# Weather, Credit, and Economic Fluctuations: Evidence from China

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**Abstract**

We constructed an Actuary Climate Index to measure extreme weather risks in China. Analyzing macroeconomic data through a structural vector auto-regression model suggests that a negative weather shock leads to persistently low GDP and credit obtained by non-financial firms. In our regression analysis of a panel of firms listed in China, the negative effects of weather shocks on firm level loans were statistically and practically significant. Further analysis suggests that credit risk and expectations are two important impact channels. A high existing credit risk or low confidence among firm managers, amplifies the negative effects of extreme weather on loans.

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# 1 Introduction

A large body of scientific literature claims that climate change has led to more frequent extreme weather events, such as abnormal temperatures and precipitation (Stott, 2016; Allan et al., 2021). The years 2000 to 2019 saw a worldwide record of more than 11,000 extreme weather events, resulting in a total loss of $2.56 trillion (Eckstein et al., 2021). Existing evidence speaks of adverse climate events significantly and immediately impacting aggregate economic output, (Dell et al., 2012; Burke et al., 2015; Kim et al., 2021) and organizational performance (Carleton and Hsiang, 2016; Cai et al., 2018; Somanathan et al., 2021), through physical damage, labor productivity loss, and other channels. China, a large developing country and an important stakeholder in the global climate actions, is subject to many extreme weather events. Based on the Global Climate Risk Index constructed by Eckstein et al. (2021), China ranked 41 in climate risks from 2000 to 2019. But in terms of China's economic losses and fatalities, the country held the first and fifth position, respectively.

This study examines the impact of extreme weather events on the Chinese economy at the macroeconomic and firm levels. Using daily data published by the China Meteorological Data Service Center, we constructed an Actuary Climate Index (ACI) to measure climate-related extreme weather risks in China. At the macroeconomic level, a structural vector autoregression (SVAR) model is estimated for ACI, gross domestic product (GDP), consumer price index (CPI), interest rate, and total credit obtained by non-financial firms, from 2001 Q1 to 2020 Q4. Our microeconomic analysis included panel regressions of loans obtained, and value-added produced by listed firms on the ACI, from the 2006 Q1 to 2020 Q4.

We obtained three key findings at the macroeconomic level. First, weather shocks have a significant negative impact on the GDP and credit financing. After a negative weather shock hits the economy, the GDP and credit obtained by non-financial firms remain persistently low up to the 24th quarter. In particular, following a one standard deviation shock to ACI index, GDP drops by 0.5% in the third quarter. Second, variance decomposition indicates that ACI shocks account for 14.2% of the variation in GDP in the long term, illustrating the importance of weather risks to China's macroeconomy. Third, our counterfactual analysis indicates that if the central bank does not react to weather shocks, the size of the drop in GDP following a one-standard-deviation weather shock will worsen from -0.42% to -0.49% in the long term. Aggregate evidence confirms the contractionary effect of weather shocks, and show that credit is an important mechanism for propagating the impact of weather shocks on the real economy.

Our panel regression analysis focuses on the significance of credit and credit-related factors, in economic responses to weather shocks, providing three principal findings. First, extreme weather events reduce loans obtained by listed firms and the drop in loans obtained precedes the drop in firm-level output. Second, turning to the determination of credit, we examine whether credit risk is an important channel of extreme weather affecting credit. We find supportive evidence in that expected default risk rises after extreme weather shocks. Consistent with the notion that collateral assets reduce credit risk, firms with higher collateral assets experience a smaller drop in credit, following extreme weather shocks. Macroeconomic factors that contribute to credit risk, such as tight monetary policies or economic uncertainty, worsen the negative effects of extreme weather. Third, expectations are another channel of impact. We find that extreme weather shocks cause stock analysts to downgrade the ratings of listed firms and reduce their profit forecasts. In addition, we examine two macro-level indicators related to general expectations, the entrepreneurs' confidence index and the production managers' index (PMI), and show that weather shocks reduce loans by a larger magnitude when expectations are weak. Value-added of firms drop after weather shocks, corroborating the macroeconomic finding that GDP is negatively affected by weathers. Overall, the firm-level regressions provide strong evidence that credit risk and expectations are two important channels of extreme weather that affect credit.

Our research is related to the literature on the economic impact of extreme weather events. Researchers have studied and established the effects of temperature and other weather shocks, on GDP, employment, agricultural output, productivity, investment, health, and consumption (Dell et al., 2012; Graff Zivin and Neidell, 2014; Burke et al., 2015; Burke and Emerick, 2016; Zhang et al., 2017; Jessoe et al., 2018; Lai et al., 2022). The present study is closely related to Gallic and Vermandel (2020) and Kim et al. (2021), who estimated the impulse responses of economic variables to weather shocks using time-series data. The former study applied the SVAR model to data from New Zealand, and built general equilibrium model with an agricultural sector to explain the mechanism. The latter study used US data to estimate the responses of industrial output, CPI, unemployment rate, and federal funding rate, in a smooth transition vector autoregression model (STVAR), discovering that the adverse effects of extreme weather becomes more prominent over time. While we also estimate the impact of weather shocks on output, our study differs from the above. We emphasize the role of credit in the propagation of weather shocks, and provide firm-level evidence to complement the macroeconomic analysis.

The present study also belongs to the emerging literature, that assesses the financial implications of climate change (see Hong et al. (2020) for a review of recent research). Climate change elevates credit risk in sections of the financial market studied, but the effects are nuanced. In the bond market, climate risk causes high-exposure counties to pay more underwriting fees and initial yields, to issue long-term municipal bonds (Painter, 2020). In the real estate market, climate risk negatively affects the prices of residential property (Giglio et al., 2021) (albeit the effect can be muted by weak beliefs about climate change (Baldauf et al., 2020)), induces risk sharing by mortgage securitization in hurricane prone regions (Ouazad and Kahn, 2019), but fails to capture the attention of mortgage lenders in property valuation (Garbarino and Guin, 2021). Relative to the literature, we choose to focus on the process of climate change's effect on Chinese firms' credit access. This is because, as typical in developing economies, the Chinese financial system is dominated by banks and credit plays the most important role in the Chinese firms' financing.

This study makes two contributions to the literature on climate risk's economic impacts. First, we construct a novel Chinese ACI, which summarizes the frequency and severity of extreme weather and estimates its economic consequences in China from 1990 to 2020. We provide substantial evidence that extreme weather adversely impacts output and credit at both macroeconomic and microeconomic levels. By conducting counterfactual analysis, our study suggeests that monetary policies should adequately address weather shocks in an environment with significant climate change.

Second, this study analyzes two mechanisms by which climate risks affect firm-level credit access. Extreme weather shocks elevate credit risk, thus dropping firms' obtained credit. Our findings based on bank credit, complement the existing literature on climate change and bond financing (Nguyen et al., 2020; Painter, 2020), showing that banks consider climate risk when extending credit to borrowers. Furthermore, we show that the negative effects of extreme weather on loans are amplified when expectations and confidence are lower. Our evidence on expectation channel matches with recent studies that emphasize the importance of beliefs in the pricing of assets sensitive to climate change (Choi et al., 2020; Krueger et al., 2020).

The remainder of this paper is organized as follows. Section 2 describes the construction of the ACI. The results of the macroeconomic and firm-level analyses are reported and discussed in Sections 3 and 4, respectively. Section 5 concludes the paper and discusses future research.

## 2 Measuring extreme weather in China

The original ACI was proposed by the American Academy of Actuaries, Canadian Institute of Actuaries, and Casualty Actuarial Society and Society of Actuaries in 2020. The index aims to monitor and quantify the frequency of extreme weather events, helping policymakers and the general public to understand the potential impact of climate change on the economy and society. Using the Chinese Surface Climate Daily Data, published by the China Meteorological Data Service Center, we applied the formula of original ACI, to construct the monthly time series of the Chinese ACI.

Specifically, we computed the average temperature, average precipitation, and average wind speed of the 840 surface stations, obtaining the following ACI component variables.

1. Extreme high temperature (P90): the variable takes a value of 1, if the average daily temperature is above the 90th centile of all daily averages in the sample, and 0 otherwise. The daily value can then be aggregated to the monthly level, which takes the value in [0,31].

2. Extreme low temperature (P10): the variable takes a value of 1, if the average daily temperature is below the 10th centile of all daily averages in the sample, and 0 otherwise. We then aggregate the daily value to the monthly level.

3. Concentrated precipitation (R): the variable is equal to the maximum precipitation level in a 5-day window within a month.

4. Drought (D): the maximum number of consecutive days with daily precipitation less than 1 mm.

5. Strong wind (W): the variable takes a value of 1, if the daily average wind power is above the 90th centile of all daily averages in the sample, and 0 otherwise. We then

aggregate the daily value to the monthly level.

Standardization of each variable, helped combine these component variables. As our main data range is from 1990 to 2020, we take the first half (January 1990 to December 2005) as the reference period. For each month $m = 1, 2,...,12$ and for each variable $x$, we subtract from $x$ the mean of $x$ values in month $m$ for all years in the reference period, and divide the difference by the corresponding standard deviation of $x$ from the reference period. Thus, the standardized variables measure extreme weather patterns relative to the reference period.

In the last step of construction, we aggregate the five component variables to obtain the Chinese ACI.

$$ACI_t = P90_t^{std} - P10_t^{std} + R_t^{std} + D_t^{std} + W_t^{std} \tag{1}$$

where superscript $std$ denotes the standardized variables. We follow the original definition of the ACI, such that $P10_t^{std}$ enters with a negative sign because a reduction in cold extremes is posited to increae weather risks. The mean ACI in the sample range was -0.073, with a standard deviation of 1.89. The variable ranged from -4.09 to 8.91.

Figure 1 shows the resulting monthly Chinese ACI. It initially trended downward, before rapidly rising after 2015. The end of the sampling period saw the highest 5-year average ACI, since 2000. In addition to the long-term trends, ACI substantially varies and indicates frequent short-term weather shocks. The monthly ACI reached its maximum value in September 2019 because $P90^{std}$ and $D^{std}$ were extremely high. Indeed, the China Meteorological Administration reports experiences of a 50% to 90% decreased precipitation since late July, in the eastern area of Hubei Province, the central and eastern areas of Hunan Province, most of Jiangxi Province, the southern area of Anhui Province, and the central and northern areas of Fujian Province, relative to normal years. This precipitation level was lowest, relative to corresponding periods since 1961. In September, the national average temperature was 1.1 degrees Celsius higher than normal, reaching the third-highest level since 1961.

We plot the five components of ACI from 1990 to 2020, in Figure 2. Post 2015 saw frequent cases of extremely high temperatures, with rarer occurrence of extremely low temperatures, indicating a rise in average Chinese temperature. Incidences of concentrated precipitation reached the lowest levels in spring and summer of 2011. Increasingly frequent and severe droughts peaked in August 2019. The time series for strong winds, showed notable spikes in September 2008 and January 2018.

