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

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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

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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 investigate 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):

$$Y_t = A_0 + A_1 Y_{t-1} + \cdots + A_P Y_{t-P} + \varepsilon_t, \qquad Y_t = \{FS_t, TEMP_t\} \tag{1}$$

where Y represents each research variable, FS represents financial stability index, TEMP represents average temperature, A_0, $A_1 \ldots A_{\mathrm{P}}$ is the n order coefficient matrix, and ε_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 (∞) process, as follows equation (2):

$$Y_t = \alpha + \psi_0 \varepsilon_t + \psi_1 \varepsilon_{t\text{-}1} + \psi_2 \varepsilon_{t\text{-}2} + \cdots = \alpha + \sum_{j=0}^{\infty} \psi_j \varepsilon_{t-\mathrm{j}} \tag{2}$$

where $\Psi_0 = I_n$, $\psi_s = \frac{\partial Y_{t+s}}{\partial \varepsilon'_t}$ are n-dimensional matrices. $\partial Y_{i,t+s} / \partial \varepsilon_{ji}$ is the element in row i and column j in Ψ_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):

$$TEMP_t = TEMP_0 + TEMP_t{}^{+} + TEMP_t{}^{-} \tag{3}$$

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):

$$TEMP_t{}^{+}=\sum\nolimits_{j=1}^{t} \Delta TEMP_j^{+} = \sum\nolimits_{j=1}^{t} \max\left(\Delta TEMP_j, 0\right) \tag{4}$$

$$TEMP_t{}^{-}=\sum\nolimits_{j=1}^{t} \Delta TEMP_j^{-} = \sum\nolimits_{j=1}^{t} \min\left(\Delta TEMP_j, 0\right) \tag{5}$$

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

$$FS_t = \beta^{+} TEMP_t{}^{+} + \beta^{-} TEMP_t{}^{-} + \varepsilon_t \tag{6}$$

where β^{+} represents the long-term transmission effect of increasing average temperature on financial stability, β^{-} 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):

$$\begin{aligned}\Delta FS_t = {} & \alpha_0 + \rho FS_{t-1} + \theta^{+} TEMP_{t-1}^{+} + \theta^{-} TEMP_{t-1}^{-} \\ & + \sum\nolimits_{j=1}^{p-1} \alpha_j \Delta FS_{t-j} + \sum\nolimits_{j=0}^{q-1} \left(\pi_j^{+} \Delta TEMP_{t-j}^{+} + \pi_j^{-} \Delta TEMP_{t-j}^{-}\right) + \varepsilon_t\end{aligned} \tag{7}$$

where *FS* represents financial stability, and *TEMP* represents climate change. Δ represents the first-order difference. ε represents the residual term. p 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):

$$\Delta FS_t = \rho\, \xi_{t-1} + \sum\nolimits_{j=1}^{p-1} \alpha_j \Delta FS_{t-j} + \sum\nolimits_{j=0}^{q-1} \left(\pi_j^{+} \Delta TEMP_{t-j}^{+} + \pi_j^{-} \Delta TEMP_{t-j}^{-}\right) + \varepsilon_t \tag{8}$$

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 itemπ_j^{+}andπ_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_{PSS} 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):

$$M_h^+ = \sum_{j=0}^{h} \frac{\partial FS_{t+j}}{\partial TEMP^+}, \quad h=0,1,2\cdots \tag{9}$$

$$M_h^- = \sum_{j=0}^{h} \frac{\partial FS_{t+j}}{\partial TEMP^-}, \quad h=0,1,2\cdots \tag{10}$$

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).

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

Table 1.
The index system of financial stability

$$Z'_{it} = \frac{Z_{it} - \min(Z_i)}{\max(Z_i) - \min(Z_i)} \tag{11}$$

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.

