Assessing the impacts of climate change to financial stability: evidence from China

Zhonglu Liu
School of Finance, Shandong Technology and Business University, Yantai, China, and
Haibo Sun and Songlin Tang
School of Economics, Shandong Technology and Business University, Yantai, China

Abstract

Purpose – Climate change not only causes serious economic losses but also influences financial stability. The related research is still at the initial stage. This paper aims to examine and explore the impact of climate change on financial stability in China.

Design/methodology/approach – This paper first uses vector autoregression model to study the impact of climate change to financial stability and applies NARDL model to assess the nonlinear asymmetric effect of climate change on China’s financial stability using monthly data from 2002 to 2018.

Findings – The results show that both positive and negative climate shocks do harm to financial stability. In the short term, the effect of positive climate shocks on financial stability is greater than the negative climate shocks in the current period, but less in the lag period. In the long term, negative climate shocks bring larger adjustments to financial stability relative to positive climate shocks. Moreover, compared with the short-term effect, climate change is more destructive to financial stability in the long run.

Originality/value – The paper provides a quantitative reference for assessing the nexus between climate change and financial stability from a nonlinear and asymmetric perspective, which is beneficial for understanding climate-related financial risks.

Keywords China, Climate change, Financial stability, Asymmetric effect

Paper type Research paper

1. Introduction

Climate change is a common concern of the international community and one of the most serious challenges facing mankind (Chou et al., 2016; Gaffney and Steffen, 2017; Wei et al., 2014). Climate change affects agriculture, health and other fields and causes the invisible crisis in some places (Akbari et al., 2020; Shakhawat Hossain et al., 2020; Zhang et al., 2020; Si et al., 2021). The most striking feature of climate change is uncertainty. Therefore, it is
very difficult to accurately evaluate the influence of climate change on the global economy. But there is a consensus among economists that economic losses from climate change will increase at higher temperatures (IPCC, 2014; Wu et al., 2020). Natural disasters caused by climate change have did tremendous damage to global financial assets, with losses up to US $24tn (Dietz et al., 2016). Meanwhile, to address climate change, governments have made lots of climate policies. However, the conversion to a low-carbon economy too fast or too sudden can also trigger financial risks (ESRB, 2016). Thus, climate change has become a source of risk for financial system stability that cannot be ignored (Turnbull, 2020).

Ever since Mark Carney, the Bank of England governor, gave a keynote titled “Breaking the Tragedy of the Horizon-Climate Change and Financial Stability” in 2015, the climate-related financial risks have received increasing attention. Climate change affects financial stability mainly through physical risks mechanism and transition risks mechanism. The physical risks mean that as the frequency and severity of climate disasters increase, the economic damages and bank credit risk increase. The transition risks are generated by the strong market volatility caused by the impact of climate policies, technology and the success or failure of the conversion to a low-carbon economy (Bank of England, 2015). At the Paris “One Planet Summit” in December 2017, eight supervisors and central banks (including China, France, The Netherlands, etc.) established the Network of Central Banks and Supervisors for Greening the Financial System (NGFS). Members of NGFS realize the threat of climate-related financial risks and hold that it is necessary assess and manage risks through prudential regulation and other means. Nowadays, the Bank of England, the European Systemic Risk Board and the financial authorities of The Netherlands and Sweden have carried out assessment of financial risks related to climate change. The People’s Bank of China has also explicitly supported banks and other financial institutions in assessing environmental risks. Arguably, once climate change becomes a problem that determines the stability of the financial system, it is too late to discuss how to deal with it (Carney, 2015). Establishing a comprehensive research framework to quantify the influence of climate change on financial stability is a research topic with important theoretical significance and practical value.

The contributions of this paper are mainly reflected in three aspects. First, existing research lacks empirical evidence on the impact of climate change on financial stability. This paper takes China as the research object to empirically test the relationship between climate change and financial stability. Second, this paper discusses the asymmetric transmission effect of climate change on financial stability from short-term and long-term perspectives. Third, NARDL model is adopted to empirically test in this paper and the model is still more robust in the case of small samples. The results can help policymakers better understand the climate-related financial risks and the ways in which an increase or a decrease in average temperature can affect financial stability.

The outline is presented as follows. Section 2 is literature review. The empirical model used in this paper is introduced in Section 3. Variable descriptions and data sources are in detail described in Section 4. The estimation results of empirical model and corresponding discussions are presented in Section 5. The final section concludes the paper and provides policy implications.

2. Literature review

Finance is the lifeblood of a national economic. Scholars all over the world pay close attention to the influence of climate change on financial stability. Due to the uncertainty of
climate change, the frequency and intensity of natural disasters caused by climate change cannot be accurately predicted, which also makes it difficult to evaluate the economic impact of climate change (Liu and Pan, 2012; Zhang et al., 2018). Most scholars believe that the emissions of greenhouse gases in the process of macroeconomic operation will the frequency and intensity of climate disasters (Nordhaus, 1993; Nordhaus and Yang, 1996). Meanwhile, policies aimed at mitigating climate change maybe have an adverse effect on the macro economy (Cardarelli et al., 2011). Climate policies can induce economic recession and increase the instability of financial system (Allen et al., 2012; IPCC, 2012). Thus, climate change will increase the uncertainty of financial operations and attack the financial stability (Fontana and Sawyer, 2016; Stern and Taylor, 2007).

