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The impacts of climate policy uncertainty on the volatility and tail dependence of Chinese and US stock markets

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Abstract: This paper measures China's daily and monthly climate policy uncertainty (CPU) from Jan 2000 to Mar 2022 based on Chinese news data for the first time. Then, the nonlinear and lag impacts of the US CPU and China's CPU on stock market volatilities in both countries are investigated by using GARCH (1,1) and the distribution lag nonlinear model (DLNM), respectively. Furthermore, the changes in mean correlation and low tail dependence between Chinese and US stock market volatilities caused by CPUs also are compared by adopting the copula function and DLNM method. The stock market data include the Shanghai Composite Index (SSCI) and NASDAQ from Jan 2000 to Mar 2022 from the Choice database, and the Shenzhen Composite Index (SCI) and S&P 500 are used for the robustness test. The empirical results indicate that (1) the growth trend of China's CPU index is similar to that of the US. However, there are significant differences between the impacts of these two CPUs on the volatility, correlation and tail dependence of stock markets. (2) For China, only high climate policy uncertainty could increase stock volatility in the current period and reduce the low tail dependence, and the higher the CPU is, the stronger the reduction effect. Beyond that, this effect requires a lag of more than approximately two months to be observed. (3) For the US, under a low CPU level, lags of approximately two and six months increase stock market volatility. For a high CPU level, the effect diminishes to zero after a lag of more than 6 months. CPU does not improve the low tail correlation of Chinese and US stock market volatilities in the current period, but it has a significant positive effect after more than 2 months.

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Keywords: Climate policy uncertainty; Stock market volatility; Distribution lag nonlinear model; Low tail dependence; Nonlinear and lag effects

1 Introduction

Climate change is one of the most serious challenges faced by human beings in the 21st century and also is the focus of current governments (Koh et al., 2021; Boulange et al., 2021). According to '*Climate Change 2022: Impacts, Adaptation and Vulnerability*', issued by the Intergovernmental Panel on Climate Change (IPCC), the impacts and risks of climate change are increasingly complex and difficult to manage. Multiple climate risks and nonclimate risks will interact, leading to multiple climate disasters occurring simultaneously, such as droughts, typhoons, fires and floods (Boulange et al., 2021). It also could lead to varying degrees of negative impacts on economic growth, employment, agricultural losses, renewable energy consumption and population health (Dafermos et al., 2018; Galaz et al., 2018; Yang, 2019; Solaun and Cerdá, 2019; Oremus, 2019).

In addition to the above effects, based on climate economics and financial vulnerability theory, the impact of climate change on the economy and residents' lives will be transmitted to the financial system through the real economy, so governments and financial institutions are increasingly aware of the need to take climate and environmental risks into consideration in the risk assessment process of the financial system (Battiston et al., 2017). Due to the advancement of globalization, countries have shown strong linkage effects in trade, investment, production and finance, and the financial systems of countries have significant contagion characteristics. The financial risks caused by climate change will further expand (Bardoscia et al., 2018). Governments, central banks and financial regulators are beginning to recognize that they have an active role to play in tackling climate change. In December 2015, the Financial Stability Board (FSB) of the G20 set up the Task Force on Climate-related Financial Disclosure (TCFD). The group divides climate change risks into physical and transformational risks. Physical risks include all kinds of natural disasters and events related to the environment and climate, while transition risks include policy and legal risks, technological risks, market risks and goodwill risks.

To protect against the risks of climate change, various policies to combat climate change have been published, and they have the potential to cause economic and financial shocks to varying degrees (Dafermos et al., 2018; Paroussos et al., 2019). For example, the low-carbon transition policy may cause the share price of fossil energy companies to fall, while the subsidy policy of new energy vehicles may cause the share price of related energy-saving car companies to rise. Uncertainty over transformational policies to address climate change could raise equity risk, as entrepreneurs who do not know whether future policies will be aggressive or conservative can do little more than wait and see and may scale back their long-term investments. Some expansionist companies' blind investment in climate policies also will increase financial risks. In addition, policies to deal with sudden large-scale climate disasters can influence financial markets and cause financial risks by means of transfer payments or compulsory administrative orders (Stevanović et al., 2016; Landis and Bernauer, 2012).

Although climate policy uncertainty is an important factor in the volatility of China's stock market, due to the lack of accurate measurement of climate policy uncertainty, it is difficult to effectively capture its impact, including its nonlinear and lag effects on stock market volatility. Furthermore, for different countries, such as China and the US, climate policy uncertainty may have different impacts, and this comparison has not been involved in existing research. Considering the volatility spillover effect in international stock markets, the influence of the correlation between different stock markets also should be valued.