Factor	Eigenvalue	Proportion	Cumulative
Factor1	4.089	0.454	0.454
Factor2	2.158	0.240	0.694
Factor3	1.013	0.113	0.807

Table 2. Results of common factor extraction

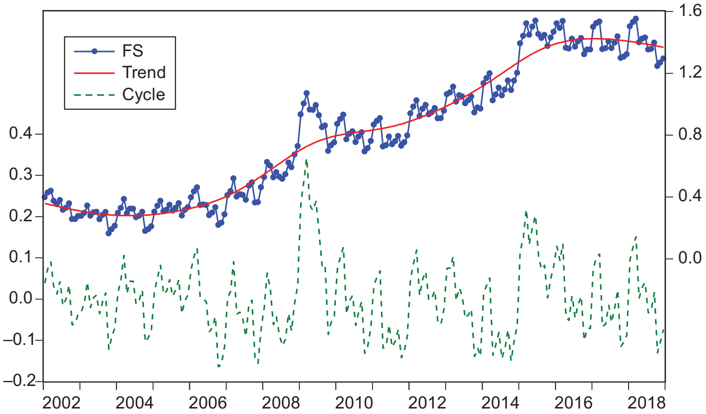

Figure 1.
HP filter decomposition of financial stability index

The descriptive statistics of financial stability index (FS), average temperature (TEMP), temperature increase sequence TEMP_i and temperature decrease sequence TEMP_d are reported in Table 3.

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):

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

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

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

Table 3.
Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
FS	204	0.813	0.432	0.163	1.551
TEMP	204	11.537	9.687	−6.621	25.119
TEMP_i	204	2.314	2.709	0.000	10.156
TEMP_d	204	−2.311	2.982	−10.631	0.000

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

Variable	ADF T-statistic	ADF P-value	PP T-statistic	PP P-value
FS	−3.903**	0.012	−3.809**	0.016
TEMP	−3.954***	0.002	−6.114***	0.000
TEMP_i	−3.847***	0.003	−4.375***	0.000
TEMP_d	−3.485***	0.009	−4.106***	0.001

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

Table 4. Results of unit root test

Lag		LogL	LR	FPE	AIC	SC	HQ
TEMP_i	0	−604.534	NA	1.390	6.005	6.038	6.019
	1	−159.034	877.766	0.018	1.634	1.732	1.674
	2	−137.893	41.236*	0.015*	1.464*	1.628*	1.531*
TEMP_d	0	−623.426	NA	1.676	6.192	6.225	6.206
	1	−161.808	909.524	0.018	1.661	1.760	1.701
	2	−113.476	94.272*	0.012*	1.223*	1.386*	1.289*

Note: *Indicates the lag order selected according to the corresponding criterion

Table 5. Determination of lag order of VAR model

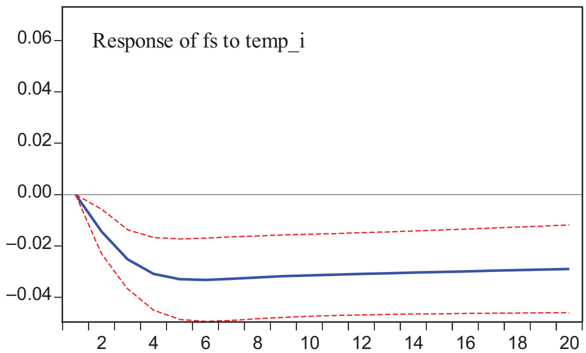

Figure 2. Impulse response of financial stability to TEMP_i

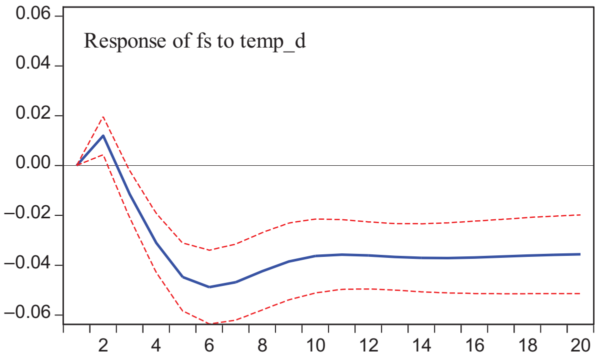

Figure 3.
Impulse response of financial stability to TEMP_d

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 β^{+} 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 β^{-} is

