0.681* (0.565)	1.117 (0.887)
Temperature	0.418** (0.188)	0.371 (0.274)
Unemployment Rate	-0.000 (0.088)	0.199*** (0.057)
HPI	-0.002 (0.002)	-0.002 (0.003)
State-by-year FE	Yes	Yes
Month FE	Yes	Yes

Note: This table presents the effects of temperature and precipitation on the probability of 30-89 days or 90+ days delinquency. Precipitation and temperature are calculated as the average over the last ten months. All the estimates are based on equation (22). All standard errors are clustered at the year-month level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

term delinquency rates, while precipitation extremes display a negative and significant effect. A decreasing effect of precipitation extremes on short-term mortgage delinquency rates indicates that higher levels of precipitation during the winter are associated with lower short-term mortgage delinquency rates. This might seem counterintuitive, but increased winter precipitation could be beneficial for agricultural output, particularly in areas where water may be scarce at other times of the year. This can lead to a more stable income for those employed in agriculture and related industries, ultimately improving financial stability. For long-term delinquency rates, the results show insignificant coefficients for both temperature and precipitation extremes. This suggests that over longer periods, both weather-related variables do not show a statistically measurable impact on mortgage delinquency rates.

Subsequently, both precipitation and temperature extremes are included to the regression model separately, of which the results are presented in Table 15. In the case of short-term delinquency rates, extreme temperature stays highly significant when included with or without the precipitation variable and the control variables. This indicates that extreme temperature is a robust estimator for short-term mortgage delinquency rates in the winter period. Additionally, for extreme precipitation, we observe a significant and negative coefficient when included with the control variables, but without the temperature variable. However, when

Table 15: Alternative regression results for the winter period

30-89 days					
Intercept	3.420***	3.838***	4.881***	2.801***	2.926***
	(1.041)	(0.447)	(0.918)	(0.117)	(0.997)
Precipitation		-0.664	-0.984*		
		(0.493)	(0.529)		
Temperature				0.496***	0.494***
				(0.129)	(0.156)
Unemployment	0.009		0.011		-0.003
	(0.085)		(0.084)		(0.087)
HPI	-0.001		-0.002		-0.000
	(0.002)		(0.002)		(0.002)
90+ days					
Intercept	2.261***	0.797	0.999	1.822***	2.014**
	(0.942)	(0.940)	(1.174)	(0.259)	(0.888)
Precipitation		1.605	0.849		
		(1.039)	(0.799)		
Temperature				0.507*	0.247
				(0.305)	(0.212)
Unemployment	0.210***		0.209***		0.204***
	(0.060)		(0.059)		(0.058)
HPI	-0.004		-0.002		-0.004
	(0.003)		(0.002)		(0.003)

Note: This table presents the effects of temperature and precipitation on the probability of 30-89 days or 90+ days delinquency. Precipitation and temperature are calculated as the average over the last ten months. All the estimates are based on equation (22). All standard errors are clustered at the year-month level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

extreme precipitation is the only variable included in the model, the effect becomes insignificant. This result underscores that the effect of extreme precipitation on short-term mortgage delinquency rates are not direct but are mediated through its interactions with other weather and economic variables.

For the long-term delinquency rates, extreme precipitation shows no significant relationship in any of the model setups, indicating the absence of a relationship. Interestingly, extreme temperature displays a significant coefficient when it is the only variable included in the model. This suggests that while temperature extremes do influence delinquency rates, their impact is generally less pronounced or gets absorbed within the broader economic conditions represented by the control variables.

Table 16: Regression results for each state for the winter period

	Alabama	**Arkansas**	**Florida**	**Georgia**	**Louisiana**	**Mississippi**	**North Carolina**	**South Carolina**	**Tennessee**
30-89 days									
Precipitation	0.371	-0.857	-3.115***	-1.467**	-0.409	1.185	-0.579	-0.850	-0.133
	(0.721)	(0.771)	(1.096)	(0.747)	(0.727)	(1.994)	(0.931)	(0.706)	(0.559)
Temperature	0.836**	0.698***	-0.481	0.135	0.701***	0.647**	0.281	0.241	0.142
	(0.338)	(0.241)	(0.511)	(0.333)	(0.201)	(0.304)	(0.364)	(0.296)	(0.163)
90+ days									
Precipitation	1.534**	1.141	-1.115	2.994*	1.098	2.592**	3.472**	1.842	1.746**
	(0.660)	(0.722)	(2.554)	(1.559)	(0.779)	(1.241)	(1.539)	(1.468)	(0.788)
Temperature	0.340	0.555**	0.394	0.479	0.396*	0.398	0.964*	0.619	0.271
	(0.255)	(0.238)	(1.064)	(0.488)	(0.233)	(0.273)	(0.528)	(0.420)	(0.181)

Note: This table presents the effects of temperature and precipitation on the probability of 30-89 days or 90+ days delinquency. Precipitation and temperature are calculated as the average over the last ten months. All the estimates are based on equation (22). All standard errors are clustered at the year-month level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Finally, the regression is performed for each state separately, of which the results are presented in Table 16. We observe a negative and significant relationship between precipitation extremes and short-term mortgage delinquency rates only in Florida and Georgia. This finding indicates that these states effectively leverage their extreme weather conditions, particularly with Florida's robust tourism industry that thrives even during wet winters, and Georgia's agricultural sector that benefits from winter precipitation for crop health. Furthermore, the effect of extreme temperature on short-term delinquency rates is positive and significant in Alabama, Arkansas, Louisiana and Mississippi, which is likely due to a combination of high economic vulnerability to heat, less adaptive infrastructure, and higher energy costs impacting household budgets.