Therefore, compared with previous studies, there are two main innovations in this paper. First, based on the methods used in Huang and Luk (2019), which measure economic policy uncertainty, this paper measures the level of climate policy uncertainty in China for the first time. In contrast to the vocabulary adopted in Huang and Luk (2019), the vocabulary about policy and uncertainty are added, and this paper proposes a new collection of words about climate change, environmental governance and low-carbon transition on the basis of Li et al. (2020), which could provide a reference for research on climate policy uncertainty. Specifically, we provide a daily and monthly index of China's climate policy uncertainty from January 1, 2000, to March 7, 2022. The time trend chart of the index is similar to that of the US reported in Li et al. (2020). Climate policy uncertainty is similar to economic policy uncertainty, which can better reflect the fluctuations of climate policy and help predict the development prospects of related industries and technologies, such as new energy vehicles, the photovoltaic industry, clean energy, technical emission reduction technology and green bonds. In this paper, higher the daily and monthly CPU values indicates the higher the uncertainty.

Second, this paper notices the impact of climate policy uncertainty on stock market volatility and provides a quantitative analysis of this point. We confirm that climate policy uncertainty has significant, nonlinear and lag impacts on stock market volatility and that these impacts are different under different levels of climate policy. The intensity of influence corresponding to different lag periods also is reported. The differences in these complex impacts of climate policy uncertainty on stock market volatility in China and the US are compared for further analysis. Beyond that, the influence of climate policy uncertainty on the correlation between Chinese and US stock market volatility also attracts our interest. Specifically, this paper quantitatively analyzes its effect on the mean correlation between different stock market volatilities, and the point of low tail dependence also is involved, i.e., whether increased climate policy uncertainty leads to an increased correlation of extreme risk in stock markets.

The rest of this paper is structured as follows. Section 2 presents a review of the literature. Section 3 explains the data and methods. Section 4 reports the empirical results. Section 5 presents the conclusions, and Section 6 lists the limitations of the research.

2 Literature review

This part first sorts out the research on the correlation of stock market risk and the impact of climate change on economy and finance, and then we review relevant studies on policy uncertainty assessment. Finally, the current research on climate policy from the perspective of policy uncertainty is sorted out and analyzed.

2.1 Research on the correlation of stock market risk

The correlation of stock market risk is mainly due to risk correlation caused by economic correlation and risk correlation caused by investor behavior (Litimi et al., 2016; Chang et al., 2020). Specifically, they include international trade linkages (Corea and Radev, 2014), capital market and money market linkages (Pagano and Sedunov, 2016), transnational credit (Bastos and Pindado, 2013), international investment (Cipriani et al., 2013), industrial linkages (Tashjian et al., 2016), investor expectation effects (Ahmad and Oriani, 2022), and leverage and debt correlations (Drehmann and Juselius, 2014).

In terms of empirical research, most of the studies use econometric models, complex network methods, signal decomposition technology, input–output analysis and information entropy to analyze the correlation between stock market risk and stock market volatility (Dimpfl and Peter, 2014; Yang et al., 2016; Wang and Hui, 2017). Liu et al. (2017) used the BEKK–GARCH model and stock market data of G20 countries to construct a regional stock market network and analyze its volatility spillover relationship. Silva et al. (2016) studied the evolution of global financial market network topology and found that the network was relatively fragile before the 2008 financial crisis but subsequently became more resilient. It provides important theoretical support for revealing the law of financial risk dynamic contagion and preventing financial risk contagion. Bardoscia et al. (2018) found that the topological characteristics of network structure would affect the ease of crisis spreading in the system and analyzed the stability process of the financial system, pointing out that market integration and diversification would form a cyclical structure, which would further promote the instability of the financial system, thus exacerbating the financial crisis.