Variable	coefficient	standard deviation	T-statistic	p-value
FS(−1)	−0.1077***	0.0320	−3.37	0.001
$TEMP^{+}(-1)$	−0.0047***	0.0008	−6.02	0.000
$TEMP^{-}(-1)$	−0.0051***	0.0008	−6.41	0.000
ΔFS(−1)	−0.3262***	0.0674	−4.84	0.000
$\Delta TEMP^{+}$	−0.0167***	0.0031	−5.35	0.000
$\Delta TEMP^{+}(-1)$	−0.0056**	0.0027	−2.12	0.035
$\Delta TEMP^{-}$	0.0096***	0.0025	3.88	0.000
$\Delta TEMP^{-}(-1)$	0.0061*	0.0031	1.96	0.051
Cons	0.1659***	0.0204	8.14	0.000
β^{+}	−0.044*** {8.460}			0.004
β^{-}	0.048*** {9.661}			0.002
Asymmetry and Co-integration test				
W_{LR}	149.800***	W_{SR}	59.270***	
t_{BDM}	−3.366***	F_{PSS}	16.224***	

Notes: The superscripts '+' and '−' indicate positive and negative partial sums, respectively. Δ is the first difference operator. $\beta^{+}$and β^{-} 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

Table 6. Results of NARDL model

−0.048, and 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, W_{LR} 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. W_{SR} is significant at the 1% significance level, meaning that there is a short-term asymmetric transmission effect between climate change and financial stability. Judging from the absolute value of the coefficients, 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. Moreover, from the absolute value of long-term and short-term coefficients, the long-term coefficient of climate change on financial stability is far greater than the short term, showing that the long-term damage of climate change on financial stability is greater than the short term.