To validate the ACI, we compared our time series with the China Climate Risk Index (available from July 2016 to December 2018), published by the National Climate Center (NCC) of China, and found the correlation coefficient between the two series was 0.44. The left panel of Figure 3 indicates the similarity between the two series, in major movements; however, the NCC China Climate Risk Index is much smoother than ours.

One difference in methodology is that the NCC index regards extreme cold as a factor positively related to weather risks, whereas in our index (constructed by following the methodology of the American Academy of Actuaries and Canadian Institute of Actuaries), the relationship is presumed to be negative. Thus, we compute an alternative ACI series, in which the extreme cold variable ($P10^{std}$) enters with a positive sign. The correlation coefficient between the alternative ACI index and NCC China Climate Risk Index increases to 0.50. Alternative ACI is shown in the right-hand panel of Figure 3. As shown in the robustness checks, our results are not sensitive to the treatment of extreme cold.

Overall, our ACI series provides a reasonable measure of weather risks from 1990 to 2020, based on official Chinese meteorological data. To match with the quarterly macroeconomic and firm-level variables, we convert our monthly ACI into a quarterly ACI (plotted in Figure 4) by taking the quarterly mean. The mean, minimum, maximum and standard deviation of the quarterly ACI are, -0.017, -1.66, 2.16, and 0.86.

## 3 Effect of weather risks on the macroeconomy

To examine the effect of weather risks on China's macroeconomy, we estimate a quarterly five-variable SVAR of ACI, gross domestic product (GDP), consumer price index (CPI), interest rate (rate), and total credit obtained from non-financial firms (Credit). The SVAR is specified as

$$B_0 Y_t = c + B_1 Y_{t-1} + B_2 Y_{t-2} + \cdots + B_p Y_{t-p} + w_t \tag{2}$$

where $Y_t = \{ACI, ln(GDP), ln(CPI), Rate, ln(Credit)\}$ is the observation matrix, $c$ is the intercept vector, and $B_0, B_1, \cdots, B_p$ are the coefficient matrices. Vector $w_t$ is the vector of structural shocks that satisfy $E(w_t) = 0$ and $E(w_s' w_t) = 0$.

As we are primarily interested in identifying weather shocks, similar to Kim et al. (2021), we put the ACI in the first position in the SVAR, and perform a Cholesky decomposition to recover structural shock to ACI. The ordering of variables means that weather shocks have contemporaneous effects on all other variables but not vice versa. We take an agnostic position on the temporal interactions between the other variables.

We obtain the GDP, CPI, and interest rate from the WIND database. Our measure of interest rate is the 7-day inter-bank repo rate (the R007 interest rate), which is a key money market interest rate in China. We choose R007 over similar interest rates because it is available for a long period and because it is a market-based measure of the cost of funds. The total credit obtained from non-financial firm leverage was retrieved from the Research Center for the National Balance Sheet. We set the lags to two, based on the Akaike information criterion (AIC) and other information criteria.

The estimation of the SVAR model yields the impulse response functions (IRFs) in Figure 5. From the figure, it can be seen that after a one-standard-deviation weather shock, GDP displays a persistent negative response, with a drop of 0.2% in the first quarter and a maximum drop of 0.5% in the third quarter. The subsequent responses are smaller in magnitude; however, the drop in GDP remains approximately 0.4%. The CPI inflation response is hump-shaped, and while the response is not initially significant, it becomes negative and significant starting from the 12th quarter and reaches approximately -0.1%. The results indicate weather shocks leading to persistently low economic activities.

The negative response of the interest rate is short-lived, as it drops after two quarters, reaching the lowest point of -0.1% in the third quarter, and returning to zero in the long-term. The initial IRFs of interest are similar to those of GDP, indicating that the central bank is likely to ease monetary policy in response to weather shocks. However, such adjustments in monetary policy are temporary and do not fully counteract the long-term negative impact of weather shocks.

Figure 5 shows that the credit obtained by non-financial firms drops at the impact. Despite the second quarter experiencing slightly improved credit access (interest rate is lowest here), it exhibits a long-term significant decline. This pattern again suggests that short-term monetary easing is insufficient for averting the long-term impact of weather shocks on credit access.

To quantify how the impact of weather risks changed over time, we performed historical and variance decompositions for the estimated SVAR. First, after detrending and demeaning the variables in SVAR, we decompose the *actual* deviation of a variable from its trend into contributions from external shocks to the five variables in each period. The visual results are shown in Figure 6.

The impact of weather risks on the GDP varies over time. A visual inspection of Figure 2 and Figure 6 suggests that between 2001 and 2006, the adverse effect of weather shocks is likely caused by the fact that the drought indicator ($D^{std}$) is above sample average. Between 2011 and 2015, weather shocks had either an insignificant or a positive effect on GDP growth. During this period, the indicator for concentrated precipitation ($R^{std}$) was historically low, and the extreme low temperature indicator ($P10^{std}$) became more positive. From 2013 to 2015, the strong wind indicator ($W^{std}$), drought indicator ($D^{std}$), and concentrated precipitation indicator ($R^{std}$) were all subdued.

In 2020, the weather shocks increased significantly, explaining a 1% drop in GDP. Notable weather events in 2020 were a lower number of occurrences of extremely low temperatures and more cases of concentrated precipitation during the first quarter. Meanwhile, our SVAR model implies that other shock, such as shock to GDP during the COVID-19 pandemic is the main reason behind the collapse in the growth rate, as it accounts for a 6% drop in GDP.

Second, we perform a variance decomposition for the estimated SVAR to assess the importance of different shocks in explaining the fluctuations of the variables. Table 1 presents the variance decomposition in the 1st, 4th, 8th, 16th, and 200th quarters, among which the 200th quarter approximates the infinite horizon. The impact of weather risks remains significant over the long term. Taking GDP as an example: weather risks accounts for only 2.8% of the variance in GDP Q1, but in the Q16, this fraction increases to a maximum of 18.3%. Over time, it settles to the long-term level of 14.2% in the 200th quarter. Similarly, weather shocks negligibly affect the variation of CPI in Q1. However, they account for 11.5% of the long-term CPI variation, indicating a substantial lag between the impact and CPI fluctuations. Regarding interest rates and credit obtained by non-financial firms, weather risks can explain 4.7% and 13.8% of their variation in the long term, respectively.

Overall, weather shocks are quantitatively important in explaining fluctuations in the GDP, CPI, and credit obtained by non-financial firms. Weather shocks account for less variation in interest rates, presumably reflecting that the central bank has not regarded climate risk as an important factor in monetary policy until recently. The persistence of the impact of weather shocks on variance decomposition is consistent with IRFs.

We conducted a counterfactual analysis to examine the role of monetary policy in the transmission of weather shocks in the macroeconomy. We impose a counterfactual restriction that monetary policy does not react to weather shocks by generating a sequence of hypothetical monetary policy shocks that offset the interest rate decrease triggered by weather shocks. This approach has been widely used in the literature for counterfactual analyses (e.g., see Hamilton and Herrera (2004) and Kilian and Lewis (2011)).

In Figure 7, we compare the means of counterfactual IRF and factual IRF. The results indicate whether monetary policy reacts to weather shocks or not, the output level is persistently below its initial level after the shock. Meanwhile, if the central bank does not react to weather shocks, the drop in output is significantly larger after the 4th quarter. Under the counterfactual, the drop in GDP ather the 20th quarter following a one-standard-deviation weather shock is -0.49%, which is deeper than the drop of -0.42% estimated from the actual data. The results suggest that the central bank should adequately consider the effects of weather shocks when implementing monetary policy.

To ensure that our counterfactual analysis does not involve unduly large shocks, we compute the 'modesty statistic' of Leeper and Zha (2003) for the implied offsetting shocks that deliver the counterfactual constraint of a constant interest rate. As shown in Figure 8, the absolute value of the modesty statistics is well below the critical value of two at all the horizons, meaning that the offsetting shocks are 'modest' and their materialization is unlikely to induce agents to adjust their expectation formation and beliefs about the structure of the economy.

# 4 Firm-level Evidence

Our SVAR analysis provides evidence that extreme weather shocks have persistent negative effects on the aggregate output and credit obtained by non-financial firms. A natural question is how the effects of extreme weather can propagate beyond the initial physical damage. In this section, we use firm-level panel regressions to focus on the mechanisms through which weather shocks could affect credit access in the firm sector.

## 4.1 Firm-level data

We obtained data on companies listed in China between the first quarter of 2006 and fourth quarter of 2020 from the WIND database. We excluded financial companies, companies with the designation 'ST' or 'PT, ' and companies reporting missing values.[1]

Our eventual dataset included an unbalanced panel of 4,186 firms and 251,160 firm-quarter observations. The summary statistics are reported in Table 2. The mean ratio of bank loans to total assets was 14.84%, with a standard deviation of 13.84%. The variable range is 0.11% to 68.20%; thus, the degree of dependence on bank loans varies considerably among the firms. Within the sample, 72.7% of firm-quarter observations are accounted for by non-state-owned enterprises (non-SOEs). Relative to SOEs, non-SOE firms are more likely to be financially constrained, making them more sensitive to extreme weather conditions.

## 4.2 Firm-level Panel Regression Results

### 4.2.1 Baseline credit regressions

First, we test whether extreme weather affects bank loans obtained by companies, using the following fixed-effects regression model:

$$(loan/asset)_{i,t} = \beta_1 ACI_{t-1} + \beta_2 X_{i,t-1} + d_t + d_i + \epsilon_{i,t} \tag{3}$$

where $i$ and $t$ are the indices for the firms and quarters, respectively. The dependent variable was the ratio of bank loans to total assets. $ACI_t$ denotes the Chinese climate risk index we constructed. The vector of control variables $X_{i,t}$ includes the log of firm-level assets (*lnasset*), firm age (*age*), fraction of tangible assets in total assets (*tangible*), and

[1] The designation 'ST' (Special Treatment) and 'PT' (Particular Transfer), indicates that a firm has reported a negative profit for two consecutive years and three consecutive years, respectively. These firms face a significant risk of de-listing due to regulatory rules in China.

return on assets ($ROA$). Quantities $d_t$ and $d_i$ are the time- and firm-fixed effects in the regression, respectively. Considering that the impact of weather risks on credit most likely occurs with a lag, we use a one-quarter lag of $ACI$ in the regression.

Table 3 presents the results of the main regressions. In the first column, we run a simple regression of credit on the ACI and time fixed effects. As expected, we find that extreme weather reduces bank loans obtained by companies. An $R^2$ value of 0.175 indicates that a significant portion of the variation in loans can be accounted for by the ACI and time fixed effects.[2] Column (2) is our baseline specification, and according to it, a one-unit increase in $ACI$ causes the bank loans to assets ratio to drop by 0.232 percentage point. The estimated effect is significant in both statistical and economic terms.