With the global temperatures gradually rising, economic losses caused by natural disasters such as floods, hurricanes and droughts are increasing, which greatly increase the financial risks in the affected areas (IPCC, 2012). And, the rising concentration of greenhouse gases in the atmosphere will also increase the probability of climate disasters, causing indirect damage to the economy by breaking the global supply chains and thus attacking financial stability (Stern and Taylor, 2007). Due to the feedback loop relationship between climate change and financial risks, the traditional dynamic stochastic general equilibrium (DSGE) model is no longer applicable (Farmer et al., 2015). So a series of models have been proposed to explore the physical risks. In these studies, the integrated assessment model (IAM), the stock-flow consistent (SFC) model and a stock-flow-fund (SFF) model are used to explore the financial risks caused by climate change (Bovari et al., 2018; Dafermos et al., 2018; Dietz et al., 2016). The findings suggest that climate change has a negative effect on financial stability.

The empirical research on the relationship between climate disasters and financial stability can be divided into two categories. First, climate disaster losses will increase financial risks (Noth and Schüwer, 2017; Strobl, 2011; Nand and Bardsley, 2020). They explore the effect of climate-related natural disasters on bank risk and find that natural disasters significantly increase the operational risk of banks in affected areas. Second, the negative impact of climate disaster losses on financial stability is not significant (Murshed et al., 2021; Cavallo et al., 2013; Klomp, 2014). They argue that the effect of climate induced natural disasters on economic growth and financial stability of developed countries is negligible.

Scholars also discuss the impact of climate policies on financial stability. The implementation of climate policies will directly affect the fossil fuel sector, leaving assets of energy-intensive companies stranded (Mo et al., 2018; Coffel and Mankin, 2021). The stranded assets will not only lead to economic losses, credit default of enterprises, lost market value of companies, but also have a negative impact on investor sentiment, and may even cause financial crisis and chain effect in the whole interconnected financial system (Yan and Chen, 2017). In theoretical model, Campiglio et al. (2015) explain how climate policies trigger financial risks in the framework of a Post-Keynesian SFC model. Comerford and Spiganti (2016) construct a macroeconomic model containing financial frictions, and find that climate policies have a negative impact on infrastructure investment of alternative energy, resulting in economic depression and financial crisis. Dunz et al. (2018) also study the potential influence of “carbon tax” and “green subsidy” policies on financial system stability based on the SFC model. In empirical research, the method of climate stress test is selected to assess the impact of climate policies on the portfolio of overseas energy projects of the China Export-Import Bank and China Development Bank, and the results show that the negative climate shocks are mainly concentrated on coal and oil projects (Monasterolo et al., 2018). Some scholars take the
economic data of the Eurozone as a sample and find that the comprehensive risk exposure of industries affected by climate policies is very large (Battiston et al., 2017). Moreover, other scholars employ the financial network approach to access the effect of climate policies on the financial sector by identifying the feedback loop between the real economy and financial sector (Stolbova et al., 2018).

Recent research emphasize that increased temperatures will have significant, nonlinear effects on the global economy (Diffenbaugh and Burke, 2019; Lamperti et al., 2018; Schlenker and Roberts, 2009). Weitzman (2009) finds that the effect of climate change on financial stability are distinctively nonlinear and path-dependent, whether it is physical risks or transition risks. When the temperature exceeds a certain threshold, the influence of climate change on financial stability is not gradual process, but it is instantly multiplied several times like the domino effect. Therefore, the influence of positive and negative climate shocks on financial stability are different (Chen et al., 2020). Besides, there are often time mismatches between long-term and short-term decisions of investors and governments. This will lead positive and negative climate shocks on financial stability to show long-term and short-term differences. To the best of our knowledge, no empirical study has been done in the context of China to investigate the effects of climate change on financial stability.

This paper investigates the nexus between climate change and financial stability in the context of China, revealing the nonlinear and asymmetric impact of climate change on financial stability from a short-term and long-term perspective.

3. Econometric methodology

3.1 Vector autoregression model

The vector autoregression (VAR) model can be expressed as equation (1):

\[ Y_t = A_0 + A_1 Y_{t-1} + \cdots + A_P Y_{t-P} + \varepsilon_t, \quad Y_t = \{FS_t, TEMP_t\} \]  

where \( Y \) represents each research variable, FS represents financial stability index, TEMP represents average temperature, \( A_0, A_1, \ldots, A_P \) is the \( n \) order coefficient matrix, and \( \varepsilon_t \) is the random error term.