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

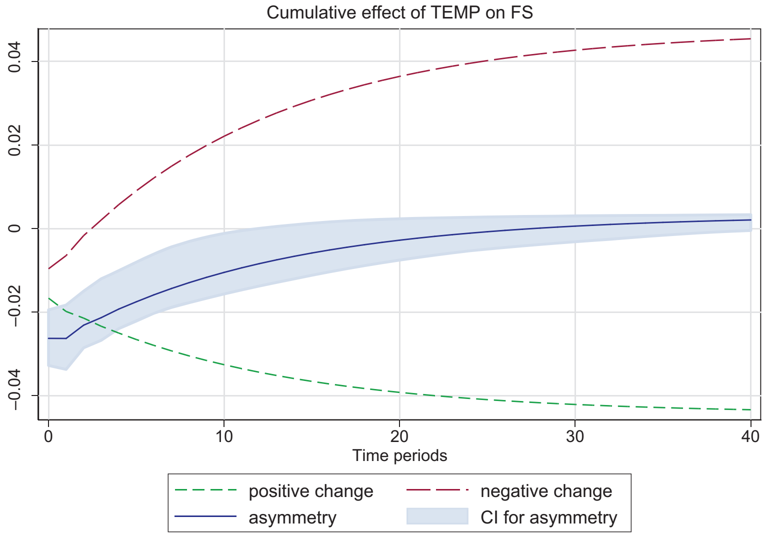

Figure 4.
Cumulative effect of TEMP on FS

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

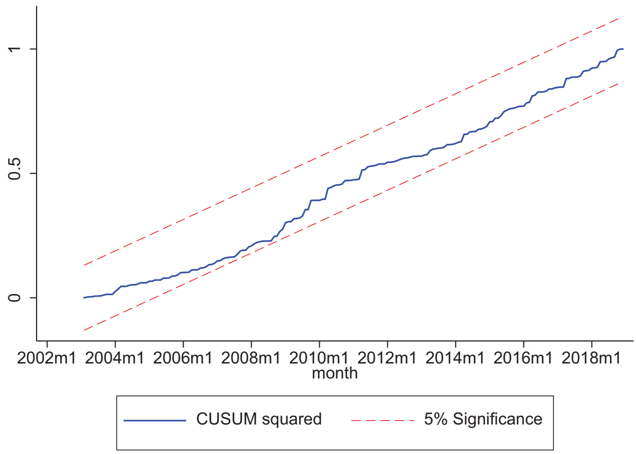

Figure 5.
CUSUM of squares test for the NARDL regression in Table 6

Variable	coefficient	standard deviation	T-statistic	p-value
FS(−1)	−0.0898**	0.0349	−2.58	0.011
$CO2^{+}(-1)$	−0.0105***	0.0027	−3.86	0.000
$CO2^{-}(-1)$	−0.0156***	0.0035	−4.41	0.000
ΔFS(−1)	−0.0574	0.0641	−0.90	0.372
$\Delta CO2^{+}$	−0.0160	0.0104	−1.53	0.127
$\Delta CO2^{+}(-1)$	0.0592***	0.0092	6.42	0.000
$\Delta CO2^{-}$	−0.0491***	0.0099	−4.92	0.000
$\Delta CO2^{-}(-1)$	0.0361***	0.0113	3.18	0.002
Cons	−0.0203	0.0154	−1.31	0.191
β^{+}	−0.117* {3.305}			0.071
β^{-}	0.174** {3.916}			0.049
		Asymmetry and co-integration test		
W_{LR}	5.831**	W_{SR}	6.247**	
t_{BDM}	−2.576**	F_{PSS}	12.174***	

Notes: The superscripts '+' and '−' indicate positive and negative partial sums, respectively. Δ 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

Table 7. Results of robustness test

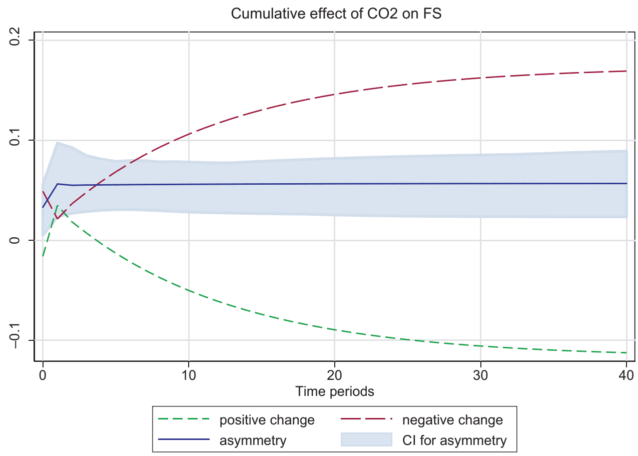

Figure 6. Cumulative effect of carbon dioxide concentration on FS

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

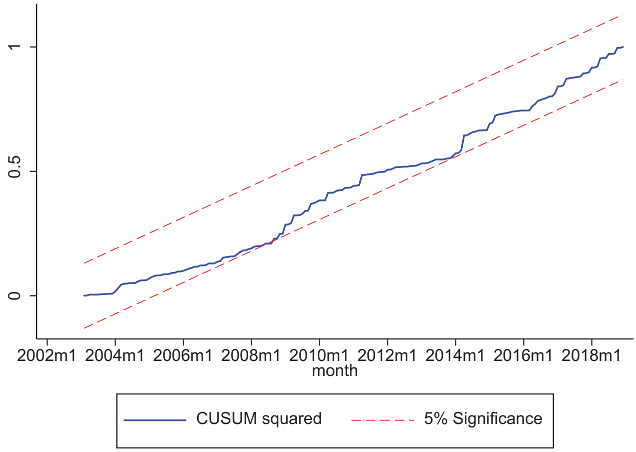

Figure 7.
CUSUM of squares test for the NARDL regression in Table 7

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, 2015). 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

Allen, F., Babus, A. and Carletti, E. (2012), "Asset commonality, debt maturity and systemic risk", *Journal of Financial Economics*, Vol. 104 No. 3, pp. 519-534.

Akbari, M., Alamdarlo, H.N. and Mosavi, S.H. (2020), "The effects of climate change and groundwater salinity on farmers' income risk", *Ecological Indicators*, Vol. 110, p. 105893.