In columns (3) and (4), we use jump indicators for the ACI as alternative independent variables to estimate the effect of extreme weather shocks. In column (3) (respectively, column (4)), we define a jump event as a situation where the Hodrick-Prescott (HP) filtered ACI index (the original ACI time series) exceeds the mean value by more than 1.65 times the standard deviation. The ACI jump indicator takes the value of one if at least one jump event occurs in a quarter and zero otherwise. The coefficient on the jump indicator in column (3) (column (4)) indicates that if a jump event or events occurs in a quarter, the bank loan to assets ratio will drop by 0.374 (0.568) percentage point.

We exclude observations from 2008 to 2009 from the regression in column (5) to check whether the estimated effect of the ACI is confounded by the effects of demand shocks during the global financial crisis. Similarly, in Column (6), we exclude observations from 2020 to ensure that our findings are not driven by the devastating effect of the COVID-19 pandemic. In these two columns, the estimated coefficients at -0.140 and -0.214 are somewhat smaller in magnitude than the benchmark of -0.232 but remain significant. To rule out the possibility that our results could be driven by global and national macroe-

[2]When we drop the time fixed effects from the regression, a bi-variate regression of loans on ACI yields an $R^2$ of 0.151.

conomic conditions, in column (7), we control for the index of global economic policy uncertainty of Baker et al. (2016), the index of US monetary policy uncertainty of Baker et al. (2016), and China's M2 growth rate, GDP growth rate, and credit gap. Again, the coefficient estimate of -0.247 is very similar to that of the baseline in column (2). Overall, there is strong evidence that ACI shocks reduce companies' bank loans.

To ensure that our results are not driven by other unobserved aggregate events, we perform a placebo test based on 500 artificial samples generated by randomly resampling the ACI index. We re-estimate the baseline regression (column (2) in Table 3) using the artificial samples. Figure 9 shows the distributions of the estimated coefficients and p-values. The mean of the coefficient estimates is 0.0015, which is close to zero, and more than 90 percent of the estimates are not statistically different from zero. Our baseline coefficient (-0.232) from the real-world sample is considerably smaller than that of the first centile (-0.048) of all estimates from artificial samples. Thus, we conclude that other aggregate events are unlikely to explain the observed drop in bank loans following weather shocks. In the next two subsections, we examine whether the effects of extreme weather shocks affect loans through credit risk and expectation channels.

#### 4.2.2 The credit risk channel

In this section, we examine the roles of the four types of credit risk-related factors in the propagation or moderating effects of extreme weather shocks. First, we study whether extreme weather shocks reduce loans through expected default frequency (EDF), a measure of default risk. We construct the EDF index at the firm-quarter level by following the methods of Bharath and Shumway (2008) and Brogaard et al. (2017) and regress it on ACI. In the first column of Table 4, the results indicate that weather risks significantly increase the expected default probability. In the second column, when firm-level controls are added, we still find that extreme weather shocks raise the expected default probability. As default risk is naturally associated with a lower level of bank loans, taken together, the results suggest that weather risks depresse bank loans by elevating firm-level default risk.

Second, we analyzed the role of collateral assets. On the one hand, if extreme weather shocks inflict significant damage on fixed assets that can be used as collateral, firms' ability to obtain loans will be hindered. However, a large stock of fixed assets can help a firm retain credit access in the aftermath of extreme weather shocks. To estimate the net influence of collateral, Table 5 sequentially includes the interactions of three proxy variables for collateral assets with $ACI$. The three proxy variables (*low* $fixed$*-assets*, *low non-current-assets* and *low tangible-assets*[3]) are indicators of a firm with specified assets below the median level in the previous quarter. The interaction coefficients are all significant and negative, indicating that firms with less collateral face more difficulty in obtaining bank loans after extreme weather shocks. Thus, the availability of collateral assets moderates the effects of weather shocks.

Third, we examine whether macroeconomic credit risk interacts with extreme weather to cause a larger drop in financing. As central bank policies may mitigate or amplify the impact of weather shocks, we introduce an indicator for tight monetary policy (*tight* $MP$) and its interaction with extreme weather. The variable *tight* $MP$ is an indicator variable that takes the value of one for an increase in the quarterly average of the R007 interest rate and zero otherwise. In column (1) of 6, the coefficients of $ACI$ remain negative and the interaction between *tight* $MP$ and extreme weather is negative. The negative sign of the interaction term suggests that the adverse effects of extreme weather on firm-level loans are more severe when monetary policy is tighter. Intuitively, when the economy is hit by extreme weather in a tight monetary environment, firms face additional challenges in financing and maintaining their level of output.

In addition to monetary policy, we introduce three variables that capture different aspects of aggregate credit risk: the economic policy uncertainty (EPU) index of Baker et al. (2016), financial stress index of Park and Mercado (2014), and aggregate leverage

[3]We compute tangible-assets as the difference between total assets and intangible assets.

of non-financial firms (defined as the ratio of non-financial firms' total debt to GDP). EPU is an important indicator of credit risk, as it is associated with higher interest rates on bank loans and, hence, borrowers' credit risk (Ashraf and Shen, 2019). The financial stress measure proposed by Illing and Liu (2006) and adopted by Park and Mercado (2014) is a commonly used gauge of financial stress, and it is found to be positively related to expected financial loss, risk, or uncertainty. Hennessy and Whited (2007) make the case that the leverage ratio provides a measure of financial friction because the leverage ratio provides information about bankruptcy costs.[4]

Columns (2) through (4) in Table 6 report the regressions with economic policy uncertainty, financial stress, and leverage. The coefficients of the interaction terms are all negative and statistically significant, except for in the fourth column. Therefore, extreme weather, in general, has a more adverse effect on bank loans obtained by firms when economic policy uncertainty levels and financial stress are high.

Finally, we explore the cross-province variation in local government debt to provide further evidence for the credit risk channel. Our premise is that if the credit environment is more fragile in provinces where local government borrowing crowds out corporate borrowing, the drop in loans obtained by listed companies following an extreme weather shock should be larger in magnitude. To test this conjecture, we include in the regression the per capita value of outstanding bonds issued by all financing vehicles owned by all levels of government in a province (*LGFV bond*) and its interaction with ACI.[5] Column (6) shows that the interaction term is negative and significant. Overall, we can conclude that the drop in loans is greater when macroeconomic credit risk is higher.

[4]While Hennessy and Whited (2007) focuses on leverage at the firm level, we use its aggregate counterpart, because the aggregate leverage ratio likely indicates credit risk at the firm level.

[5]Up to 2015, local governments were prohibited from issued government bonds in the financial market. To circumvent this restrictions, local provinces use financing vehicles (LGFVs) to raise funds from the corporate bonds market. Throughout the sample, the value of outstanding bonds by LGFVs provide a consistent measure of implicit indebtedness of governments at the provincial level.

### 4.2.3 The expectation channel

Besides interacting with credit risk, extreme weather can reduce loans obtained by listed companies, by dampening the expectations of the financial markets and firms. First, when extreme weather disrupts a firm's normal operations, analysts' and investors' expectations become more pessimistic. To directly test the expectation channel, we regress four measures of firm-level ratings by stock analysts (obtained from the CSMAR database), on the ACI. To be specific, the rating-related measures are the mean rating (average ratings based on the opinions of 'buy', 'increase', 'neutral', 'reduce' and 'sell'), the modal rating, a discrete measure of average rating (defined as the rating in the five categories that is the closest to mean rating score), and mean analysts' forecast of net profit. In the first three regressions in Table 7, the estimated coefficients are all negative and statistically significant. In column (4), the results show extreme weather shocks significantly decreasing analysts' forecasts of firm profits. These findings provide evidence that, extreme weather dampens market expectations, in turn hindering the credit access of listed companies.

For further analysis, we run regressions with interactions between the ACI and several expectation-related macroeconomic variables. They are indicators of the Entrepreneurs' Confidence Index (ECI), the Purchasing Managers' Index (PMI), and the new-order component of the PMI index.[6] Our conjecture is that, when the corporate sector is more confident, the negative effect of extreme weather on loans is likely to be mitigated. Table 8 shows that all interaction terms of confidence-related variables have positive and significant coefficients. Thus, higher corporate confidence moderates negative effects of weather shocks. Overall, both sets of regressions provide strong evidence for the expectation channel.

[6]These three variables are from National Bureau of Statistics.

### 4.3 Heterogeneity

#### 4.3.1 Firm-level heterogeneity

Because the impact of ACI shocks may be more severe on underprivileged or more fragile firms, especially in a developing country such as China, we examine three types of firm heterogeneity: ownership, firm age, and firm size. We include the interactions of four variables that measure heterogeneity with $ACI$ in the regressions, and report the results in Table 9. In the first column, the variable $NonSOE$ identifies companies not controlled by state shareholding in the previous quarter. The interactive coefficient is negative, indicating a higher drop in non-SOE firm bank loans, compared to that obtained by SOE firms. This finding confirms that, SOEs have better access to financing.

In the second column, the variable *young* identifies firms aged below the median level in the previous quarter. The negative and significant ACI-*young* coefficient shows that the credit financing of younger firms are reduced to a greater extent following an extreme weather shock. The variable *small-size* (respectively, *small-sales*) is an indicators of previous quarter's asset bearing firms (sales) below the median level. Columns (3) and (4) portrays the negative and significant coefficients of the interactions of these two variables, with $ACI$. Therefore, smaller firms' credit financing is more vulnerable to extreme weather shocks.

#### 4.3.2 Sector-level heterogeneity

While much of the climate-impact literature focus on agriculture and manufacturing, weather shocks likely affect a wide range of economic activities. Therefore, we run separate regressions for loans obtained by listed firms, in three main economic sectors: primary (agricultural), secondary (industrial), and tertiary (services). Table 10 shows negative and similar ACI coefficients. However, for the primary sector listed firm subsample, ACI has an insignificant coefficient, with a t-statistic of 1.137. We believe that the lack of statistical significance is likely caused by the relatively smaller sample size. In columns (4)–(6), the interaction terms between $ACI$ and log *non-current asset* are also added. The sign, size, and significance level of the ACI coefficients, are comparable to those in columns (1)–(3). Meanwhile, the interaction term between the ACI and *non-current asset*, is positive and significant in the secondary sector. These results suggest that, the impact of extreme weather on loans is less severe for firms in the secondary sector which have higher non-current assets.

## 4.4 Robustness checks and extensions

This subsection presents two sets of robustness checks, and a set of extension results with value-added as the dependent variable. First, we used alternative credit financing measures as dependent variables. Second, we explored different methods of measuring extreme weather. Finally, mirroring the analysis of macroeconomic data, we used value-added as the dependent variable, to verify the drop in firm-level output after weather shocks.

### 4.4.1 Alternative dependent variables

We consider three alternative financial indicators as dependent variables: change in long-term debt-to-assets ratio, change in short-term debt-to-assets ratio, and log interest expenses. The first two columns of the estimation results reported in Table 11, show the association of extreme weather with reduced long- and short-term loans. In addition, long-term loans experience larger impact of climatic risks, than short-term loans. This is presumably due to the higher importance of credit default risk, in banks' decisions to grant long-term loans.