2.2 Economic and financial impacts of climate change

Many studies have confirmed that climate change has a significant impact on the economy, social production, energy and people's lives (Koh et al., 2021; Solaun and Cerdá, 2019). Specifically, regarding the impact of climate change on the economy, Pretis (2020) believed that the estimation of the impact of climate change on the economy is crucial for policy decisions and proved that the climate energy balance model is equivalent to an econometric cointegration system, which can be estimated in discrete time. The estimated parameters can be used to quantify the uncertainties in a comprehensive assessment model of the economic impacts of climate change. Calel et al. (2020) pointed out that many assessments of the economic impacts of climate change rely only on a small number of climate–economic coupling models. These assessments account for the economic costs of cognitive uncertainty stemming from the inability to accurately estimate key model parameters, such as equilibrium climate sensitivity. Therefore, we must pay attention to the analysis of uncertainty in dealing with climate change. In view of the impact of climate change on energy, Solaun and Cerda (2019) sorted out relevant studies on the response of solar, wind, hydraulic and other renewable energy power generation technologies to the impact of climate change from the perspective of quantitative analysis and pointed out that research on the impact of climate change on renewable energy is becoming increasingly important. Yang (2019) used numerical simulation to study the relationship between energy-intensive industries and climate change, providing a reference for regional climate negotiations from the perspective of externalities. In view of the impact of climate change on fisheries, Oremus et al. (2019) adopted the North Atlantic Oscillation Index (NAO) as a proxy variable of climate change to analyze the impact of climate change on fisheries in England. It was found that climate shocks not only reduced regional catches and incomes in the new sector but also reduced county wages and employment in related industries. For each standard deviation increase in climate mean, county-level fishery employment decreased by 13% on average. Holsman et al. (2020) evaluated the management strategies of major US fisheries in the eastern Bering Sea. The study found that climate change has significant negative impacts on fisheries, and climate-driven changes may exceed the adaptive capacity of current fisheries management after 2050. In view of the impact of climate change on social welfare, Yan et al. (2016) constructed the Bergson–Samuelson social welfare function based on the basic concepts of climate change science and welfare economics theory to evaluate social and economic vulnerability and economic welfare risk under the background of climate change. In addition, the economic losses and welfare risks of climate disasters under climate change scenarios in China from 2016 to 2030 are estimated by a regional weighted method, a special national adaptation fund must be established that is designed in an overall and forward-looking way from the strategic perspective of climate equity and climate security, and adaptation resources and inputs must be prioritized for the most vulnerable regions to meet their basic needs and promote long-term sustainability. Stevanović et al. (2016) pointed out that climate change threatens global agricultural productivity and leads to rising food prices.

In addition to the above impacts, some scholars also have noted the financial risks caused by climate change. As one of the major factors leading to structural changes in the financial system, climate change is long-term, structural and overall is attracting the attention of global financial institutions and investors (Dietz et al., 2016). Financial risks caused by climate change can be generally divided into two categories: (1) physical risks, namely, financial risks caused by failure to effectively solve the problem of climate change, such as the losses of residents and enterprises caused by large-scale climate disasters, which ultimately affect the stock market (Hirabayashi et al., 2013); and (2) transformation risks, namely, the risk of financial system inadaptability caused by effective policies and actions taken by public or private sectors to control climate change (Guilhot, 2022). These two types of risks will have a significant impact on macroeconomic and financial variables through channels such as asset revaluation, balance sheets, collateral value changes, exposure to risk positions, policy uncertainty and expected market volatility, and then impact financial stability and the macroeconomy.

Under the financial accelerator and collateral constraint mechanisms, market signals may amplify the severity of climate-related risks, making their impact on individual financial institutions evolve into systemic risks (Klomp, 2014). Beyond that, the impact of climate risk on the financial system and the macroeconomy is characterized by ‘cyclic feedback’, which has a wider and more far-reaching impact than other risks (Coeure, 2018). Losses from climate disasters will lead to a contraction in credit, which will further weaken household and corporate balance sheets, affecting potential growth and the output gap (Bos et al., 2022). The intrinsic externality of climate change leads to the failure of market price signals, which requires proper intervention and guidance by the "visible hand" of the government (Dafermos et al., 2018). In view of the possible systemic impact of climate change on the financial system, central banks, as macropolicy managers, should be forward-looking enough to effectively deal with climate-related risks (Battiston et al., 2017). Monasterolo et al. (2019) pointed out that traditional climate economics and financial risk models cannot well consider the characteristics of climate risk and the opportunities brought about by climate change due to the constraints of equilibrium conditions and linear effects as well as representative factors and intertemporal optimization. At present, research in this field urgently needs a new model that incorporates the uncertainties and complexities of climate impacts on socioeconomic systems and can consider the uncertainties and complexities of climate responses to socioeconomic systems. In this regard, approaches rooted in evolutionary economics and complexity science can provide complementary insights to traditional climate economic models. Campiglio et al. (2018) believed that climate change poses important challenges for central banks and financial institutions, and that current assessments of climate-related financial risks are hampered by various challenges. First, the data needed to conduct a comprehensive climate stress test are often nonexistent or too low-resolution for researchers outside financial regulators to access. Second, a comprehensive assessment of climate-related financial risks cannot rely on static snapshots alone: it needs to model the dynamic interactions among the macroeconomy, the financial system, climate change and environmental policies.