Interestingly, where Table 14 showed no relationship of both extreme precipitation and extreme temperature on long-term delinquency rates, there seem to be some significant relationships when we investigate each state separately. Alabama, Georgia, Mississippi, North Carolina and Tennessee display significantly positive coefficients for extreme precipitation. This indicates that extreme precipitation can have a prolonged impact on mortgage delinquency rates. These states have significant agricultural sectors that can be sensitive to extreme weather events. Heavy precipitation, particularly during winter, can disrupt agricultural activities, damage crops, and lead to financial instability for those dependent on farming incomes. While the short-term effects of increased winter precipitation can be beneficial and can improve financial stability for the agricultural sector, leading to a decrease in short-term mortgage delinquency rates, the long-term consequences of excessive rainfall may impose burdens that destabilize this, potentially resulting in higher long-term delinquency rates.

5.4 Robustness

We performed alternative regressions where we included the extreme precipitation and extreme temperature variable with a different number of lags. In our baseline model, both are calculated as the average over the past year.

5.4.1 Summer

Table 17 presents the results for each variable and multiple variations of lags in the summer period. For short-term delinquency, the effects of extreme precipitation are all insignificant, except for the one month lag, confirming our previous results. Extreme temperature shows a positive and significant coefficient for all numbers of lags except for the one month lag, confirming the robustness of this estimator.

Table 17: Regression results for lagged variables for the summer period

Lag	**30-89 days**	**90+ days**
Precipitation		
$t-1$	0.239** (0.114)	0.087 (0.144)
$(t-1, t-5)$	-0.022 (0.094)	0.163** (0.083)
$(t-1, t-10)$	-0.138 (0.385)	1.470** (0.708)
$(t-1, t-20)$	-0.396 (0.483)	-2.542*** (0.660)
$(t-1, t-30)$	0.044 (0.628)	-3.225*** (1.116)
Temperature		
$t-1$	0.092 (0.056)	0.094 (0.094)
$(t-1, t-5)$	0.096** (0.046)	-0.004 (0.061)
$(t-1, t-10)$	0.232* (0.190)	0.575** (0.298)
$(t-1, t-20)$	0.426** (0.195)	-0.249 (0.229)
$(t-1, t-30)$	0.723** (0.276)	0.107 (0.233)

Note: This table presents the effects of temperature and precipitation on the probability of 30-89 days and 90+ days delinquency. All the estimates are based on equation (22). All standard errors are clustered at the year-month level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Conversely, the effects of precipitation extremes on long-term delinquency rates is significantly negative for the 20- and 30-month lag, while significantly positive for the shorter lags. This pattern indicates that, over a longer period, the negative consequences of extreme precipitation events might be offset by recovery and aid efforts, leading to an improved financial capacity to meet mortgage obligations. The effect of extreme temperature is only significant in our baseline model and insignificant for all other alternative lag specifications, which highlights its lack of robustness.

5.4.2 Winter

Similarly, the regression results for alternative lag specifications are displayed in Table 18. The effects of precipitation extremes depict a similar picture for both short- and long-term delinquency rates, with negative and significant coefficients for longer lags and significantly positive coefficients for shorter lags, which can be explained in a similar way as before for the summer period.

Table 18: Regression results for lagged variables for the winter period

Lag	**30-89 days**	**90+ days**
Precipitation		
$t-1$	0.374 (0.255)	0.492** (197)
$(t-1, t-5)$	0.836*** (0.219)	0.484** (0.219)
$(t-1, t-10)$	-0.681* (0.565)	1.117 (0.887)
$(t-1, t-20)$	-2.330*** (0.611)	-3.451*** (0.593)
$(t-1, t-30)$	-4.251*** (0.804)	-3.705*** (0.922)
Temperature		
$t-1$	0.197 (0.128)	-0.046 (160)
$(t-1, t-5)$	0.550*** (0.100)	0.183* (0.103)
$(t-1, t-10)$	0.418** (0.188)	0.371 (0.274)
$(t-1, t-20)$	0.134 (0.200)	-0.525** (0.205)
$(t-1, t-30)$	-0.098 (0.237)	-0.064 (0.228)

Note: This table presents the effects of temperature and precipitation on the probability of 30-89 days and 90+ days delinquency. All the estimates are based on equation (22). All standard errors are clustered at the year-month level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Extreme temperature shows a different picture. For short-term delinquency rates, the effect of extreme temperature is positive and significant for shorter lags and insignificant for longer lags. This suggests that immediate increases in temperatures can lead to increased financial burdens on households. This might be due to heightened energy costs for cooling, reduced productivity in temperature-sensitive industries, or health-related expenditures, which can strain household budgets quickly. Furthermore, for long-term delinquency rates, we observe a significantly positive coefficient for the 5-month lag and a significantly negative coefficient for the 20-month lag, confirming its expected lack of robustness.