The third column indicates that extreme weather increases firms' interest rate expenses. This result is consistent with the theory of Bernanke et al. (1999), that credit premiums are negatively related to firms' net worth. Extreme weather aggravates default risk of firms, and lowers their net worth, leading banks to demand a higher credit premium.

#### 4.4.2 Alternative measure of weather risks

Our climate index construction used the base period of 1995-2005. To ensure that our results are not driven by the choice of the base period, we constructed an alternative climate index ($ACI\_b$) with a base period of 1960-1989. In the loan regression reported in column (1) of Table 12, the coefficient of $ACI\_b$ is -0.264, which is similar in magnitude to the coefficient of the ACI in the benchmark regression (-0.232).

In columns (2)–(6), we use each of the five components of the ACI as key independent variables. Extremely high and low temperatures, concentrated precipitation, and drought are all negatively related to financing at the firm level. However, strong winds have positive effects which is curious.

While the negative effect of extremely low temperatures is inconsistent with the original ACI methodology, which we followed in constructing the benchmark ACI for China, it supports the treatment of extremely low temperatures in the NCC China Climate Risk Index. The negative sign of $P10$ in the ACI methodology (see equation (1)) reflects the assumption that the absence of extremely low temperatures leads to disasters such as glacier melting and pest outbreaks. Meanwhile, extremely low temperatures can lead to economic losses, such as freezing of valuable crops and delays in construction activities. If the adverse effects of low temperature dominate (as suggested by column (3) of Table 12), then $P10$ should carry a positive sign in the climate risk index.

To ensure the robustness of our results, we introduce another measure ($ACI\_c$) in which the low-temperature indicator ($P10$) enters with a positive sign. In other words, we treat extremely low temperatures as a risk rather than a benefit. In column (7), the coefficient of this alternative climate risk index is -0.347, which is larger than the benchmark. Thus, our results remained robust to alternative treatments at extremely low temperatures in the climate risk index.

Similarly, the positive effect of strong winds is inconsistent with the original ACI methodology. While there is no obvious mechanism that justifies the positive effect, we can verify the robustness results by constructing another climate measure ($ACI\_d$), in which the strong wind indicator ($P10$) carries a negative sign. As the results in column (8) indicate, the coefficient of $ACI\_d$ (-0.240) remains similar to that of the benchmark estimate (-0.232).

#### 4.4.3 Value-added regression

Our analysis of macroeconomic data suggests that extreme weather shocks have significant and negative effects on GDP. In this subsection, we examine whether there is a similar drop in firm-level output. Thus, we use value added as the dependent variable and estimate the following model:

$$ln(value\ added_{i,t}) = \gamma_1 ACI_{t-2} + \gamma_2 X_{i,t-1} + d_t^{VA} + d_i^{VA} + \epsilon_{i,t-2} \quad (4)$$

where $i$ and $t$ are the indices for the firms and quarters, respectively. The dependent variable was log value added. The vector of the control variables is the same as in the baseline regression for loans. Quantities $d_t^{VA}$ and $d_i^{VA}$ are the time fixed effects and firm fixed effects in the value-added regression, respectively. We use the two-quarter lag of $ACI$ in the value added regression because of its better fit.

In the absence of value-added reported by listed companies in their financial statements, we construct value-added by applying the value-added method in GDP accounting of China to information from the balance sheet and income statements. The value added of a firm is calculated as the sum of employee compensation, business taxes and surcharges, depreciation of fixed assets, and operating profits. Employee compensation and operating profits are readily available from quarterly financial statements, but business taxes, surcharges, and fixed assets depreciation must be imputed. We apply the prevailing sales tax rate to the sales volume, wherever applicable, to obtain the estimated business taxes and surcharges.[7] We set the depreciation of fixed assets equal to a quarter of the reported

[7]The sales tax was applied to nine types of industries and economic activities before 2016. These

fixed asset depreciation in the annual statement.

A comparison of the loan and value-added regressions, shows extreme weather affecting credit with a one-quarter lag, and value-added with a two-quarter lag. This indicates that, the response in the credit market is faster than that in the output market. While it is plausible that the drop in credit propagates the impact of the weather shock on output, exploring the dynamics of loans and output at the firm level is beyond the scope of the current study.

Table 13 reports the value-added regression results, which mirror the loan regressions in Table 3. Columns (1) and (2) show that whether we include the control variables or not, the coefficients of $ACI$ are negative, statistically significant, and similar in magnitude. According to column (2), which is our benchmark, a one-unit change in the ACI index reduces a firm's value-added by 0.8% ($-0.008 \cdot 100\%$). In columns (3) and (4), when we use jump indicators to replace the $ACI$, similar results are obtained. In columns (5) (respectively, column (6)), we exclude observations from 2008 to 2009 (from 2020), and the results confirm that our findings are not driven by these specific years. In column (6), we control for a set of global and national macroeconomic variables and obtain similar results, indicating that other macroeconomic events are unlikely to drive our benchmark value-added results.

Similar to the loan regressions, we check whether the some unobserved aggregate events could drive our results by performing a placebo test. We re-estimate the benchmark regression from Table 13 column (2) with 500 artificial samples generated by random resampling of the ACI. Figure 10 depicts the distribution of the estimated coefficients of the ACI and the corresponding p-values. Overall, most of the coefficient estimates were statistically insignificant. The mean of the estimates was 0.00001, which is very close to

industries and activities are transportation (3% tax rate), construction (3%), telecommunication (3%), culture and sports (3%), finance and insurance (5%), services (5%), transfer of intangible assets (5%), sales of real estate (5%), and entertainment (5%–20%). In 2016, the sales tax was replaced by a value-added tax. Hence, we do not include the imputed sales tax in the value-added for firm observations, in and after 2016.

zero. Our baseline coefficient (-0.008) from the real-world sample is smaller than the first cen tile of all estimates (-0.0006). Hence, it is unlikely that unobserved aggregate events account for our results in value-added regressions.

Finally, we examine whether the effects of the ACI on loans and value-added are regime-specific. Specifically, we construct a indicator variable that takes the value of one if the value of the ACI index is positive and zero otherwise. We interact this indicator for a high-weather-risk regime with ACI to capture the regime-specific effects of extreme weather shocks and report the results in Table 14. The estimated coefficients on the interaction term are significant and negative for both loan and value-added regressions. Therefore, the effect of the ACI shock appears to be asymmetric, in that the negative effects of weather shocks are stronger in the high-weather-risk regime.

#### 4.4.4 Suggestive evidence on the supply and demand of loans

For our firm-level analysis, the dependent variable measures the loans obtained by firms and it is clearly an equilibrium quantity. When we observe a drop in loans obtained following an ACI shock, it may be caused by the drop in supply or demand of loans. Because it is extremely difficult to obtain transaction-level loan data which contain information about both banks and firms, we are unable to separate the supply effect and demand effect in estimation. In this subsection, we present evidence that our results are robust when we control for factors related to the aggregate supply of loans.

We add to the benchmark regression two variables that are associated supply of loans at the aggregate level. In the first column of Table 15, we control for the ratio of commercial banks's excess reserve to deposits at the aggregate level. Our premise is that when commercial banks are reluctant to extend loans, the excess reserve ratio will rise. In the second column, we add the overall capital adequacy ratio of the banking sector which is positively related with commercial banks' ability in making loans. In the third column, both variable are included. The results indicate that the loans obtained by listed firms are negatively (positively) related to the excess reserve ratio (capital adequacy ratio). In all regressions, the negative effects of ACI remain after we introduce these variables related to supply of loans.

To explore the potential effect of ACI on supply of loans, we regress the bank-level loans on ACI, controlling for national demand for loans. To be precise, the dependent variable is the log loans reported on quarterly balance sheets of 42 listed banks from 2006 to 2020. The first column of Table 16 shows that bank loans drop after an ACI shock. The negative result remains, albeit smaller magnitude, after we control for the national loan demand index (*demand*) published by People's Bank of China, log assets of the bank, and the deposit to loan ratio for the bank. Thus, the results from the second column provides suggestive evidence that climate risk likely reduces the supply of bank loans.

# 5 Conclusion

Climate change has had significant economic consequences. An important impact pathway, is the physical damage inflicted by weather events. China has a large land area, that frequently experience extreme weather events. This study constructs an ACI to measure Chinese extreme weather between 2001 and 2020, and estimates its effect on China's macroeconomy and its listed firms.

We first estimate a SVAR model of ACI, GDP, CPI, interest rate, and total credit obtained by non-financial firms from 2001 to 2020. The main finding is that a negative weather shock depresses GDP and credit in the long term, and lowers the interest rate in the short term. Following a one standard deviation shock to ACI index, GDP drops by 0.5% in the third quarter. The variance decomposition suggests that weather shocks account for 14.2% of GDP fluctuations in the long run. In the counterfactual analysis, we find that the impact of a weather shock becomes more severe if monetary policy does not loosen after the weather shocks.

Using a panel dataset of firms listed in China from 2006 to 2020, we then estimate the effects of extreme weather on firms' credit financing. Similar to our macroeconomic analysis, we find that loans drop after weather events. We find evidence of extreme weather shocks impacting credit financing, through the credit risk and the expectation channels. The effect of extreme weather shocks is more pronounced when firm-level and macro-level credit risks are higher. Regarding the expectation channel, we find that extreme weather shocks dampen market expectations, and their impact on firms is larger when firm managers' expectations and confidence are low. Taken together, our macroeconomic and microeconomic analyses provide strong evidence that extreme weather has a significant impact on the Chinese economy, particularly on the credit access of Chinese firms.

This study explores the infrequently traversed area of the effects of extreme weather conditions, on the Chinese economy. There is considerable future scope of research, to quantify the economic consequences of climate change in China and other countries. Our future intention is to use additional Chinese micro and regional data, for further similar studies. It would also be worthwhile, to study the process of monetary and credit policy usage, by central banks and financial authorities, to mitigate the effects of extreme weather conditions.

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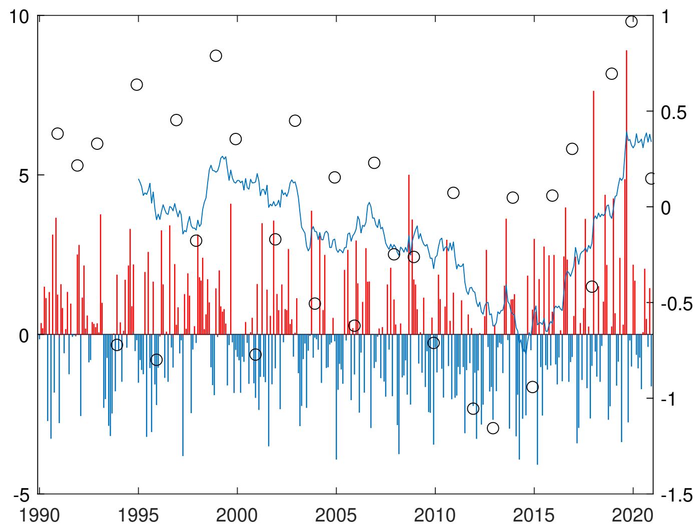


Figure 1: Monthly Actuaries Climate Index (ACI) of China

Source: Author's calculations. The bars are the monthly ACI values (left axis), the black dots are the annual ACI values (right axis) and the solid blue line (right axis) is the five-year moving average of the ACI index.