Because it is difficult to explain the parameters’ economic significance, this paper focuses on the impulse response function. Let us express the VAR model as an infinite order vector MA (\( \infty \)) process, as follows equation (2):

\[ Y_t = \alpha + \psi_0 \varepsilon_t + \psi_1 \varepsilon_{t-1} + \psi_2 \varepsilon_{t-2} + \cdots = \alpha + \sum_{j=0}^{\infty} \psi_j \varepsilon_{t-j} \]  

where \( \Psi_0 = I_n, \psi_s = \frac{\partial Y_s}{\partial \varepsilon_s} \) are n-dimensional matrices. \( \partial Y_{t+s}/\partial \varepsilon_s \) is the element in row \( i \) and column \( j \) in \( \Psi_s \), and can still be a function of time interval \( s \). The function is the impulse response function. It measures the impact of a unit shock of the random disturbance term of the \( j \) endogenous variable in period \( t \) on the value of the \( i \) endogenous variable in period \( t+s \).

3.2 Nardl model

NARDL model is an asymmetric effect model proposed by Shin et al. (2014). In this model, the independent variable is decomposed into the positive partial sum and the negative partial sum to investigate the nonlinear long-term and short-term effects and
asymmetric transmission effects of positive and negative shocks of independent variables on dependent variables. First, the independent variable TEMP is decomposed as follows equation (3):

$$ TEMP_t = TEMP_0 + TEMP_t^+ + TEMP_t^- $$

where $TEMP_t^+$ and $TEMP_t^-$ represent the partial sum process of positive and negative variation in average temperature, respectively. Their specific forms are as follows equation (4) and equation (5):

$$ TEMP_t^+ = \sum_{j=1}^{t} \Delta TEMP_j^+ = \sum_{j=1}^{t} \max(\Delta TEMP_j, 0) $$

$$ TEMP_t^- = \sum_{j=1}^{t} \Delta TEMP_j^- = \sum_{j=1}^{t} \min(\Delta TEMP_j, 0) $$

Considering the long-term asymmetry between variables, the following equation (6) is used:

$$ FS_t = \beta^+ TEMP_t^+ + \beta^- TEMP_t^- + \varepsilon_t $$

where $\beta^+$ represents the long-term transmission effect of increasing average temperature on financial stability, $\beta^-$ represents the long-term transmission effect of decreasing average temperature on financial stability.

Based on the above decomposition, a NARDL model can be obtained. The specific form is as follows equation (7):

$$ \Delta FS_t = \alpha_0 + \rho FS_{t-1} + \theta^+ TEMP_{t-1}^+ + \theta^- TEMP_{t-1}^- + \sum_{j=1}^{p-1} \alpha_j \Delta FS_{t-j} + \sum_{j=0}^{q-1} \left( \pi_j^+ \Delta TEMP_{t-j}^+ + \pi_j^- \Delta TEMP_{t-j}^- \right) + \varepsilon_t $$

where $FS$ represents financial stability, and $TEMP$ represents climate change. $\Delta$ represents the first-order difference. $\varepsilon$ represents the residual term. $\rho$ represents the maximum lag order of the dependent variable, and $q$ represents the maximum lag order of the independent variable.

Further, rewrite equation (7) to equation (8):

$$ \Delta FS_t = \rho \xi_{t-1} + \sum_{j=1}^{p-1} \alpha_j \Delta FS_{t-j} + \sum_{j=0}^{q-1} \left( \pi_j^+ \Delta TEMP_{t-j}^+ + \pi_j^- \Delta TEMP_{t-j}^- \right) + \varepsilon_t $$

where $\xi_{t-1} = FS_{t-1} - \beta^+ TEMP_{t-1}^+ - \beta^- TEMP_{t-1}^-$. The asymmetric long-term coefficient $\beta^+ = -\theta^+/\rho$ and $\beta^- = -\theta^-/\rho$, respectively, describe the long-term relationship between the positive and negative climate shocks and financial stability. The parameters of the asymmetric distribution lag item $\pi_j^+$ and $\pi_j^-$, respectively, reflect the short-term transmission effects of positive and negative climate shocks on financial stability.

According to the research of Shin et al. (2014), the hypothesis $H_0: \rho = 0, H_1: \rho < 0$ can be tested by constructing $t_{BDM}$ statistics subject to $t$ distribution and $F_{ESS}$ statistics subject to $F$ distribution. If the null hypothesis is rejected, it shows that there is a long-term nonlinear equilibrium nexus between climate change and financial stability. Besides, the hypothesis...
$H_0: \beta^+ = \beta^-$ can be tested by constructing Wald statistics. If the null hypothesis is rejected, it indicates that the long-term impact of climate shocks on financial stability is asymmetric. For short-term asymmetry test, Wald statistics can be constructed to test $H_0: \sum_{j=0}^{q-1} \pi_j^+ = \sum_{j=0}^{q-1} \pi_j^-$. If the null hypothesis is rejected, it indicates that the short-term transmission effect of climate change on financial stability is asymmetric.