Andersson, M.P.B. and Frédéric, S. (2016), "Governance and climate change: a success story in mobilizing investor support for corporate responses to climate change", *Journal of Applied Corporate Finance*, Vol. 28 No. 2, pp. 29-33.

Bank of England (2015), "The impact of climate change on the UK insurance sector", available at: www.bankofengland.co.uk/prudential-regulation/publication/2015/the-impact-of-climate-change-on-the-uk-insurance-sector

Battiston, S., Antoine, M., Irene, M., Franziska, S. and Gabriele, V. (2017), "A climate stress-test of the financial system", *Nature Climate Change*, Vol. 7 No. 4, pp. 283-288.

Bouwer, L.M. (2011), "Have disaster losses increased due to anthropogenic climate change", *Bulletin of the American Meteorological Society*, Vol. 92 No. 1, pp. 39-46.

Bovari, E., Giraud, G. and Isaac, F.M. (2018), "Coping with collapse: a stock-flow consistent monetary macrodynamics of global warming", *Ecological Economics*, Vol. 147 No. 5, pp. 383-398.

Campiglio, E., Godin, A. and Stephen, K. (2015), "The economic implications of the transition to a low-carbon energy system: a Stock-Flow consistent model", *Presentation at the 11th Biennial Conference of the European Society for Ecological Economics, Leeds*.

Cardarelli, R., Elekdag, S. and Lall, S. (2011), "Financial stress and economic contractions", *Journal of Financial Stability*, Vol. 7 No. 2, pp. 78-97.

Carney, M. (2015), "Breaking the tragedy of the horizon–climate change and financial stability", *Speech given at Lloyd's of London*.

Cavallo, E., Galiani, S., Noy, I. and Pantano, J. (2013), "Catastrophic natural disasters and economic growth", *Review of Economics and Statistics*, Vol. 95 No. 5, pp. 1549-1561.

Charfeddine, L. and Barkat, K. (2020), "Short- and long-run asymmetric effect of oil prices and oil and gas revenues on the real GDP and economic diversification in oil-dependent economy", *Energy Economics*, Vol. 86, p. 104680.

Chen, Y., Liu, A. and Cheng, X. (2020), "Quantifying economic impacts of climate change under nine future emission scenarios within CMIP6", *Science of the Total Environment*, Vol. 703, pp. 134950.

Chou, J., Dong, W. and Yan, X. (2016), "The impact of climate change on the socioeconomic system: a mechanistic analysis", *Chinese Journal of Atmospheric Sciences*, Vol. 40 No. 1, pp. 194-203.

Christophers, B. (2017), "Climate change and financial instability: Risk disclosure and the problematics of neoliberal governance", *Annals of the American Association of Geographers*, Vol. 107 No. 5, pp. 1108-1127.

Coffel, E.D. and Mankin, J.S. (2021), "Thermal power generation is disadvantaged in a warming world", *Environmental Research Letters*, Vol. 16 No. 2, pp. 40-43.

Comerford, D. and Spiganti, A. (2016), "The carbon bubble: climate policy in a fire-sale model of deleveraging", available at: https://economicdynamics.org/meetpapers/2017/paper_734.pdf

Cosmas, N.C., Chitedze, I. and Mourad, K.A. (2019), "An econometric analysis of the macroeconomic determinants of carbon dioxide emissions in Nigeria", *Science of the Total Environment*, Vol. 675, pp. 313-324.

Dafermos, Y., Nikolaidi, M. and Galanis, G. (2018), "Climate change, financial stability and monetary policy", *Ecological Economics*, Vol. 152, pp. 219-234.

Dickey, D.A. and Fuller, W.A. (1979), "Distribution of the estimators for autoregressive time series with a unit root", *Journal of the American Statistical Association*, Vol. 74, pp. 427-431.

Dietz, S., Bowen, A., Dixon, C. and Gradwell, P. (2016), "Climate value at risk' of global financial assets", *Nature Climate Change*, Vol. 6 No. 7, pp. 676-679.