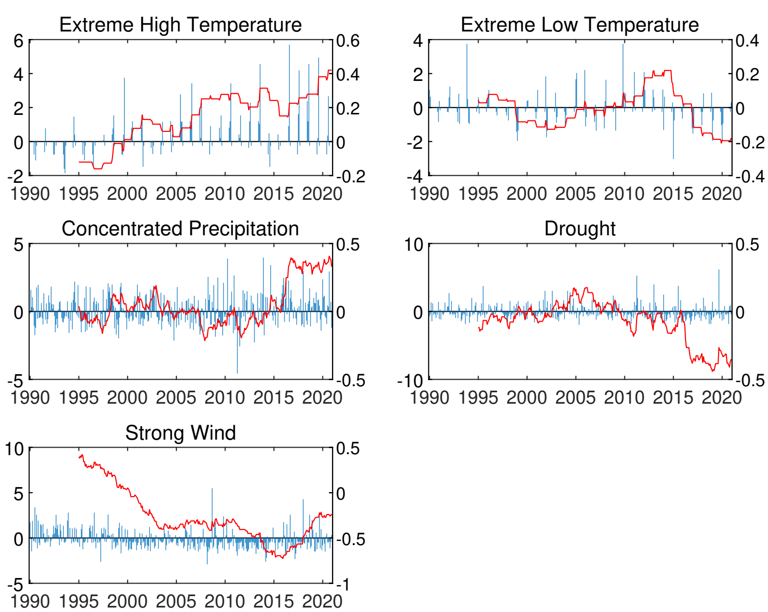


Figure 2: Components of Monthly ACI of China

Source: Author's calculations. The blue bars are the monthly series for the five components of the ACI index, and the red lines are the corresponding 5-year moving averages.

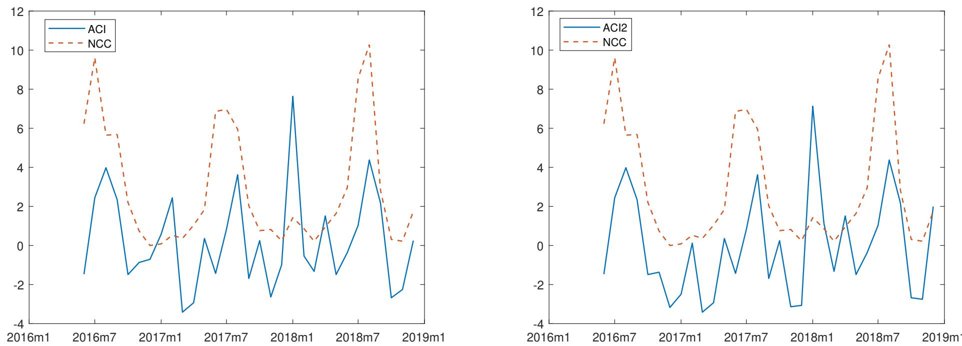


Figure 3: ACI vs NCC China Climate Risk Index

Source: Authors' calculations and the National Climate Center (NCC) of China. The ACI in the left panel is constructed using the original definition. The ACI in the right panel adopts an alternative definition in which extreme colds are presumed to add to weather risks.

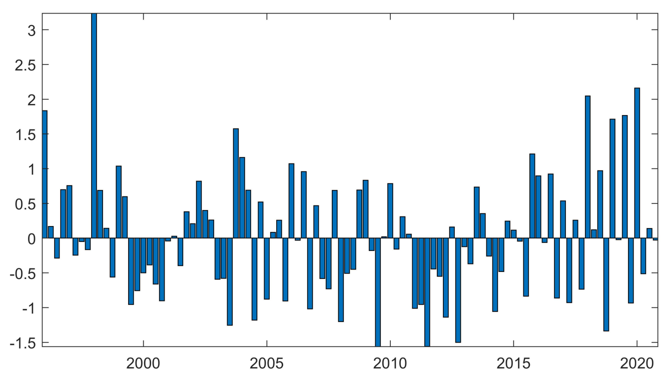


Figure 4: Quarterly ACI of China

Source: Author's calculations. The bars are the quarterly ACI values which are obtained by averaging the monthly ACI index.

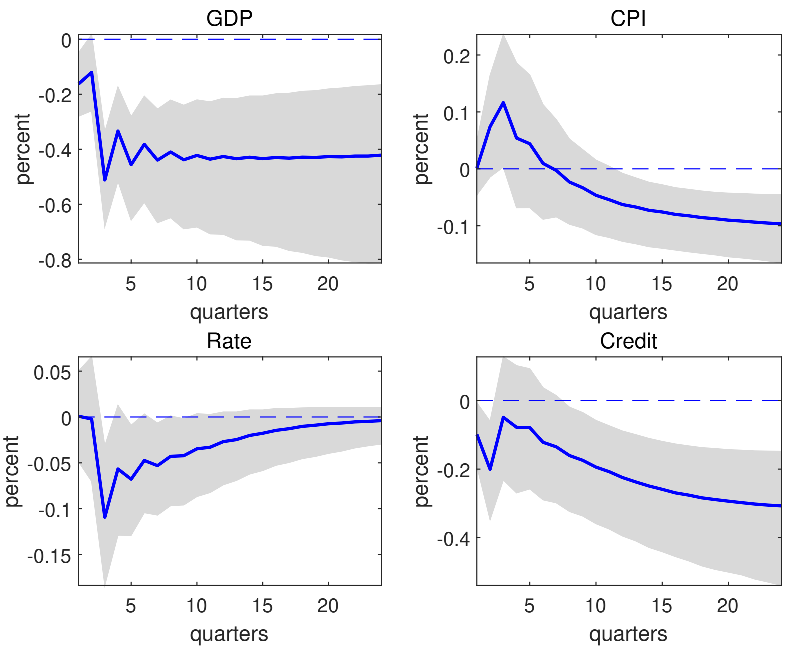


Figure 5: Impulse Responses to A One Standard Deviation Weather Shock

Note: The solid lines represent the mean impulse responses and the shaded area represents the 95% confidence interval.

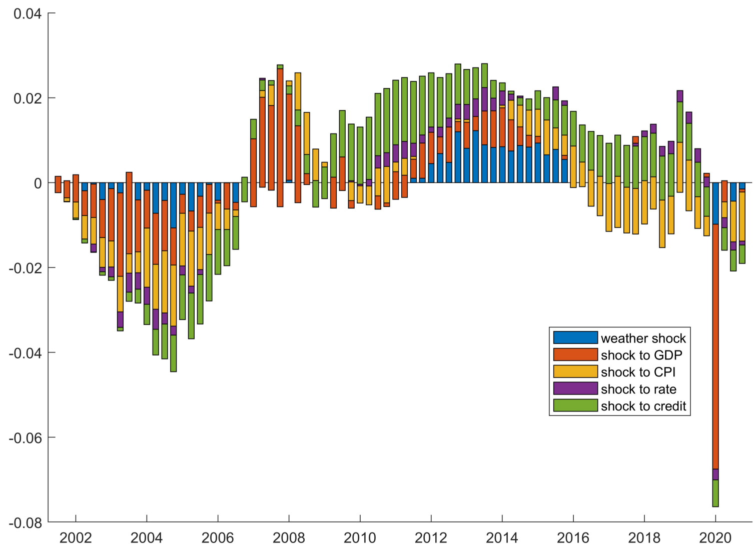


Figure 6: Historical Decomposition for GDP

Source: Authors' calculations. After detrending and demeaning the variables in the SVAR, we decompose the actual deviation of a variable from its trend into contributions from exogenous shocks to the five variables in each period.

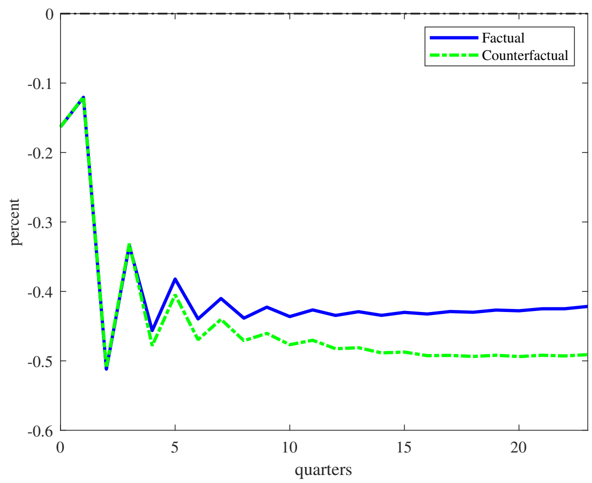


Figure 7: Counterfactual Analysis: Monetary Policy Does Not React to Weather Shocks
Source: authors' calculations. The green dashed line presents the would-be responses of output to a one standard deviation weather shock in a counterfactual scenario in which monetary policy does not react to the weather shock.

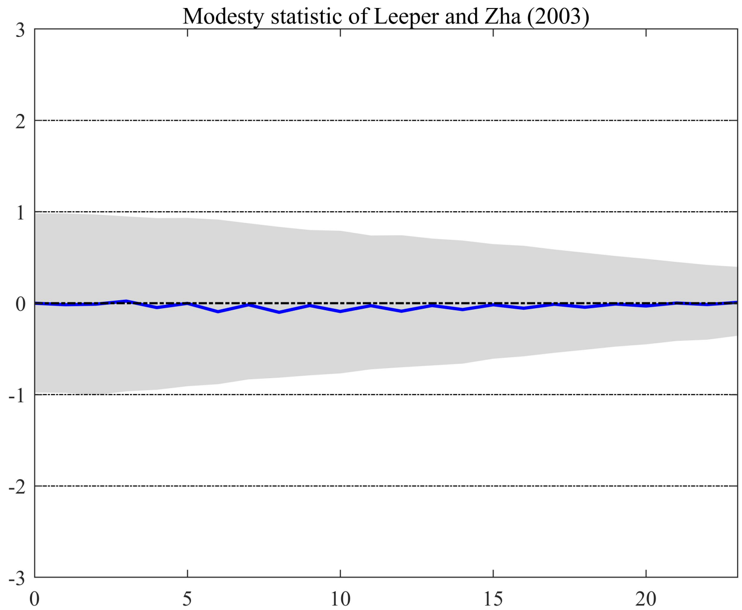


Figure 8: The Modesty Statistic for Counterfactual Analysis

Source: Authors' calculations. The modest statistic of Leeper and Zha (2003) tests whether the offsetting shocks used in the counterfactual analysis are large enough to alter agents' expectation. The critical values are -2 and 2.