Overall, the observed lag effects suggest a nuanced interaction between the timing of extreme weather events and their financial impacts on households. While immediate and short-term effects are predominantly positive, and thus increasing delinquency rates, long-term effects tend to be mitigated, possibly due to adaptation, financial recovery, or aid.

6 Discussion

This research investigates the impact of extreme weather conditions, characterized by temperature and precipitation extremes, on short-term and long-term mortgage delinquency rates. For this research, we utilized a heteroscedastic extremes approach in a space-time framework to obtain a trend of extremes, which was then used in a fixed effects regression model to measure the effect on mortgage delinquency rates. Our findings revealed a significantly positive effect of both temperature and precipitation extremes on long-term mortgage delinquency rates in the summer period, suggesting that as the frequency and intensity of these weather extremes increase, so does the likelihood of mortgage delinquencies exceeding 90 days. Furthermore, the analysis of short-term mortgage delinquency rates during the summer period showed a significant and positive impact of temperature extremes, while no such significant result was found for precipitation extremes. This suggests a nuanced and temporally contingent influence of climatic factors on financial stability, with temperature extremes manifesting a more immediate impact on households' financial distress, as indicated by short-term delinquency rates. Conversely, during the winter period no significant result for both temperature and precipitation extremes was found on the long-term delinquency rates. However, precipitation extremes have a negative and significant effect the short-term delinquency rates, while the effect of temperature extremes is significantly positive.

Our research closely aligns with existing literature, demonstrating how extreme weather events impact mortgage delinquency rates. It specifically underscores the recognized financial risks of climate change, revealing that extreme temperatures significantly elevate short-term delinquency rates. The upwards effect of extreme temperatures on short-term mortgage delinquency rates suggests that periods of extreme temperature may strain homeowners' financial stability, leading to increased rates of mortgage delinquency. The main reason for this was proposed by Deng et al. (2021) and says that exposure to high temperatures can alter an individual's perception of climate change risks, leading them to view their current living situation as less desirable. This reassessment can result in changed behaviors, including a higher likelihood of mortgage default, due to a reduced sense of utility or satisfaction from their home and location. However, due to its insignificance, this does not necessarily hold for extreme precipitation. Regarding long-term mortgage delinquency rates, the significantly positive findings for both extreme temperature and precipitation during the summer period in our baseline model indicate that long-term mortgage delinquency rates are sensitive to extreme weather conditions. Overall, our results are in line with previous literature regarding the effects of extreme weather on mortgage delinquency rates.

Furthermore, the state-specific analysis revealed a heterogeneous impact across different states, suggesting that local economic conditions, policies, and climate resilience measures play a crucial role in how weather extremes affect mortgage delinquency rates. In states heavily reliant on agriculture, such as Georgia, North Carolina and Arkansas, extreme weather can dramatically influence income stability, directly affecting financial health. Meanwhile, states like Florida and Louisiana, with advanced preparedness and robust infrastructure for managing hurricanes and floods, show a greater resilience to the immediate economic shocks caused by such weather events. This disparity underscores the importance of region-specific strategies to mitigate the adverse effects of climate extremes on mortgage delinquencies.

Finally, the differing impacts of temperature and precipitation extremes on short- and long-term mortgage delinquency rates, as indicated by varying lag lengths in our analysis, offer insightful revelations about the temporal dynamics of extreme weather effects on financial stability. The observed lag effects suggest a nuanced interaction between the timing of extreme weather events and their financial impacts on households. Immediate and short-term impacts generally lead to an increase in delinquency rates, whereas long-term effects appear to be lessened, likely as a result of adaptation measures, financial recuperation, or assistance. The shift from positive to negative impacts, especially for precipitation, highlights the importance of adaptation measures and recovery assistance in mitigating the financial aftermath of extreme weather events. However, this analysis also confirmed the robustness, or absence thereof, for certain variables.

This study's findings on how temperature and precipitation extremes, as aspects of climate change, affect mortgage delinquency rates offer significant insights for both economic theory and the development of climate policy. This research underscores the importance of incorporating climate risk into financial risk assessment and management practices, particularly within the housing and mortgage sectors. Given the significant impact of both temperature and precipitation extremes on long-term mortgage delinquency, financial institutions, policymakers, and stakeholders in the real estate market must consider these findings in their planning, risk assessment models, and mitigation strategies.