Dietz, S. and Stern, N. (2015), "Endogenous growth, convexity of damage and climate risk: How nordhaus' framework supports deep cuts in carbon emissions", *The Economic Journal*, Vol. 125 No. 583, pp. 574-620.

Diffenbaugh, N.S. and Burke, M. (2019), "Global warming has increased global economic inequality", *Proceedings of the National Academy of Sciences*, Vol. 116 No. 20, pp. 9808-9813.

Dunz, N. Monasterolo, I. and Raberto, M. (2018), "Don't forget climate sentiments: Real and financial markets' reactions to climate risks", available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3264181

Esrb, A.S.C. (2016), "Too late, too sudden: Transition to a Low-Carbon economy and systemic risk", available at: www.esrb.europa.eu//pub/pdf/asc/Reports_ASC_6_1602.pdf

Farmer, J.D., Hepburn, C., Mealy, P. and Teytelboym, A. (2015), "A third wave in the economics of climate change", *Environmental and Resource Economics*, Vol. 62 No. 2, pp. 329-357.

Fontana, G. and Sawyer, M. (2016), "Towards Post-Keynesian ecological macroeconomics", *Ecological Economics*, Vol. 121, pp. 186-195.

Gaffney, O. and Steffen, W. (2017), "The anthropocene equation", *The Anthropocene Review*, Vol. 4 No. 1, pp. 53-61.

IPCC (2012), "Managing the risks of extreme events and disasters to advance climate change adaptation", *A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change, Field, C.B. et al. (Eds)*, *Cambridge University Press*.

IPCC (2014), *Climate Change 2014–Impacts, Adaptation and Vulnerability: Regional Aspects*, *Cambridge University Press*.

Jeffrey, K. (2019), "The asymmetric linkage between energy use and economic growth in selected african countries: evidence from a nonlinear panel autoregressive distributed lag model", *Energy Economics*, Vol. 83, pp. 475-490.

Klomp, J. (2014), "Financial fragility and natural disasters: an empirical analysis", *Journal of Financial Stability*, Vol. 13, pp. 180-192.

Lamperti, F., Dosi, G., Napoletano, M., Roventini, A. and Sapio, A. (2018), "Faraway, so close: coupled climate and economic dynamics in an Agent-Based integrated assessment model", *Ecological Economics*, Vol. 150, pp. 315-339.

Liu, J. and Bi, Z. (2019), "Research on the monetary policy based on financial stability target", *South China Journal of Economics*, No. 3, pp. 1-16.

Liu, C. and Pan, J. (2012), "Climate change uncertainties, the economic impact and policy implications", *China Population, Resources and Environment*, No. 11, pp. 13-18.

Mo, J., Duan, H., Fan, Y. and Wang, S. (2018), "China's energy and climate targets in the Paris agreement: integrated assessment and policy options", *Economic Research Journal*, Vol. 53 No. 9, pp. 168-181.

Monasterolo, I., Roventini, A. and Foxon, T.J. (2019), "Uncertainty of climate policies and implications for economics and finance: an evolutionary economics approach", *Ecological Economics*, Vol. 163, pp. 177-182.

Monasterolo, I. Zheng, J.I. and Battiston, S. (2018), "Climate-Finance and climate transition risk: an assessment of china's overseas energy investments portfolio", available at: https://ssrn.com/abstract=3163335

Mork, K.A. (1989), "Oil and the macroeconomy when prices go up and down: an extension of hamilton's results", *Journal of Political Economy*, Vol. 97 No. 3, pp. 740-744.

Murshed, S., Paull, D.J., Griffin, A.L. and Islam, M.A. (2021), "A parsimonious approach to mapping climate-change-related composite disaster risk at the local scale in coastal Bangladesh", *International Journal of Disaster Risk Reduction*, Vol. 55, p. 102049.

Nand, M. and Bardsley, D. (2020), "Climate change loss and damage policy implications for pacific island countries", *Local Environment*, Vol. 25 No. 9, pp. 725-740.