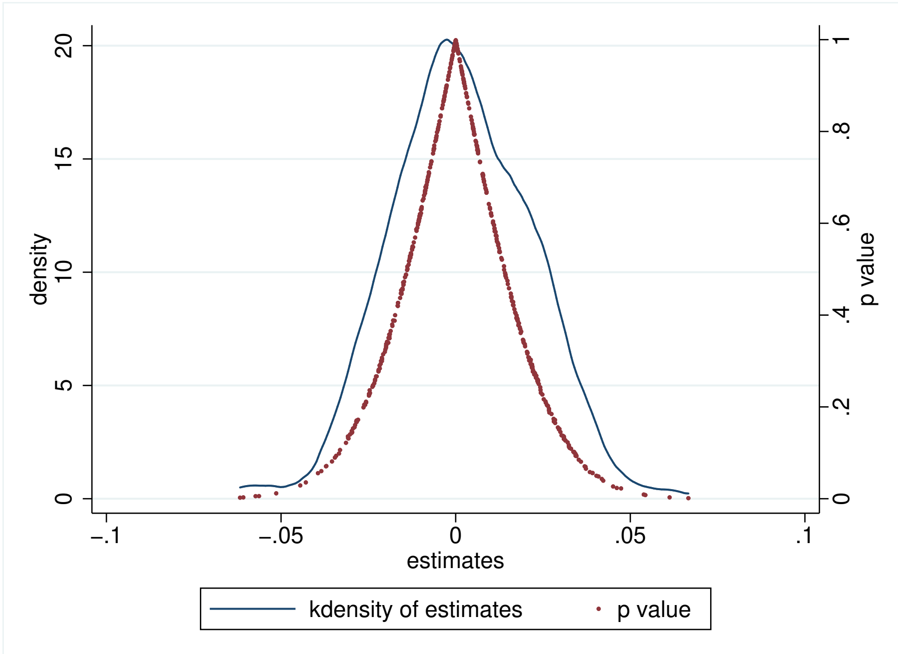


Figure 9: Distribution of Estimates of Bank Loans in the Placebo Test

Source: Authors' calculations. The figure presents the distribution of the estimated coefficients on the ACI index from loan regressions in a placebo test. The placebo test is conducted by randomly assigning values of the ACI index across time, and re-estimate the baseline specification using the randomized data. This simulation is repeated 500 times. The solid line plots the kernel density for estimated coefficients which is produced using the Epanechnikov kernel. Dashed line plots the p-value for testing the null that the estimated coefficient is zero.

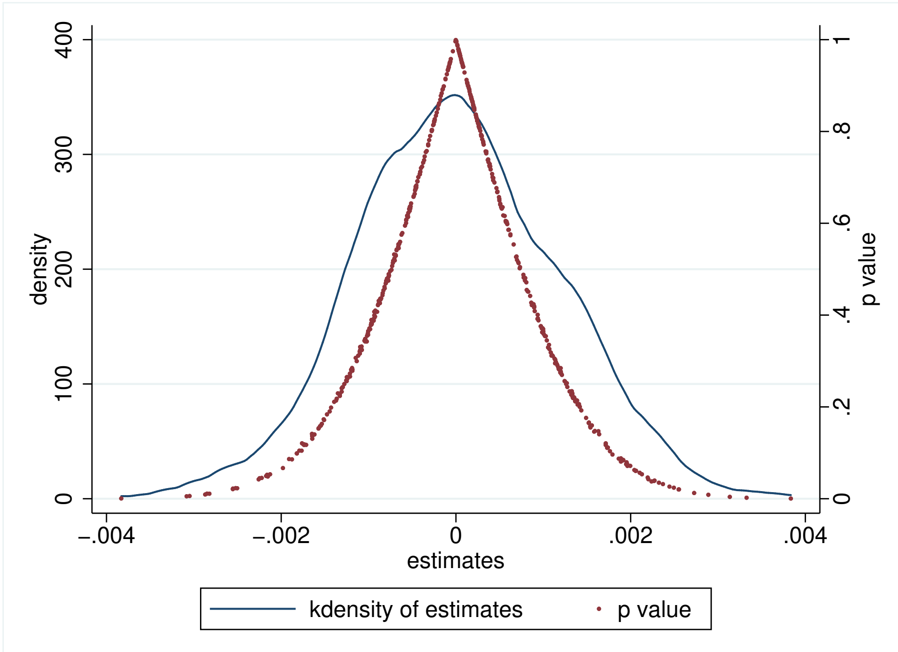


Figure 10: Distribution of Estimates of Value Added in the Placebo Test

Source: Authors' calculations. The figure presents the distribution of the estimated coefficients on the ACI index of value added regressions from a placebo test. The placebo test is conducted by randomly assigning the ACI index across time, and re-estimate the baseline specification using the randomized data. This simulation is repeated 500 times. The solid line plots the kernel density for estimated coefficients which is produced using the Epanechnikov kernel. Dashed line plots the p-value for testing the null that the estimated coefficient is zero.

Table 1: Variance Decomposition

| Variables | ACI | GDP | CPI | Rate | Credit |
|---|---|---|---|---|---|
| Q1 | 100 | 2.797469 | 0.001821 | 0.000553 | 1.689482 |
| Q4 | 96.53816 | 14.59756 | 1.854872 | 3.163351 | 2.187733 |
| Q8 | 95.21549 | 18.06606 | 1.558176 | 4.368398 | 2.968091 |
| Q16 | 94.31764 | 18.2578 | 3.386986 | 4.697204 | 8.41753 |
| Q200 | 94.13994 | 14.20422 | 11.51271 | 4.740766 | 13.81998 |

Note: Table 1 presents the variance decomposition at the 1st quarter, 4th quarter, the 8th quarter, 16th quarter, and the 200th quarter (which approximates the infinite horizon). The numbers are the percentage of variation of each variable that is explained by ACI shocks.

Table 2: Summary Statistics of Firms Listed in China

| | Unit | Obs | Mean | Std.Dev. | Min | Max |
|---|---|---|---|---|---|---|
| *loan/asset* | % | 122,002 | 14.842 | 13.836 | 0.110 | 68.195 |
| *value-added* | millions of 2020 yuan | 135,866 | 810.415 | 1934.400 | 0.078 | 17041.230 |
| *sales* | millions of 2020 yuan | 135,816 | 4236.334 | 10887.840 | 16.000 | 99112.550 |
| *asset* | millions of 2020 yuan | 135,866 | 11522.930 | 28818.700 | 120.000 | 276931.900 |
| *tangible* | % | 135,864 | 46.428 | 23.220 | -22.181 | 91.749 |
| *ROA* | % | 135,861 | 3.657 | 4.565 | -10.475 | 26.284 |
| *long-debt* | % | 74,978 | 8.598 | 9.673 | 0 | 106.996 |
| *short-debt* | % | 107,876 | 12.844 | 11.562 | 0.001 | 433.167 |
| *interest* | millions of 2020 yuan | 127,348 | 204.549 | 554.824 | 0.061 | 5229.057 |
| *NonSEO* | indicator | 135,866 | 0.609 | 0.488 | 0 | 1 |
| *age* | year | 135,808 | 16.963 | 5.830 | 1 | 32 |

Notes: (1) The variable *loan/asset* is the firm-level bank loans ratio to total assets, *tangible* is the fraction of tangible assets in total assets, *ROA* is the return on asset, *long-debt* is long-term debt to asset ratio, *short-debt* is the short-term debt to asset ratio, *interest* is the interest expenses, and *NonSOE* is an indicator for companies in which the state is not the controlling shareholder in the previous quarter.

(2) The average exchange rates of Chinese yuan to one US dollar, one UK pound, and one Euro in 2020 were 6.904, 8.857, and 7.878, respectively.

Table 3: Baseline Regressions

| Dep. Variable:*loan/asset* | (1) | (2) base | (3) jump | (4) jump | (5) w/o 2008-2009 | (6) w/o 2020 | (7) macro |
|---|---|---|---|---|---|---|---|
| *ACI* | -0.305*** | -0.232*** | -0.374*** | -0.586*** | -0.140*** | -0.214*** | -0.247*** |
| | (0.038) | (0.030) | (0.092) | (0.103) | (0.032) | (0.031) | (0.032) |
| *tangible* | | -0.180*** | -0.180*** | -0.180*** | -0.185*** | -0.182*** | -0.180*** |
| | | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| *ROA* | | -0.153*** | -0.153*** | -0.153*** | -0.153*** | -0.159*** | -0.148*** |
| | | (0.010) | (0.010) | (0.010) | (0.011) | (0.012) | (0.010) |
| *age* | | 0.181* | 0.183* | 0.182* | 0.212** | 0.062 | 0.170* |
| | | (0.096) | (0.096) | (0.096) | (0.098) | (0.113) | (0.096) |
| *ln(asset)* | | 0.274*** | 0.279*** | 0.278*** | 0.053 | 0.268*** | 0.284*** |
| | | (0.084) | (0.084) | (0.084) | (0.090) | (0.091) | (0.084) |
| *leverage* | | -0.005 | -0.004 | -0.013 | -0.077*** | 0.130*** | -0.538*** |
| | | (0.012) | (0.012) | (0.012) | (0.014) | (0.015) | (0.035) |
| *gepu* | | | | | | | -0.004* |
| | | | | | | | (0.002) |
| *mpu_us* | | | | | | | 0.006*** |
| | | | | | | | (0.002) |
| *vix* | | | | | | | -0.052*** |
| | | | | | | | (0.009) |
| *m2* | | | | | | | 0.022 |
| | | | | | | | (0.027) |
| *gdp* | | | | | | | -0.133*** |
| | | | | | | | (0.020) |
| *credittogdp* | | | | | | | 0.433*** |
| | | | | | | | (0.027) |
| *_cons* | 21.168*** | 19.993*** | 19.740*** | 19.835*** | 23.834*** | 22.808*** | 17.258*** |
| | (0.099) | (2.519) | (2.519) | (2.519) | (2.689) | (2.782) | (2.577) |
| *Dependent Variable's Mean* | 14.842 | 14.842 | 14.842 | 14.842 | 14.842 | 14.842 | 14.842 |
| *Controls* | N | Y | Y | Y | Y | Y | Y |
| *Time FE* | Y | Y | Y | Y | Y | Y | Y |
| *Firm FE* | N | Y | Y | Y | Y | Y | Y |
| $N$ | 121137 | 108225 | 108225 | 108225 | 98723 | 96087 | 108225 |
| $R^2$ | 0.175 | 0.593 | 0.592 | 0.592 | 0.600 | 0.601 | 0.594 |