This research contributes to an expanding body of evidence demonstrating the tangible effects of climate change on the financial system. Previous studies have highlighted the relationship between climate change and economic outcomes. Our study deepens this understanding by offering insights into how temperature and precipitation extremes affect financial stability in the mortgage sector. This not only corroborates the findings of earlier research but also provides a nuanced analysis that refines our understanding of climate risk as a multifaceted financial threat. Among the new insights contributed by this study is the identification of precipitation extremes as a potentially suitable predictor of long-term mortgage delinquency rates. Additionally, our research highlights the regional variability in the impacts of climate extremes, underscoring the importance of localized climate risk assessments and adaptation strategies.

While our research provides evidence of the impact of extreme temperature and precipitation on mortgage delinquency rates, it is crucial to address certain methodological limitations that have emerged from our analysis. Firstly, while our methodology effectively identifies relationships between extreme weather events and mortgage delinquency rates, attributing these patterns directly to climate change presents challenges. Differentiating the direct impact of climate change from natural variability in weather patterns requires a more nuanced approach, as the current model does not distinctly separate climate change-induced events from those occurring naturally. This limitation suggests the need for a mechanism or model that more accurately attributes extreme weather events to climate change, enhancing the robustness of our findings. Secondly, our methodology might inadvertently assume homogeneity in both weather and economic data, potentially oversimplifying the complex dynamics at play. The impact of extreme weather on mortgage delinquency is likely to vary across different locations and economic contexts, driven by regional differences in housing markets, mortgage practices, and vulnerability to specific types of extreme weather events such as hurricanes versus floods. This assumption of homogeneity overlooks the heterogeneous nature of these impacts, which could lead to misinterpretations of how climate change influences mortgage delinquency rates across various regions. Additionally, the relatively limited range of control variables used in the regression also imposes a challenge. The inclusion of other weather variables that may have an effect on both the dependent and independent variables, such as wind and snow, could potentially improve this study. Moreover, there could be other macro-economic variables that also play a role in this study, but were omitted. However, the trade-off between bad controls and over-controlling should always be taken into account.

The findings of this research offer valuable insights into the intersection of climate change and financial stability, prompting several recommendations for future research directions. First of all, it could be interesting to further look into each state specifically, as they all have different economic and geographic characteristics. Looking into the economic and climate policies, the frequency and intensity of extreme weather events, and the demography would give an even more insightful picture for each state. Future studies should also aim to extend the geographic scope, examining the relationship between climate change and mortgage delinquency across different regions with varying climate patterns and socio-economic contexts. This would enhance the generalizability of findings and provide a more comprehensive understanding of climate risk. Furthermore, exploring not only the frequency but also the magnitude of extreme weather events would provide a more holistic understanding of their effects, offering a fuller picture of how these extremes impact economic and financial outcomes. Additionally, another interesting perspective on this research could be to take the homeowners' characteristics into account, personally as well as geographically. This could provide an additional layer and interesting insight when comparing the homeowner's feasibility to pay their mortgage based on income or geographical location. Finally, the different lag specifications depict an interesting picture of the impact of extreme temperature and precipitation across different lag specifications. Future research could focus on a detailed temporal analysis, as understanding these temporal dynamics could provide valuable insights into the economic and social mechanisms at play.

7 Conclusion

This research aimed to investigate how climate change, manifested through extreme weather events, affects mortgage delinquency rates. Delving into the areas of temperature and precipitation extremes, we leveraged an extensive dataset encompassing nine southeastern U.S. states from January 2008 to December 2022. Our regression model, complemented by the heteroscedastic extremes approach and incorporating space-time trends, enabled us to discover patterns and relationships within our data, providing fresh insights into the extreme weather impacts on mortgage delinquency. The findings conclusively demonstrate that both precipitation and temperature extremes significantly elevate long-term mortgage delinquency rates during the summer period, which also holds for the effect of extreme temperature on short-term delinquency rates in the same period. Conversely, during the winter period, the effect of weather extremes on long-term delinquency rates is not significant, while both variables do report significant effects on the short-term delinquency rates.

We performed an extensive analysis, utilizing monthly data on mortgage delinquency rates and daily weather data from January 2008 to December 2022 across nine southeastern U.S. states. Employing a heteroscedastic framework, we analyzed the space-time trend of weather extremes and their impacts on mortgage delinquencies, controlling for economic factors and incorporating state-by-year and month fixed effects in our regression model. The process revealed significant regional variations in how weather extremes affect mortgage delinquency rates. This thesis contributes new insights by quantifying the relationship between extreme weather events and mortgage delinquency, a previously underexplored aspect. It highlights the pronounced effect of temperature and precipitation extremes and enriches the understanding of climate change's financial impacts, emphasizing the need for climate-resilient financial policies and practices.