Finally, this paper calculates the asymmetric dynamic multiplier $M_{h^+}^+$ and $M_{h^-}^-$ for the positive and negative climate change. The formulas are as follows equations (9) and (10):

$$M_{h^+}^+ = \sum_{j=0}^{h^+} \frac{\partial FS_{h^+}}{\partial TEMP^+}, \quad h^+=0,1,2\cdots$$  \hspace{1cm} (9)

$$M_{h^-}^- = \sum_{j=0}^{h^-} \frac{\partial FS_{h^-}}{\partial TEMP^-}, \quad h^-=-0,1,2\cdots$$  \hspace{1cm} (10)

$M_{h^+}^+$ describes the dynamic transmission process of a unit of positive climate change to financial stability during period $h$. $M_{h^-}^-$ describes the dynamic transmission process of a unit of negative climate change to financial stability during period $h$. According to the dynamic multiplier, we can clearly observe the asymmetric transmission path of climate change to financial stability.

4. Variables and data

4.1 Index system of China’s financial stability

To explore the effect of climate change on China’s financial stability, the first problem to be solved is how to measure China’s financial stability. This paper refers to the research of Nasreen et al. (2017), Liu and Bi (2019), and selects nine indicators covering financial development, macroeconomic situation and the functioning of financial markets. Table 1 shows the specific indicators. The indicators are monthly data from 2002 to 2018. The data comes from Wind database and EPS data platform.

There are two problems that need to be solved for these selected indicators. One is that there is the dimensional problem between different indicators. Accordingly, this paper uses the method of Min-Max standardization to process the data to eliminate the influence of dimension. The specific formula is as follows equation (11).

<table>
<thead>
<tr>
<th>Dimensions</th>
<th>Indicators</th>
<th>Expected impact on financial stability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Financial development</td>
<td>Ratio of loan to GDP</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>Ratio of market value of bond market to GDP</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>Ratio of income of insurance premiums to GDP</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>Ratio of market value of listed company to GDP</td>
<td>+</td>
</tr>
<tr>
<td>Macroeconomic situation</td>
<td>GDP growth rate</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>Ratio of current account deficits to GDP</td>
<td>–</td>
</tr>
<tr>
<td>Functioning of financial markets</td>
<td>Loan-to-deposit ratio</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>National housing sensitive index</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Exchange rate fluctuation</td>
<td>–</td>
</tr>
</tbody>
</table>

Table 1.
The index system of financial stability
where \( Z'_{it} \) represents the value of index \( i \) after period \( t \) normalization. \( \max(Z_i) \) and \( \min(Z_i) \) represent the maximum and minimum values of indicator \( i \) in the sample period, respectively.

The other is that the influence of each indicator on China’s financial stability is inconsistent. To ensure that each indicator has the same direction of influence on the financial stability index, this paper takes the opposite of all negative indicators.

### 4.2 Integration of China financial stability index

This paper uses factor analysis method to integrate into China’s Financial Stability Index (FS). Before carrying out factor analysis, Bartlett test and KMO test are adopted to determine whether the sample data selected is suitable for factor analysis. The KMO test statistic value is 0.610, which is greater than 0.5. The \( p \)-value of Bartlett test is 0.000. It can be concluded that the sample data selected in this paper can be used for factor analysis. Table 2 shows the eigenvalues, proportion of variance contribution rate and cumulative variance contribution rate of each factor. According to the principle that the eigenvalue is greater than 1, this paper extracts the first three factors as common factors. The cumulative variance contribution rate of these three common factors is 80.7\%, indicating that these three common factors contain 80.7\% information of the indicators in the financial stability index system. This also reflects that the results of extracting common factors are reasonable.

According to the results of common factor extraction, the variance contribution rate of each common factor is selected as the weight, and the weighted average method is used to calculate China’s financial stability index. Figure 1 shows the HP filter decomposition of financial stability index. China’s financial stability index shows a rising trend, indicating that the stability of the Chinese financial system is constantly improving. But China’s financial stability index has obvious volatility characteristics, confirming the financial instability hypothesis.

### 4.3 Indicator of climate change

Climate change refers to the change of climate state over a long period, which can usually be reflected by the change of temperature. This paper uses the average temperature as an alternative variable of climate change. The data comes from the monthly dataset of 173 basic and reference surface meteorological observation stations and automatic stations from 2002 to 2018. This data set is the informative data of the “Monthly Report of Surface Meteorological Records” reported monthly by the climate data processing departments of 30 provinces in China, and can reflect the changes in China’s temperature. In this paper, the average monthly data of 173 stations is used as the proxy variable of climate change.

<table>
<thead>
<tr>
<th>Factor</th>
<th>Eigenvalue</th>
<th>Proportion</th>
<th>Cumulative</th>
</tr>
</thead>
<tbody>
<tr>
<td>Factor1</td>
<td>4.089</td>
<td>0.454</td>
<td>0.454</td>
</tr>
<tr>
<td>Factor2</td>
<td>2.158</td>
<td>0.240</td>
<td>0.694</td>
</tr>
<tr>
<td>Factor3</td>
<td>1.013</td>
<td>0.113</td>
<td>0.807</td>
</tr>
</tbody>
</table>

Table 2. Results of common factor extraction
5. Empirical results discussions

5.1 Results of vector autoregression model

In this section, the VAR model is used to analyze the asymmetric impact of climate change on China’s financial stability. For this purpose, this paper refers to the study of Mork (1989) to define the temperature increase sequence $TEMP_i$ and the temperature decrease sequence $TEMP_d$. The specific formulas are as follows equation (12) and equation (13):

$$TEMP_i = \max[(TEMP_t - TEMP_{t-1}), 0]$$  (12)

$$TEMP_d = \min[(TEMP_t - TEMP_{t-1}), 0]$$  (13)

The unit root test is needed before parameter estimation of the time series model to avoid the problem of pseudo-regression. This paper uses the ADF test method proposed by Dickey and Fuller (1979) and the PP test method proposed by Phillips and Perron (1988) for unit root test. As shown in Table 4, every variable is integrated of order zero. These findings meet the necessary of the VAR approach.