Notes: (1) The dependent variable is bank loans ratio to total assets. Columns 3 and 4 use jump indicators to measure significant weather risks as large jumps in the ACI index. Columns 5 and 6 exclude observations from 2008 and 2009, and 2020. (2) *tangible* is the fraction of tangible assets in total assets; *ROA* is firm's return on assets; *age* is firm age; *ln(asset)* is the log of firm-level assets; *leverage* is the aggregate leverage of non-financial firms. *gepu* is the global economic uncertainty index; *mpu_us* is the monetary policy uncertainty for US; *vix* is the VIX index, *m2*, *gdp* and *credittogdp* are monetary supply, GDP growth rate and credit to GDP gap in China, respectively. (3) We use a one-quarter lag of *ACI* in the loan regression; (4) Robust standard errors are in parentheses. (5) All regressions include time fixed effects. Columns 2-7 include firm fixed effects. (6) ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Credit Risk Channel: Expected Default Risk

| Dep. Variable: *EDF* | (1) | (2) |
|---|---|---|
| *ACI* | 0.004*** | 0.001** |
| | (0.001) | (0.001) |
| *Dependent Variable's Mean* | 0.491 | 0.491 |
| *Controls* | N | Y |
| *Time FE* | Y | Y |
| *Firm FE* | Y | Y |
| *N* | 65444 | 65437 |
| $R^2$ | 0.354 | 0.391 |

Notes:(1) The dependent variables is expected default frequency of individual firm. (2) We use a one-quarter lag of *ACI* in the regression. (3) The numbers in parentheses are robust standard errors. (4) All regressions include control variables as in column (2) of Table 3, time fixed effects, and firm fixed effects. (5) ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Credit Risk Channel: the Role of Collateral

| Dep. Variable: *loan/asset* | (1) fixed assets | (2) non-current assets | (3) tangible assets |
|---|---|---|---|
| *ACI*low fixed assets* | -0.438*** | | |
| | (0.043) | | |
| *ACI*low non-current assets* | | -0.292*** | |
| | | (0.041) | |
| *ACI*low tangible assets* | | | -0.113*** |
| | | | (0.040) |
| *ACI* | -0.288*** | -0.257*** | -0.242*** |
| | (0.031) | (0.030) | (0.029) |
| *low fixed assets* | -0.327*** | | |
| | (0.108) | | |
| *low non-current assets* | | 0.244** | |
| | | (0.108) | |
| *low tangible assets* | | | 0.039 |
| | | | (0.110) |
| *Dependent Variable's Mean* | 14.842 | 14.842 | 14.842 |
| *Controls* | Y | Y | Y |
| *Time FE* | Y | Y | Y |
| *Firm FE* | Y | Y | Y |
| *N* | 104627 | 105574 | 105509 |
| $R^2$ | 0.593 | 0.593 | 0.606 |

Notes: (1) The dependent variable is bank loans ratio to total assets. (2) *low fixed assets* is an indicator for a firm with fixed assets below the median level in the previous quarter; *low non-current assets* is an indicator for a firm with non-current assets below the median level in the previous quarter; *low tangible assets* is an indicator for a firm with tangible assets below the median level in the previous quarter. (3) We use a one-quarter lag of *ACI* in the regression. (4) The numbers in parentheses are robust standard errors. (5) All regressions include control variables as in column 2 of Table 3, time fixed effects, and firm fixed effects. (6) ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Credit Risk Channel: Macroeconomic Risk

| Dep. Variable: *loan/asset* | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *ACI*tight MP* | -0.371*** | | | | |
| | (0.046) | | | | |
| *ACI*EPU* | | -0.206*** | | | |
| | | (0.029) | | | |
| *ACI*stress* | | | -0.289*** | | |
| | | | (0.083) | | |
| *ACI*leverage* | | | | -0.006 | |
| | | | | (0.005) | |
| *ACI*LGFV bond* | | | | | -0.107*** |
| | | | | | (0.029) |
| *ACI* | -0.206*** | -0.099** | -0.238*** | -0.248*** | -0.199*** |
| | (0.029) | (0.039) | (0.030) | (0.033) | (0.032) |
| *MP* | -0.101 | | | | |
| | (0.063) | | | | |
| *EPU* | | -0.243** | | | |
| | | (0.118) | | | |
| *stress* | | | 0.528*** | | |
| | | | (0.119) | | |
| *leverage* | | | | -0.006 | |
| | | | | (0.012) | |
| *LGFV bond* | | | | | 0.209*** |
| | | | | | (0.063) |
| *Dependent Variable's Mean* | 14.842 | 14.842 | 14.842 | 14.842 | 14.842 |
| *Controls* | Y | Y | Y | Y | Y |
| *Time FE* | Y | Y | Y | Y | Y |
| *Firm FE* | Y | Y | Y | Y | Y |
| *N* | 108225 | 108225 | 108225 | 108225 | 92810 |
| $R^2$ | 0.593 | 0.593 | 0.593 | 0.593 | 0.614 |

Notes: (1) The dependent variables is bank loans ratio to total assets. (2) *tight MP* is an indicator variable for an increase in the quarterly average of the R007 interest rate; *EPU* is the Economic Policy Uncertainty index from Baker et al. (2016); *stress* is the financial stress index from the Park and Mercado (2014); *leverage* is the aggregate leverage of non-financial firms; *LGFV bond* is the per capita value of outstanding bonds issued by all financing vehicles owned by all levels of local government in the province where a firm located. (3) We use a one-quarter lag of *ACI* in the regression. (4) Robust standard errors are in parentheses. (5) All regressions include control variables as in column 2 of Table 3, time fixed effects, and firm-fixed effects. (6) ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Expectation Channel: Rating

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dep. Variable: | avg-rate | mode-rating | discrete-avg-rating | profit-forecast |
| *ACI* | 0.008*** | 0.008*** | 0.010*** | -0.009*** |
| | (0.002) | (0.002) | (0.002) | (0.003) |
| *Dependent Variable's Mean* | 1.731 | 1.636 | 1.769 | 19.631 |
| *Controls* | Y | Y | Y | Y |
| *Time FE* | Y | Y | Y | Y |
| *Firm FE* | Y | Y | Y | Y |
| *N* | 71850 | 71850 | 71850 | 45298 |
| $R^2$ | 0.351 | 0.308 | 0.324 | 0.875 |

Notes: (1) The dependent variables are the mean rating (average ratings based on the opinions of 'buy', 'increase', 'neutral', 'reduce' and 'sell'), the modal rating, a discrete measure of average rating (defined as the rating in the five categories that is the closest to mean rating score), and mean analysts' forecast of net profit. (2) Robust standard errors are in parentheses. (3) All regressions include control variables as in column 2 of Table 3, time fixed effects, and firm-fixed effects. (4) ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Expectation Channel: Confidence

| Dep.Variable: *loan/asset* | (1) | (2) | (3) |
|---|---|---|---|
| *ACI*Confidence* | 0.019*** | | |
| | (0.003) | | |
| *ACI*PMI-New-order* | | 0.042*** | |
| | | (0.009) | |
| *ACI*PMI* | | | 0.073*** |
| | | | (0.014) |
| *ACI* | -0.271*** | -0.208*** | -0.196*** |
| | (0.031) | (0.033) | (0.034) |
| *Confidence* | -0.045*** | | |
| | (0.006) | | |
| *PMI-New* | | -0.108*** | |
| | | (0.016) | |
| *PMI* | | | -0.156*** |
| | | | (0.027) |
| *Dependent Variable's Mean* | 14.842 | 14.842 | 14.842 |
| *Controls* | Y | Y | Y |
| *Time FE* | Y | Y | Y |
| *Firm FE* | Y | Y | Y |
| *N* | 108225 | 108225 | 108225 |
| $R^2$ | 0.593 | 0.593 | 0.593 |

Notes: (1) The dependent variables is bank loans ratio to total assets. (2) *Confidence* is the entrepreneurs' confidence; *PMI-New-order* is the purchasing managers' index: new order; *PMI* is the the overall purchasing managers' index. (3) We use a one-quarter lag of *ACI* in the regression. (4) Robust standard errors are in parentheses. (5) All regressions include control variables as in column 2 of Table 3, time fixed effects, and firm-fixed effects. (6) ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Firm-level Heterogeneity

| Dep. Variable: *loan/asset* | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *ACI*NonSOE* | -0.345*** | | | |
| | (0.038) | | | |
| *ACI*young* | | -0.248*** | | |
| | | (0.042) | | |
| *ACI*low-fixed assets* | | | -0.442*** | |
| | | | (0.039) | |
| *ACI*low-sales* | | | | -0.417*** |
| | | | | (0.039) |
| *ACI* | -0.273*** | -0.271*** | -0.279*** | -0.285*** |
| | (0.029) | (0.031) | (0.029) | (0.029) |
| *small-assets* | | | -0.323*** | |
| | | | (0.121) | |
| *small-sales* | | | | -0.429*** |
| | | | | (0.114) |
| *Dependent Variable's Mean* | 14.842 | 14.842 | 14.842 | 14.842 |
| *Controls* | Y | Y | Y | Y |
| *Time FE* | Y | Y | Y | Y |
| *Firm FE* | Y | Y | Y | Y |
| *N* | 108225 | 99138 | 106713 | 106974 |
| $R^2$ | 0.593 | 0.596 | 0.594 | 0.594 |

Notes: (1) The dependent variable is bank loans ratio to total assets. (2) *NonSOE* is an indicator for companies in which the state is not the controlling shareholder in the previous quarter; *young* is an indicator for a firm with age below the median level in the previous quarter; *low-fixed assets* is an indicator for a firm with fixed assets below the median level in the previous quarter. *low-sales* is an indicator for a firm with sales below the median level in the previous quarter. (3) We use a one-quarter lag of *ACI* in the regression. (4) The numbers in parentheses are robust standard errors. (5) All regressions include control variables as in column 2 of Table 3, time fixed effects, and firm-fixed effects. (6) ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Industry-level Heterogeneity

| Dep. Variable: *loan/asset* | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | primary | secondary | tertiary | primary | secondary | tertiary |
| *ACI* | -0.222 | -0.241*** | -0.216*** | -0.242 | -0.315*** | -0.233*** |
| | (0.197) | (0.034) | (0.063) | (0.207) | (0.035) | (0.067) |
| *ACI*low non-current asset* | | | | 0.056 | 0.143*** | 0.039 |
| | | | | (0.110) | (0.015) | (0.026) |
| *Dependent Variable's Mean* | 14.842 | 14.842 | 14.842 | 14.842 | 14.842 | 14.842 |
| *Controls* | Y | Y | Y | Y | Y | Y |
| *Time FE* | Y | Y | Y | Y | Y | Y |
| *Firm FE* | Y | Y | Y | Y | Y | Y |
| $N$ | 3033 | 80822 | 24348 | 2984 | 78840 | 23888 |
| $R^2$ | 0.608 | 0.608 | 0.543 | 0.609 | 0.608 | 0.548 |