While this thesis underscores the complexity of the relationship between climate change and mortgage delinquency, we can suggest several avenues for future research. A detailed state-specific analysis considering each state's unique economic, geographic, and policy landscapes could uncover nuanced insights into climate risk. Expanding the research to cover various regions would improve the findings' applicability and offer a broader understanding of climate impacts on financial stability. Additionally, investigating both the frequency and magnitude of extreme weather events could yield a comprehensive view of their economic repercussions. Incorporating homeowners' characteristics, both personal and geographical, could further refine our understanding, revealing how individual circumstances influence mortgage payment capabilities in the face of climate-induced challenges. Finally, further investigating the temporal dynamics of both weather variables could provide insightful information into the different mechanisms.

In conclusion, this thesis underscores the complex link between climate change, manifested through extreme weather events, and mortgage delinquency rates, reinforcing the importance of incorporating climate risk into financial planning and policy-making. By shedding light on this dynamic, the study paves the way for more informed, sustainable financial and housing market strategies that can withstand the challenges posed by a changing climate.

References

Addoum, J. M., Ng, D. T., & Ortiz-Bobea, A. (2020). Temperature shocks and establishment sales. *The Review of Financial Studies*, *33*(3), 1331–1366.

Aguilar-Gomez, S., Gutierrez, E., Heres, D., Jaume, D., & Tobal, M. (2022). Thermal stress and financial distress: Extreme temperatures and firms' loan defaults in Mexico. *Available at SSRN 3934688*.

Angrist, J. D., & Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Calabrese, R., Dombrowski, T., Mandel, A., Pace, R. K., & Zanin, L. (2021). Impacts of extreme weather events on mortgage risks and their evolution under climate change: A case study on Florida. *Available at SSRN 3929927*.

Cathcart, L., Ding, Z., Dufour, A., Rossi, L., & Varotto, S. (2023). Rain or Shine, Default Risks Align: Exploring the Climate-Default Nexus in Small and Micro Firms. *Available at SSRN 4512185*.

Cathcart, L., Dufour, A., Rossi, L., & Varotto, S. (2020). The differential impact of leverage on the default risk of small and large firms. *Journal of Corporate Finance*, *60*, 101541.

Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic literature*, *52*(3), 740–798.

Deng, Y., Han, C., Li, T., & Riddiough, T. J. (2021). Whither Weather?: High Temperature, Climate Change and Mortgage Default. *High Temperature, Climate Change and Mortgage Default (May 2021). Proceedings of Paris December 2021 Finance Meeting.*

Deng, Y., Han, C., Li, T., & Riddiough, T. J. (2023). Adaptation to Climate Change Through Mortgage Default and Prepayment. *Available at SSRN 4550947*.

ECB. (2020). *Guide on climate-related and environmental risks: supervisory expectations relating to risk management and disclosure* (tech. rep.). European Central Bank.

ECB. (2021). *Climate-related risks and financial stability* (tech. rep.). European Central Bank.

Einmahl, J. H., Ferreira, A., de Haan, L., Neves, C., & Zhou, C. (2022). Spatial dependence and space-time trend in extreme events. *The Annals of Statistics*, *50*(1), 30–52.

Einmahl, J. H., Haan, L., & Zhou, C. (2016). Statistics of heteroscedastic extremes. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *78*(1), 31–51.

Fisher, R. A., & Tippett, L. H. C. (1928). Limiting forms of the frequency distribution of the largest or smallest member of a sample. *Mathematical proceedings of the Cambridge philosophical society*, *24*(2), 180–190.

IPCC. (2021). *Climate Change 2021: The Physical Science Basis.* Cambridge University Press.

Issler, P., Stanton, R., Vergara, C., & Wallace, N. (2021). Housing and mortgage markets with climate risk: Evidence from California wildfires.

Jacob, B., Lefgren, L., & Moretti, E. (2007). The dynamics of criminal behavior: Evidence from weather shocks. *Journal of Human resources*, *42*(3), 489–527.

OECD. (2021). *Financial Markets and Climate Transition Opportunities: Challenges and Policy Implications* (tech. rep.). OECD.

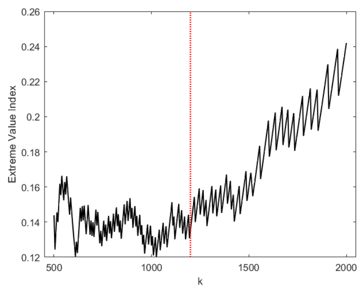
Pickands III, J. (1975). Statistical inference using extreme order statistics. *the Annals of Statistics*, 119–131.

Rossi, C. V. (2021). Assessing the impact of hurricane frequency and intensity on mortgage delinquency. *Journal of Risk Management in Financial Institutions*, *14*(4), 426–442.

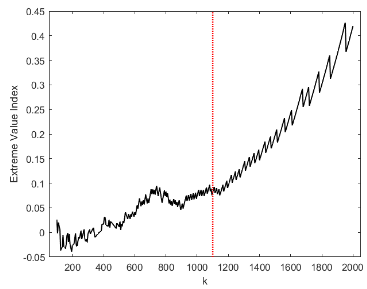
Tippett, L. H. (1925). On the extreme individuals and the range of samples taken from a normal population. *Biometrika*, 364–387.