Then, this paper uses the lag length criterion in the lag structure to determine the optimal lag order of the VAR model. Table 5 shows the results. The criteria of LR, FPE, AIC, SC, HQ all indicate that the optimal lag order of the VAR model of sequence $TEMP_i$ and sequence $TEMP_d$ are reported in Table 3.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>FS</td>
<td>204</td>
<td>0.813</td>
<td>0.432</td>
<td>0.163</td>
<td>1.551</td>
</tr>
<tr>
<td>TEMP</td>
<td>204</td>
<td>11.537</td>
<td>9.687</td>
<td>-6.621</td>
<td>25.119</td>
</tr>
<tr>
<td>TEMP_i</td>
<td>204</td>
<td>2.314</td>
<td>2.709</td>
<td>0.000</td>
<td>10.156</td>
</tr>
<tr>
<td>TEMP_d</td>
<td>204</td>
<td>-2.311</td>
<td>2.982</td>
<td>-10.631</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Table 3. Descriptive statistics
TEMP_d is second order lag. Therefore, this paper builds two VAR models with second order lags for sequence TEMP_i and sequence TEMP_d.

Figures 2 and 3 are the impulse responses of financial stability to TEMP_i and TEMP_d, respectively. As shown in Figure 2, after a shock to TEMP_i in the current period, TEMP_i has a significant negative impact on financial stability. This negative effect continues to increase during periods 1 to 5, reaches its maximum in the fifth period, and then enters a stable state. The frequency of climate disasters is affected by temperature (IPCC, 2012), and the higher the temperature, the higher the frequency of climate disasters (Bouwer, 2011), resulting in greater economic and financial losses. The increase in average temperature has a negative effect on China’s financial stability. As shown in Figure 3, after a shock to

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF T-statistic</th>
<th>P-value</th>
<th>PP T-statistic</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>FS</td>
<td>-3.903***</td>
<td>0.012</td>
<td>-3.809**</td>
<td>0.016</td>
</tr>
<tr>
<td>TEMP</td>
<td>-3.954***</td>
<td>0.002</td>
<td>-6.114***</td>
<td>0.000</td>
</tr>
<tr>
<td>TEMP_i</td>
<td>-3.847***</td>
<td>0.003</td>
<td>-4.375***</td>
<td>0.000</td>
</tr>
<tr>
<td>TEMP_d</td>
<td>-3.485***</td>
<td>0.009</td>
<td>-4.106***</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Note: *,** and ***represent significance levels at 10, 5 and 1%, respectively

<table>
<thead>
<tr>
<th>Lag</th>
<th>LogL</th>
<th>LR</th>
<th>FPE</th>
<th>AIC</th>
<th>SC</th>
<th>HQ</th>
</tr>
</thead>
<tbody>
<tr>
<td>TEMP_i</td>
<td>0</td>
<td>-604.534</td>
<td>NA</td>
<td>1.390</td>
<td>6.005</td>
<td>6.038</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>-159.034</td>
<td>877.766</td>
<td>0.018</td>
<td>1.634</td>
<td>1.732</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>-137.893</td>
<td>41.236*</td>
<td>0.015*</td>
<td>1.464*</td>
<td>1.628*</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>-161.808</td>
<td>909.524</td>
<td>0.018</td>
<td>1.661</td>
<td>1.760</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>-113.476</td>
<td>94.272*</td>
<td>0.012*</td>
<td>1.223*</td>
<td>1.386*</td>
</tr>
</tbody>
</table>

Note: *Indicates the lag order selected according to the corresponding criterion
TEMP_d in the current period, TEMP_d has a short-term positive effect on financial stability in the second period, and then the effect turned negative in other periods. In the sixth period, TEMP_d has the largest effect on financial stability, reaching $-0.049$. Subsequently, this negative effect has declined and stabilized after the eleventh period. A drop in average temperature has a positive effect on financial stability at first, but it is also harm for financial stability afterwards. To alleviate global warming, governments will issue corresponding climate policies. Climate policies can reduce the effect of climate disasters on financial stability to a certain extent. However, the conversion to a low-carbon economy is too late or too sudden, resulting in high-carbon assets stranded and attacking financial stability (Stolbova et al., 2018). It is found that a drop in average temperature has a greater impact on financial stability than a rise in temperature. In other words, compared with natural disasters caused by climate change, too fast conversion to a low-carbon economy has a greater impact on financial stability. The transition risk mechanism of climate change on financial stability should be paid more attention. This result preliminarily illustrates that the effects of climate change on financial stability is asymmetric.