Notes: (1) The dependent variable is bank loans ratio to total assets. (2) *low non-current asset* is an indicator for a firm with non-current assets below the median level in the previous quarter; Column 1 and 4 are sub-samples of primary sector; Column 2 and 5 are sub-samples of secondary sector; Column 3 and 6 are sub-samples of tertiary sector. (3) We use the one-quarter lag of *ACI* in the regression. (4) Robust standard errors are in parentheses. (5) All regressions include control variables as in column 2 of Table 3, time fixed effects, and firm-fixed effects. (6) ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 11: Additional Dependent Variables

| | (1) | (2) | (3) |
|---|---|---|---|
| Dep. Variable: | *longdebt* | *shortdebt* | *ln(interest expense)* |
| *ACI* | -0.040*** | -0.017*** | 0.030*** |
| | (0.003) | (0.003) | (0.003) |
| *Dependent Variable's Mean* | 0 | 0 | 17.106 |
| *Controls* | Y | Y | Y |
| *Time FE* | Y | Y | Y |
| *Firm FE* | Y | Y | Y |
| *N* | 72784 | 105985 | 131506 |
| $R^2$ | 0.035 | 0.042 | 0.779 |

Notes:(1) The dependent variables are the change in the long-term debt to asset ratio, the change in the short-term debt to assets ratio, and log interest expenses. To facilitate comparison, the first two dependent variables are normalized to have a mean of 0 and a standard deviation of 1. (2) We use a one-quarter lag of *ACI* in the regression. (3) The numbers in parentheses are robust standard errors. (4) All regressions include control variables as in column 2 of Table 3, time fixed effects, and firm-fixed effects. (5) ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 12: Alternative ACI Measures

| Dep. Variable: *loan/asset* | (1) 1960–1989 | (2) P90 | (3) P10 | (4) Rain | (5) Drought | (6) Wind | (7) Lowtemp | (8) Wind(negative) |
|---|---|---|---|---|---|---|---|---|
| *ACI_b* | -0.264*** | | | | | | | |
| | (0.039) | | | | | | | |
| *P90std* | | -0.673*** | | | | | | |
| | | (0.072) | | | | | | |
| *P10std* | | | -0.646*** | | | | | |
| | | | (0.078) | | | | | |
| *Rstd* | | | | -0.268*** | | | | |
| | | | | (0.047) | | | | |
| *Dstd* | | | | | -0.320*** | | | |
| | | | | | (0.045) | | | |
| *Wstd* | | | | | | 0.123* | | |
| | | | | | | (0.068) | | |
| *ACI_c* | | | | | | | -0.347*** | |
| | | | | | | | (0.027) | |
| *ACI_d* | | | | | | | | -0.240*** |
| | | | | | | | | (0.027) |
| *Dependent Variable's Mean* | 14.842 | 14.842 | 14.842 | 14.842 | 14.842 | 14.842 | 14.842 | 14.842 |
| *Controls* | Y | Y | Y | Y | Y | Y | Y | Y |
| *Time FE* | Y | Y | Y | Y | Y | Y | Y | Y |
| *Firm FE* | Y | Y | Y | Y | Y | Y | Y | Y |
| $N$ | 108225 | 108225 | 108225 | 108225 | 108225 | 108225 | 108225 | 108225 |
| $R^2$ | 0.593 | 0.593 | 0.593 | 0.592 | 0.593 | 0.592 | 0.593 | 0.593 |

Notes:(1) The dependent variables is bank loans ratio to total assets; *ACI_b* is an alternative climate index with the base period of 1960–1989; *P90std*, *P10std*, *Rstd*, *Dstd*, *Wstd* are each of the five standardized components of the climate risk index, which indicate extreme high temperature, extreme low temperature, concentrated precipitation, drought and strong wind, respectively; Climate measure *ACI_c* in which the low temperature indicator (P10) enters with a positive sign; climate measure *ACI_d* in which the strong wind indicator (P10) carries a negative sign. (2) We use a one-quarter lag of *ACI* in the regression. (3) The numbers in parentheses are robust standard errors. (4) All regressions include control variables as in column 2 of Table 3, time fixed effects, and firm-fixed effects. (5) ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 13: Value-added Regressions

| Dep. Variable:*ln(VA)* | (1) | (2) baseline | (3) jump | (4) jump | (5) w/o 2008-2009 | (6) w/o 2020 | (7) macro |
|---|---|---|---|---|---|---|---|
| *ACI* | -0.010*** | -0.008*** | -0.038*** | -0.030*** | -0.007*** | -0.003* | 0.217*** |
| | (0.002) | (0.002) | (0.005) | (0.006) | (0.002) | (0.002) | (0.028) |
| *tangible* | | 0.000 | 0.000 | 0.000 | -0.000 | 0.000* | -0.181*** |
| | | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.003) |
| *ROA* | | 0.043*** | 0.043*** | 0.043*** | 0.043*** | 0.043*** | -0.146*** |
| | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.010) |
| *age* | | 0.023*** | 0.023*** | 0.023*** | 0.023*** | 0.026*** | 0.186* |
| | | (0.005) | (0.005) | (0.005) | (0.005) | (0.006) | (0.096) |
| *ln(asset)* | | 0.709*** | 0.709*** | 0.709*** | 0.700*** | 0.700*** | 0.289*** |
| | | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.085) |
| *leverage* | | 0.001 | 0.001 | 0.000 | 0.001 | -0.004*** | -0.521*** |
| | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.036) |
| *gepu* | | | | | | | -0.002 |
| | | | | | | | (0.002) |
| *us_mpu* | | | | | | | -0.000 |
| | | | | | | | (0.002) |
| *vix* | | | | | | | -0.032*** |
| | | | | | | | (0.009) |
| *m2* | | | | | | | 0.056** |
| | | | | | | | (0.027) |
| *gdp* | | | | | | | -0.149*** |
| | | | | | | | (0.021) |
| *credittogdp* | | | | | | | 0.440*** |
| | | | | | | | (0.027) |
| *_cons* | 19.511*** | 3.363*** | 3.362*** | 3.364*** | 3.582*** | 3.524*** | 16.041*** |
| | (0.004) | (0.156) | (0.156) | (0.156) | (0.167) | (0.174) | (2.603) |
| *Dependent Variable's Mean* | 19.153 | 19.153 | 19.153 | 19.153 | 19.153 | 19.153 | 19.153 |
| *Controls* | N | Y | Y | Y | Y | Y | Y |
| *Time FE* | Y | Y | Y | Y | Y | Y | Y |
| *Firm FE* | N | Y | Y | Y | Y | Y | Y |
| *N* | 135866 | 129213 | 129213 | 129213 | 118687 | 114871 | 107267 |
| $R^2$ | 0.837 | 0.889 | 0.889 | 0.889 | 0.892 | 0.891 | 0.597 |

Notes: (1) The dependent variable is log value added. Columns 3 and 4 use jump indicators to measure significant weather risks as large jumps in the ACI index. Columns 5 and 6 exclude observations from 2008 and 2009, and 2020. (2) *tangible* is the fraction of tangible assets in total assets; *ROA* is firm's return on assets; *age* is firm age; *ln(asset)* is the log of firm-level assets; *leverage* is the aggregate leverage of non-financial firms. *gepu* is the global economic uncertainty index; *us_mpu* is the monetary policy uncertainty for US; *m2*, *gdp* and *credittogdp* are monetary supply, GDP growth rate and credit to GDP gap in China, respectively. (3) We use a two-quarter lag of *ACI* in the loan regression; (4) Robust standard errors are in parentheses. (5) All regressions include time fixed effects. Columns 2-7 include firm fixed effects. (6) ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 14: High vs. Low ACI Regimes

| | (1) | (2) |
|---|---|---|
| Dep. Variable | *loan to asset* | *ln(VA)* |
| *ACI*ACI+* | -0.292*** | -0.024*** |
| | (0.075) | (0.004) |
| *ACI* | -0.086** | -0.009*** |
| | (0.042) | (0.002) |
| *Dependent Variable's Mean* | 14.842 | 19.153 |
| *Controls* | Y | Y |
| *Time FE* | Y | Y |
| *Firm FE* | Y | Y |
| *N* | 108225 | 129213 |
| $R^2$ | 0.593 | 0.889 |

Notes: (1) The dependent variables are bank loans ratio to total assets for columns 1 and log value-added for columns 2. (2) *ACI+* is the indicator for ACI index above zero. (3) We use a one-quarter lag of *ACI* in the loan regression and two-quarter lag of *ACI* in the value added regression. (4) The numbers in parentheses are robust standard errors. (5) All regressions include control variables as in column 2 of Table 3, time fixed effects, and firm-fixed effects. (6) ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 15: Including Variables Related to Aggregate Supply of Loans

| Dep. Variable: *loan/asset* | (1) | (2) | (3) |
|---|---|---|---|
| *ACI* | -0.238*** | -0.157*** | -0.168*** |
| | (0.029) | (0.029) | (0.031) |
| *excess reserves ratio* | -0.950*** | | -0.160 |
| | (0.087) | | (0.129) |
| *capital adequacy ratio* | | 0.352** | 0.431** |
| | | (0.168) | (0.180) |
| *Dependent Variable's Mean* | 14.842 | 14.842 | 14.842 |
| *Controls* | Y | Y | Y |
| *Time FE* | Y | Y | Y |
| *Firm FE* | Y | Y | Y |
| *N* | 108225 | 95183 | 95183 |
| $R^2$ | 0.593 | 0.615 | 0.615 |

Notes: (1) The dependent variable is bank loans ratio to total assets; *ACI* is the climate risk index we construct; *excess reserve ratio* is the ratio of commercial banks' excess reserve to deposits at aggregate aggregate level; *capital adequacy ratio* is the overall capital adequacy level of the banking sector; (2) We use a one-quarter lag of *ACI* in the regression. (3) The numbers in parentheses are robust standard errors. (4) All regressions include control variables, time fixed effects, and firm fixed effects. (5) ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 16: Regression of Loans at Bank Level

| Dep.V ariable: *bank loan* | (1) | (2) |
|---|---|---|
| *ACI* | -0.015*** | -0.003** |
| | (0.005) | (0.001) |
| *demand* | | 0.001** |
| | | (0.000) |
| *Dependent Variable's Mean* | 26.900 | 26.900 |
| *Controls* | N | Y |
| *Time FE* | Y | Y |
| *Firm FE* | Y | Y |
| *N* | 1641 | 1218 |
| $R^2$ | 0.983 | 0.999 |

Notes: (1) The dependent variable is log bank loans reported on listed banks' balance sheets; *ACI* is the climate risk index we construct; *demand* is the national loan demand index published by the People's Bank of China; (2) We use a one-quarter lag of *ACI* in the regression. (3) The numbers in parentheses are robust standard errors. (4) All regressions include control variables, time fixed effects, and firm fixed effects. (5) ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.