Appendix

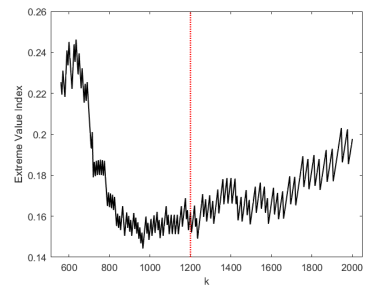
Stability plots



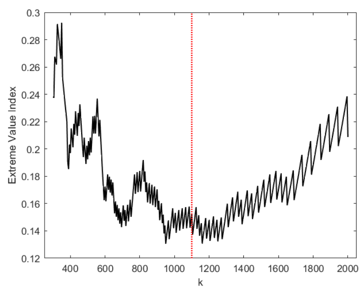
(a) Alabama



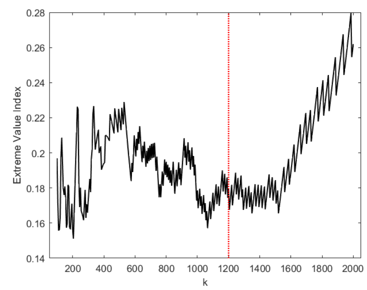
(b) Arkansas



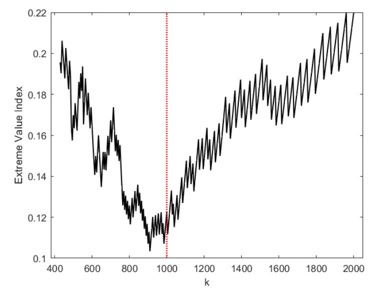
(c) Florida



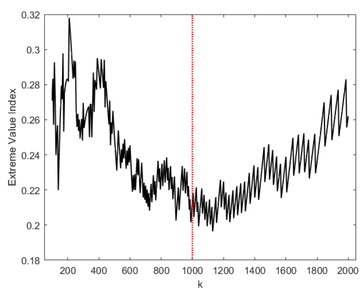
(d) Georgia



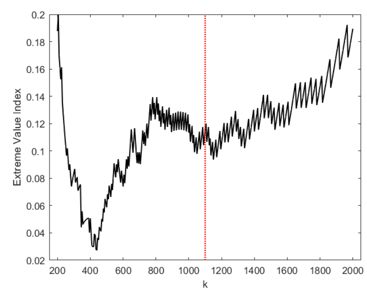
(e) Louisiana



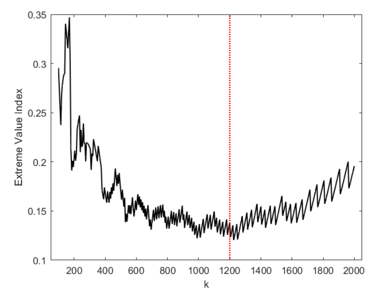
(f) Mississippi



(g) North Carolina

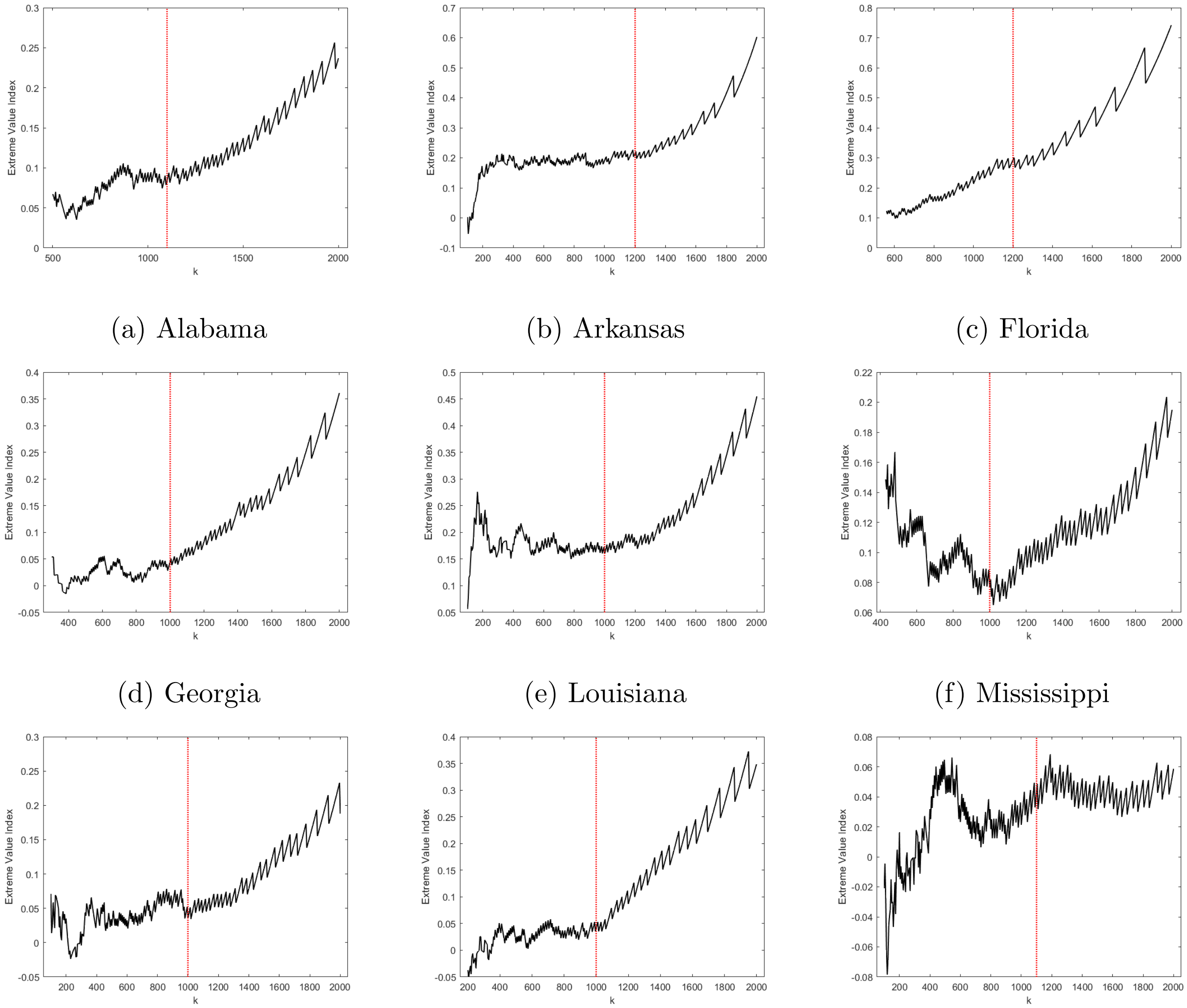