5.2 Results of NARDL model
The VAR model only preliminary explores the short-term effect of climate change on financial stability. To accurately assess the long-term and short-term nonlinear and asymmetric effects of climate change on financial stability, this paper adopts the NARDL model proposed by Shin et al. (2014). The NARDL model can not only determine whether there is a stable long-term nonlinear relationship between variables but also identify the asymmetric effects in the short-term and long-term relationships (Charfeddine and Barkat, 2020; Cosmas et al., 2019). According to the results of unit root test, the time series of FS and TEMP meet the requirements of data stationarity in NARDL model. As for the lag order of the model, this paper selects $p = 1$ and $q = 1$ according to Jeffrey (2019). Table 6 reports the regression results of the NARDL model.

As shown in Table 6, $t_{BDM}$ rejects the null hypothesis at a significance level of 5%, and $F_{PSS}$ also rejects the null hypothesis at a significance level of 1%, indicating that there is a long-term nonlinear relationship between climate change and financial stability. It is also found that the long-term effect of uncertain climate change on financial stability is tremendous. The long-term coefficient of positive climate shocks on financial stability $\beta^+$ is $-0.044$, and it is significant at the level of 1%, suggesting that an increase in average temperature of 1°C will lead to a drop of 0.044 in China’s financial stability index in the long-term. The long-term coefficient of negative climate shocks on financial stability $\beta^-$ is
It is significant at the level of 1%, suggesting that a 1°C drop in average temperature will cause China’s financial stability index to fall by 0.048 in the long-term. Meanwhile, WLR is significant at the 1% significance level, meaning that the effect of climate change positive and negative climate shocks on financial stability is significantly different in the long term. That means climate change has a long-term asymmetric transmission effect on financial stability.

The short-term effect of positive climate shocks on financial stability is $-0.0167$ in the current period, and $-0.0056$ in the lag period. They all passed the significance test, indicating that the positive climate shocks will make the financial stability index drop by 0.0167 in the current period, and drop by 0.0056 in the lag period. The short-term effect of negative climate shocks on financial stability is 0.0096 in the current period, and 0.0061 in the lag period. They all passed the significance test, suggesting that the negative climate shocks of will make the financial stability index drop by 0.0096 in the current period, and drop by 0.0061 in the lag period. WSR is significant at the 1% significance level, meaning that there is a short-term asymmetric transmission effect between climate change and financial stability.

Table 6. Results of NARDL model

<table>
<thead>
<tr>
<th>Variable</th>
<th>coefficient</th>
<th>standard deviation</th>
<th>T-statistic</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$FS(-1)$</td>
<td>$-0.1077^{***}$</td>
<td>0.0320</td>
<td>$-3.37$</td>
<td>0.001</td>
</tr>
<tr>
<td>$TEMP^+(-1)$</td>
<td>$-0.0047^{***}$</td>
<td>0.0008</td>
<td>$-6.02$</td>
<td>0.000</td>
</tr>
<tr>
<td>$TEMP^-(-1)$</td>
<td>$-0.0051^{***}$</td>
<td>0.0008</td>
<td>$-6.41$</td>
<td>0.000</td>
</tr>
<tr>
<td>$\Delta FS(-1)$</td>
<td>$-0.3262^{***}$</td>
<td>0.0674</td>
<td>$-4.84$</td>
<td>0.000</td>
</tr>
<tr>
<td>$\Delta TEMP^+(-1)$</td>
<td>$-0.0167^{***}$</td>
<td>0.0031</td>
<td>$-5.35$</td>
<td>0.000</td>
</tr>
<tr>
<td>$\Delta TEMP^-(-1)$</td>
<td>$-0.0056^{**}$</td>
<td>0.0027</td>
<td>$-2.12$</td>
<td>0.035</td>
</tr>
<tr>
<td>$\Delta TEMP^+$</td>
<td>$0.0096^{***}$</td>
<td>0.0025</td>
<td>3.88</td>
<td>0.000</td>
</tr>
<tr>
<td>$\Delta TEMP^-(1)$</td>
<td>$0.0061^{***}$</td>
<td>0.0031</td>
<td>1.96</td>
<td>0.051</td>
</tr>
<tr>
<td>Cons</td>
<td>0.1659***</td>
<td>0.0204</td>
<td>8.14</td>
<td>0.000</td>
</tr>
<tr>
<td>$\beta^+$</td>
<td>$-0.044^{***} {8.460}$</td>
<td></td>
<td></td>
<td>0.004</td>
</tr>
<tr>
<td>$\beta^-$</td>
<td>$0.048^{***} {9.661}$</td>
<td></td>
<td></td>
<td>0.002</td>
</tr>
</tbody>
</table>

Notes: The superscripts ‘+’ and ‘−’ indicate positive and negative partial sums, respectively. $\Delta$ is the first difference operator. $\beta^+$ and $\beta^-$ are the estimated asymmetric long-term coefficients associated with positive and negative changes, respectively. $t_{BDM}$ and $F_{PSS}$ are t-statistic and F-statistic, respectively, for testing the null hypothesis of no nonlinear long-term relationships in the NARDL model. $W_{LR}$ and $W_{SR}$ are Wald statistics, for testing long-term and short-term asymmetric effects, respectively. Values in brackets {} are F-statistic. *, ** and *** represent significance levels at 10, 5 and 1%, respectively.