2.3 Climate policy and the measurement of its uncertainty

To avoid climate change risks, respond to climate disasters, promote green and sustainable economic growth and ensure the safety of people's work and life, the government will issue a series of climate policies in a timely manner (Chen et al., 2021; Wesseh et al., 2022). These policies are inherently uncertain and also will affect the uncertainty of the economy and stock market (Coeure, 2018). As the stock market is characterized by obvious risk contagion, the financial risks caused by climate change will continue to spread (Dietz et al., 2016).

In fact, the impact of climate policy uncertainty on the stock market is an important realization path of climate change transition risk (Kunreuther et al., 2013). Relevant government departments will issue relevant policies to address climate risks from time to time based on the impacts of climate change mentioned above (Kunreuther et al., 2013; Stern et al., 2013; Paroussos et al., 2019). These measures include, but are not limited to, low-carbon transition policies (Guilhot, 2022; Wang and Yang, 2022; Dugan et al., 2022), renewable energy subsidies (Liu and Ronn, 2020; Bai et al., 2021; Qi et al., 2022; Zhang et al., 2022), carbon taxes (Cai et al., 2015; Cui et al., 2021), green finance (Madaleno, 2022), encouraging green consumption and travel methods (Lin et al., 2021), climate-related transfer subsidies (Landis and Bernauer, 2012), development of low-carbon energy technologies (Helveston and Nahm, 2019), water conservancy facilities planning (Fletcher et al., 2019), etc. The release of these climate policies will have complex economic and financial implications.

Batten (2018) argues that unexpected policy transitions may trigger negative macroeconomic shocks from the supply side. A sudden policy shift, for example, in the form of higher carbon taxes on fossil fuels and outright quantitative limits, would sharply raise energy prices and thus undermine global economic growth. McGlade et al. (2015) estimated that 35% of the existing global oil reserves, 52% of natural gas reserves and 88% of coal reserves would become unusable by 2050 to keep global warming below 2 °C without the use of carbon dioxide capture and storage technology. Taking these assets off the balance sheets of fossil fuel companies has a very negative impact on corporate value. In addition, in the absence of market expectations, many assets will be revalued in the short term, which will easily lead to cyclical losses and long-term tightening of financial conditions (Batten, 2018). Coeure (2018) found that a sudden tightening of the carbon emission policy could lead to a disorderly repricing of carbon-intensive assets, which would shock the price of fossil fuels and the value of the relevant enterprises, in turn affecting their solvency and the financial position of investors holding their debt or equity, and even cause systemic damage to the entire financial system.

Most existing studies focus on the economic and financial impacts of a climate policy, but the analysis from the perspective of policy uncertainty deserves more attention, and that was involved in only a few studies. The relevant studies focus more on climate decision-making in the context of uncertainty (Workman et al., 2021) or uncertainty of the two types of climate change risks (Chenet et al., 2021). In a recent study, Gavriilidis (2021) measured the uncertainty of US climate policy according to the news data of major US newspapers and found that the uncertainty of climate policy has a strong negative impact on carbon dioxide emissions. Then, based on this data, Bouri et al. (2022) analyzed its impact on green stocks. These studies provide good enlightenment. To our knowledge, no studies have measured the daily climate policy uncertainty index in China. If climate policy uncertainty cannot be accurately measured, it is difficult to quantitatively analyze its impacts on the economy or stock market with the help of regression models.

In summary, the sudden release of a climate policy or an emergency executive order in response to a major climate disaster tends to have a potentially delayed impact on the economy, which in turn affects stock market volatility. Uncertainty over various climate-related policies issued to address climate change can easily lead to economic and financial market turmoil in this way. In addition, due to the characteristics of significant risk correlation between stock markets, the climate policy issued by one country is likely to affect the correlation with stock market fluctuations of neighboring countries or regions. In addition, the impact of such policies on the macroeconomy and the stock market has a lag and nonlinear effect, which may be different under different policies or different national scenarios. Therefore, it is necessary to quantitatively analyze the impact of climate policy uncertainty on stock market volatility and volatility correlation from the perspective of hysteresis and nonlinearity.