(h) South Carolina



(i) Tennessee

Figure 6: Stability plots of average daily precipitation for the summer period for each state

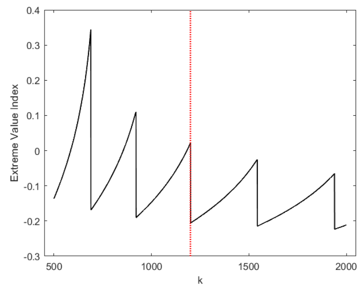


(a) Alabama (b) Arkansas (c) Florida

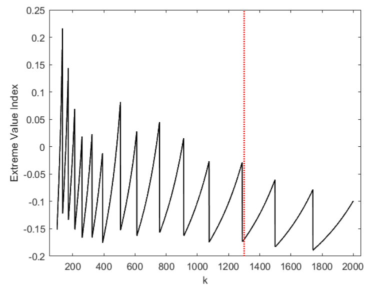
(d) Georgia (e) Louisiana (f) Mississippi

(g) North Carolina (h) South Carolina (i) Tennessee

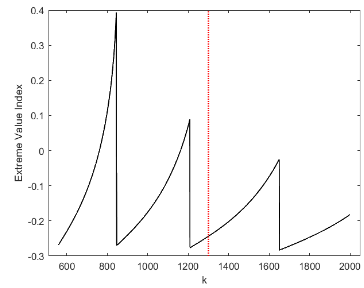
Figure 7: Stability plots of average daily precipitation for the winter period for each state