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Figure 4 shows the asymmetric dynamic cumulative effect of average temperature on the financial stability. And after the 30th period, the impact of positive and negative climate shocks on financial stability begins to stabilize, reaching a long-term equilibrium. The curves of positive and negative changes once again confirm the asymmetry of the effect of climate change on financial stability. Moreover, the dynamic multiplier curves also further show that the negative climate shocks have a greater effect on financial stability than the positive ones.
positive climate shocks. In other words, climate change has the long-term negative asymmetry path to financial stability, but the degree of negative asymmetry is not large. Figure 5 is the cumulative sum of squares recursive residuals test. The cumulative sum of squares recursive residuals curve is within the 5% critical line, indicating that the parameters and variance of the model in this paper are stable.

5.3 Robustness test
The concentration of carbon dioxide in the atmospheric is adopted as the indicator of climate change to verify the robustness of the baseline regression results. Data on carbon dioxide concentration is from NOAA monthly carbon dioxide data. The NARDL model is regressed again, and the results are shown in Table 7. Figure 6 shows the asymmetric dynamic

![Cumulative effect of TEMP on FS](image)

**Figure 4.**
Cumulative effect of TEMP on FS

![CUSUM of squares test for the NARDL regression in Table 6](image)

**Figure 5.**
CUSUM of squares test for the NARDL regression in Table 6
cumulative effect of carbon dioxide concentration on the financial stability. Figure 7 is also the cumulative sum of squares recursive residuals test. The robustness test results indicating that the previous conclusions are still valid.

5.4 Discussions
First, climate disasters can cause severe damage to infrastructure and private property, which in turn can have an impact on financial stability. Climate disasters have great uncertainty. And, it is difficult to accurately predict. However, researchers generally believe that the greenhouse gases

### Table 7. Results of robustness test

<table>
<thead>
<tr>
<th>Variable</th>
<th>coefficient</th>
<th>standard deviation</th>
<th>T-statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>FS(−1)</td>
<td>−0.0898***</td>
<td>0.0349</td>
<td>−2.58</td>
<td>0.011</td>
</tr>
<tr>
<td>CO2+(−1)</td>
<td>−0.0105***</td>
<td>0.0027</td>
<td>−3.86</td>
<td>0.000</td>
</tr>
<tr>
<td>CO2−(−1)</td>
<td>−0.0156***</td>
<td>0.0035</td>
<td>−4.41</td>
<td>0.000</td>
</tr>
<tr>
<td>ΔFS(−1)</td>
<td>−0.0574</td>
<td>0.0641</td>
<td>−0.90</td>
<td>0.372</td>
</tr>
<tr>
<td>ΔCO2+</td>
<td>−0.0160</td>
<td>0.0104</td>
<td>−1.53</td>
<td>0.127</td>
</tr>
<tr>
<td>ΔCO2−</td>
<td>0.0592***</td>
<td>0.0092</td>
<td>6.42</td>
<td>0.000</td>
</tr>
<tr>
<td>ΔCO2+(−1)</td>
<td>0.0491***</td>
<td>0.0099</td>
<td>−4.92</td>
<td>0.000</td>
</tr>
<tr>
<td>ΔCO2−(−1)</td>
<td>0.0361***</td>
<td>0.0113</td>
<td>3.18</td>
<td>0.002</td>
</tr>
<tr>
<td>Cons</td>
<td>−0.0203</td>
<td>0.0154</td>
<td>−1.31</td>
<td>0.191</td>
</tr>
<tr>
<td>β+</td>
<td>−0.117* (3.305)</td>
<td></td>
<td></td>
<td>0.071</td>
</tr>
<tr>
<td>β−</td>
<td>0.174*** (3.916)</td>
<td></td>
<td></td>
<td>0.049</td>
</tr>
</tbody>
</table>

**Notes:** The superscripts ‘+’ and ‘−’ indicate positive and negative partial sums, respectively. Δ is the first difference operator. β+ and β− are the estimated asymmetric long-term coefficients associated with positive and negative changes, respectively. tBDM and F_PSS are t-statistic and F-statistic, respectively, for testing the null hypothesis of no nonlinear long-term relationships in the NARDL model. WLR and WSR are Wald statistics, for testing long-term and short-term asymmetric effects, respectively. Values in brackets {} are F-statistic. *, ** and *** represent significance levels at 10, 5 and 1%, respectively.