Nasreen, S., Anwar, S. and Ozturk, I. (2017), "Financial stability, energy consumption and environmental quality: evidence from South Asian economies", *Renewable and Sustainable Energy Reviews*, Vol. 67, pp. 1105-1122.

Nordhaus, W.D. (1993), "Optimal greenhouse-gas reductions and tax policy in the DICE Model", *American Economic Review*, Vol. 83 No. 2, pp. 313-317.

Nordhaus, W.D. (2018), "Projections and uncertainties about climate change in an era of minimal climate policies", *American Economic Journal: Economic Policy*, Vol. 10 No. 3, pp. 333-360.

Nordhaus, W.D. and Yang, Z. (1996), "A regional dynamic general-equilibrium model of alternative Climate-Change strategies", *American Economic Review*, Vol. 86 No. 4, pp. 741-765.

Noth, F. and Schüwer, U. (2017), "Natural disaster and bank stability: evidence from the US Financial system", *AFE Working Paper Series, No. 167*.

Phillips, P.C.B. and Perron, P. (1988), "Testing for a unit root in time series regression", *Biometrika*, Vol. 75 No. 2, pp. 347-353.

Schlenker, W. and Roberts, M.J. (2009), "Nonlinear temperature effects indicate severe damages to US crop yields under climate change", *Proceedings of the National Academy of Sciences*, Vol. 106 No. 37, pp. 15594-15598.

Shakhawat Hossain, M., Arshad, M., Qian, L., Kächele, H., Khan, I., Din Il Islam, M. and Golam Mahboob, M. (2020), "Climate change impacts on farmland value in Bangladesh", *Ecological Indicators*, Vol. 112, p. 106181.

Shin, Y. Yu, B. and Greenwood-Nimmo, M. (2014), "Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework", available at: https://link.springer.com/chapter/10.1007%2F978-1-4899-8008-3_9

Si, R., Aziz, N., Liu, M. and Lu, Q. (2021), "Natural disaster shock, risk aversion and corn farmers' adoption of degradable mulch film: evidence from Zhangye China", *International Journal of Climate Change Strategies and Management*, Vol. 13 No. 1, pp. 60-77.

Stern, N. and Taylor, C. (2007), "Climate change: Risk, ethics, and the stern review", *Science*, Vol. 317 No. 5835, pp. 203-204.

Stolbova, V., Monasterolo, I. and Battiston, S. (2018), "A financial Macro-Network approach to climate policy evaluation", *Ecological Economics*, Vol. 149, pp. 239-253.

Strobl, E. (2011), "The economic growth impact of hurricanes: evidence from US coastal counties", *Review of Economics and Statistics*, Vol. 93 No. 2, pp. 575-589.

Turnbull, S. (2020), "A framework to analyze the financial effects of climate change", *The Journal of Risk*, Vol. 23 No. 2, pp. 105-146.

Wei, Y., Yuan, X., Wu, G. and Yang, L. (2014), "Climate change risk assessment: a bibliometric analysis based on web of science", *Bulletin of National Natural Science Foundation of China*, No. 5, pp. 347-356.

Weitzman, M.L. (2009), "On modeling and interpreting the economics of catastrophic climate change", *Review of Economics and Statistics*, Vol. 91 No. 1, pp. 1-19.

Wu, X., Wang, Z., Gao, G., Guo, J. and Xue, P. (2020), "Disaster probability, optimal government expenditure for disaster prevention and mitigation, and expected economic growth", *Science of the Total Environment*, Vol. 709, p. 135888.

Yan, H. and Chen, B. (2017), “Climate change, environment regulation and the firm value of carbon emissions disclosure”, *Journal of Financial Research*, No. 6, pp. 142-158.

Zhang, H., Liu, C. and Wang, Z. (2018), “Progress in damage function of integrated assessment models for climate change”, *Climate Change Research*, No. 1, pp. 40-49.

Zhang, C., Wang, X., Li, J. and Hua, T. (2020), “Identifying the effect of climate change on desertification in Northern China via trend analysis of potential evapotranspiration and precipitation”, *Ecological Indicators*, Vol. 112, p. 106141.

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