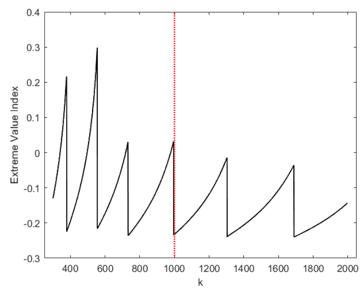
(a) Alabama



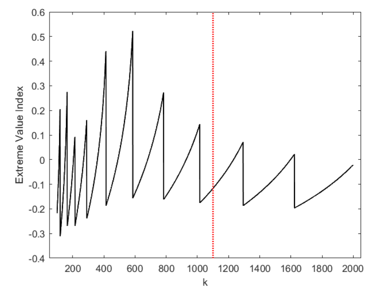
(b) Arkansas



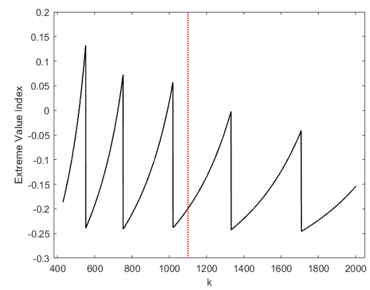
(c) Florida



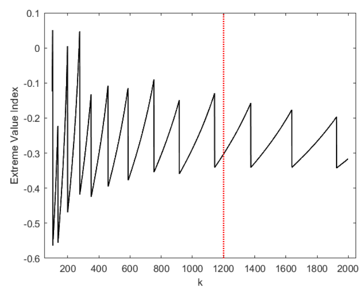
(d) Georgia



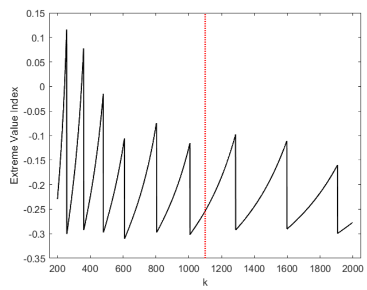
(e) Louisiana



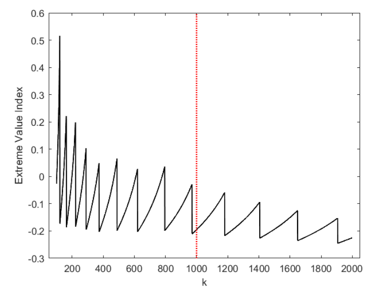
(f) Mississippi



(g) North Carolina

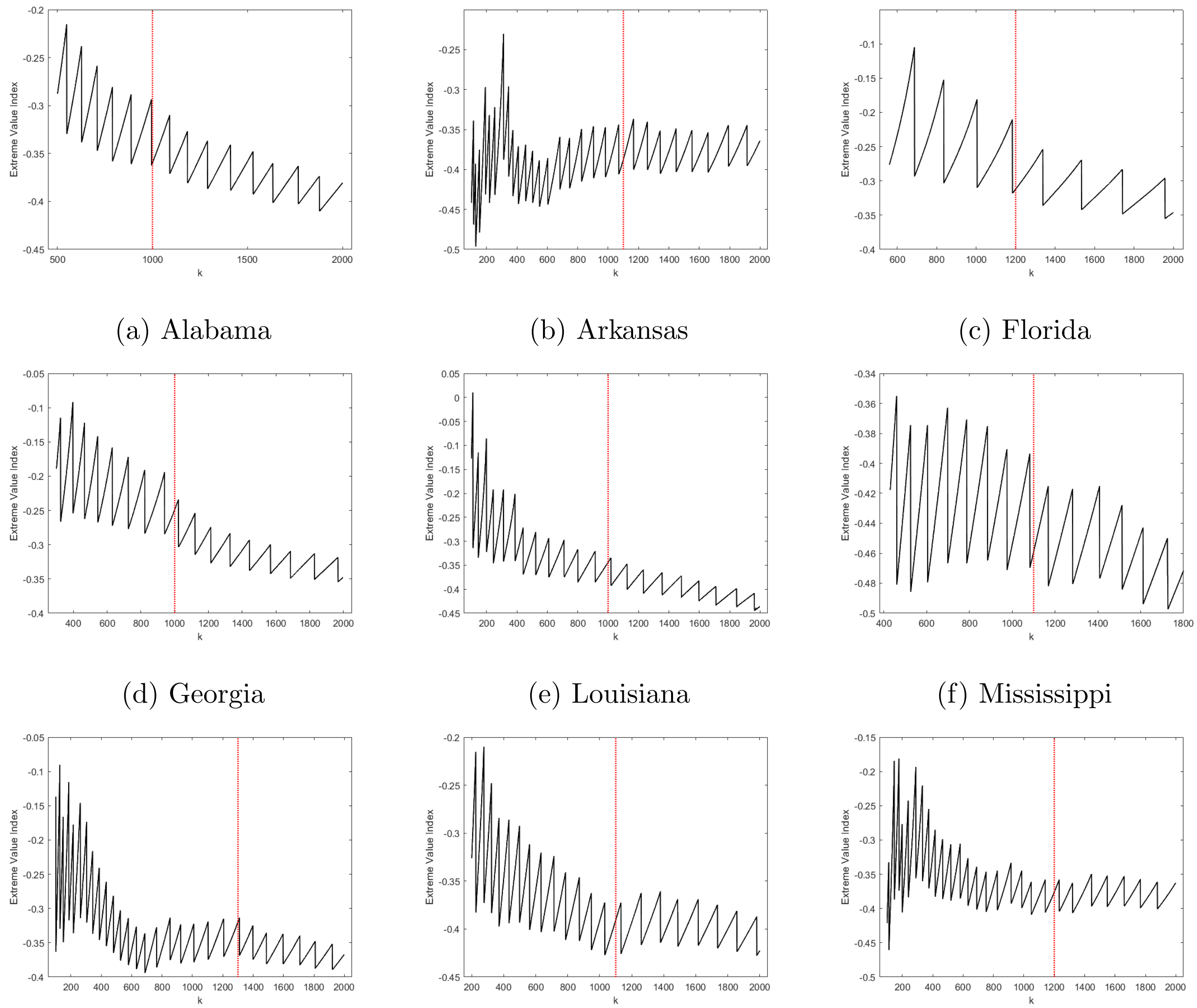


(h) South Carolina



(i) Tennessee

Figure 8: Stability plots of average daily temperature for the summer period for each state



(a) Alabama (b) Arkansas (c) Florida

(d) Georgia (e) Louisiana (f) Mississippi

(g) North Carolina (h) South Carolina (i) Tennessee

Figure 9: Stability plots of average daily temperature for the winter period for each state