Figure 6. Cumulative effect of carbon dioxide concentration on FS
emitted during the macroeconomic operation will cause the average temperature to rise, increasing the frequency and intensity of climate disasters (Nordhaus, 1993; Nordhaus and Yang, 1996). This means that the positive climate shocks will destroy the stability of financial system through physical risk mechanisms. Second, to mitigate climate change, governments have also issued corresponding climate policies. The Paris Agreement clearly required that the rise of global temperature should be controlled within 2°C. But if the conversion to a low-carbon economy is too fast, it will also bring many uncertainties. On the one hand, stricter environmental regulations may increase credit risk in the credit market. On the other hand, restrictions on total carbon emissions will make most fossil fuel reserves become stranded assets, putting the financial situation of carbon-intensive companies in crisis. In addition, litigation and claims related to climate change will also threaten corporate goodwill and cause potential economic losses. This means that the negative climate shocks will have a negative effect on financial stability through the transition risk mechanism. Whether they are positive or negative climate shocks, they will have an adverse impact on financial stability.

Moreover, in the long term, the negative climate shocks are more destructive to financial stability relative to positive shocks. In the short term, the positive climate shocks on financial stability in the current period are greater than the negative shocks, while in the lag period are less than the negative shocks. This is mainly due to the difference in the mechanism of climate change influences financial stability. For the positive climate shocks, the premise of the physical risk mechanism is climate disasters. However, the occurrence of physical risks is mainly based on specific meteorological and geographical conditions, and climate disasters are small-probability events with high losses. In contrast, for the negative climate shocks, the occurrence of transition risks mainly comes from the governments’ climate policies, control measures and the compliance pressure they bring. Then, for various entities in economics and finance, transition risks become a more normal source of risk relative to physical risks, but the physical risks triggers greater current damage relative to transition risks (Monasterolo et al., 2018). This makes the impact of negative climate shocks greater than the impact of positive climate shocks in the long term, while in the short term, the current impact of positive climate shocks is greater than negative shocks.

Besides, compared with short-term impact, climate change has a greater long-term impact on financial stability. Climate change is not only highly uncertain, but also widespread and long term (Christophers, 2017; Nordhaus, 2018). On the one hand, extreme weather events caused by climate change will be more frequent and destructive in the medium term and long term (Dietz and Stern,
On the other hand, climate policies and related measures are more volatile and uncertain in the long run (Monasterolo et al., 2019). Moreover, the ability of the financial system to deal with long-term risk is also much lower than short-term risk (Andersson and Frédéric, 2016; Carney, 2015). Therefore, the two types of risk transmission mechanisms that climate change affects financial stability are strengthened in the long term, and the long-term vulnerability of the financial system makes the impact of climate change shocks on financial stability more significant in the long term.

6. Conclusions and policy implications
Climate change is one of the greatest challenges the mankind has ever faced. Research related to climate change has been continuously concerned and deepened. However, the literature on the effect of climate change on financial stability is still in its infancy. Climate change mainly affects the financial system through physical risks and transition risks. Due to the interaction between physical risks and transition risks, the effect of climate change on financial stability shows nonlinear and asymmetric. First, this paper selects monthly data from 2002 to 2018 to construct China’s financial stability index. Then, the VAR model is used to initially identify the short-term asymmetric effect of climate shocks on financial stability. Finally, this paper examines the short-term and long-term nonlinear asymmetric effects of climate change on financial stability by using a NARDL model. The results show that both positive and negative climate shocks do harm to financial stability. There is a nonlinear and asymmetric nexus between climate change and financial stability. Specifically, in the short term, the positive climate shocks will have a greater effect on financial stability in the current period than the negative shocks, but is less than negative shocks in the lag period. In the long term, the negative climate shocks will have a greater effect on financial stability relative to the positive shocks. In addition, climate change is more destructive to financial stability in the long term than in the short term.

The research conclusions have important policy implications. First, climate change has become an important source of risk that threatens financial stability. Governments should concern the climate-related financial risks adequately, especially the transition risks. Therefore, governments must maintain consistency when making climate policies and other measures, reduce the discontinuity and uncertainty of climate policies and the contradictions between different policies, and form a stable and long-term climate change mitigation policy system. Second, financial institutions should actively carry out stress tests on climate-related financial risks. Stress testing is believed to be a good quantifier of potential systemic shocks that may affect the entire financial system. Climate stress tests can assess physical property losses, as well as the impact of transition policies, and can also capture the interaction between the two and the amplification effect of the feedback loop. By conducting climate stress tests, financial institutions can track the path of climate change affecting the financial system and prepare for short-term climate-related financial risks in advance. Third, the central bank and financial regulators should proactively introduce green financial incentive policies. The fundamental way to alleviate the effect of climate change on financial stability is to mitigate climate change. Green finance can not only affect the impact of natural disasters caused by climate change on financial stability but also effectively mitigate the financial risks brought about by the rapid conversion to a low-carbon economy. Therefore, central banks and financial regulators can introduce incentive policies for green finance, such as green quantitative easing, consideration of macro-prudential supervision of green finance, and micro-regulation to give green credit differential capital adequacy ratio. These policies can plug the climate funding gap, as well as fundamentally solve the long-term financial risks caused by climate change.
References


**Corresponding author**

Haibo Sun can be contacted at: 554988870@qq.com