3 Data, measurement of China's CPU and regression methods

3.1 Data sources

3.1.1 The data for calculating the China's CPU

This paper collects all news involving climate policy uncertainty from 9 main Chinese newspapers from January 1 2000 to February 17, 2022. We refer to Huang and Luk (2018) in the selection of newspapers, and the newspapers include *Beijing Youth Daily*, *Guangzhou Daily*, *Jiefang Daily*, *People's Daily Overseas Edition*, *Shanghai Morning Post*, *Southern Metropolis Daily*, *The Beijing News*, *Wen Hui Daily* and *Yangcheng Evening News*. *Today Evening Post* is excluded because the number of related articles was very low during 2000-2019. Based on Huang and Luk (2018), the sum of the number of related articles appearing each month is calculated as a monthly index. Beyond that, we also report a daily index of climate policy uncertainty, even though these articles are very scarce for each day. Similar to Huang and Luk (2018), all data come from the Wisers Information Portal. These newspapers focus on important policies in major Chinese cities.

3.1.2 Data for the stock market

This paper adopts the volatility of the stock market index in China and the US as the dependent variables. In this section, we collect the log rate of returns of the Shanghai (securities) Composite Index (SSEC), NASDAQ Composite Index, Shenzhen Composite Index (SCI) and S&P 500 from the Choice database. The closing price of these indices starts in Dec 1999 and ends in Mar 2022; then, the log rate of returns is calculated from Jan 2000 to Mar 2022**.**

3.2 Measurement of China's CPU

The keywords for uncertainty refer to Huang and Luk (2018). The keywords for climate change are based on Li et al. (2020), and some additional terms related to low carbon and the green economy have been added. The keywords for policy also are based on Huang and Luk (2018), and some additional terms are added according to the white paper "China's Policies and Actions on Climate Change" issued by the State Council Information Office of the People's Republic of China. The relevant Chinese keywords used to search related news are provided in Table 1.

Table 1 Chinese keywords about China's CPU Index

Criteria	Chinese and English translation
Climate	雹子(hail), 暴风雪(snowstorm), 暴雪(blizzard), 暴雨(rainstorm), 冰雹(hail), 冰暴(ice storm), 采暖季(heating season), 大风(windy), 大气(atmosphere), 大雾(fog), 大雪(heavy snow), 大雨(heavy rain), 低气压(low pressure), 低碳(low carbon), 地震(earthquake), 多云(partly cloudy), 二氧化碳(carbon dioxide), 风暴(storm), 风暴季节(storm season), 风暴损失(storm damage), 风暴影响(storm impact), 风暴云(storm cloud), 风沙(sandstorm), 风雪(snowstorm), 干旱(drought), 干涸(dry up), 哥本哈根(Copenhagen), 供暖季(heating season), 海啸(tsunami), 海震(seaquake), 寒潮(cold wave), 寒冬(cold winter), 寒冷(cold), 旱灾(drought), 洪水(flood), 极冷(extremely cold), 季风(monsoon), 减排(emission reduction), 降水(precipitation), 降雪(snowfall), 降雨量(rainfall), 久旱(long drought), 飓风(hurricane), 空气污染(air pollution), 空气质量(air quality), 酷热(extremely hot), 酷暑(hot summer), 雷暴(thunderstorm), 雷击(lightning strike), 零排放(zero emission), 龙卷风(tornado), 隆冬(midwinter), 闷热(sultry), 暖冬(warm winter), 气候变化

	(climate change), 气候风险(climate risk), 气候灾难(climate catastrophe), 气温(air temperature), 气象(meteorological), 清洁发展(clean development), 取暖季(heating season), 全球变暖(global warming), 台风(typhoon), 碳捕捉(carbon capture), 碳储备(carbon stock), 碳排放(carbon emission), 碳强度(carbon intensity), 碳足迹(carbon footprint), 天气(weather), 温度异常(abnormal temperature), 温室气体(greenhouse gas), 雾霾(smog), 严冬(severe winter), 严寒(severe cold), 炎热(hot), 野火(wildfire), 厄尔尼诺(El Niño), 拉尼娜(La Nina), 气候(climate), 绿色转型(green transition), 转型升级(upgrade), 大气污染防治法(air pollution prevention and control law), 蓝天保卫战(blue sky defense), 柴油货车治理(diesel truck management), 长江保护(Yangtze River protection), 渤海综合治理(comprehensive treatment of Bohai Sea), 黑臭水体(black and smelly water), 绿色消费(green consumption), 绿色产品(green product), 新能源(new energy), 清洁生产(clean manufacturing), 绿色低碳(green and low carbon), 清洁能源(clean energy), 过剩产能(excess capacity), 低碳发展(low carbon development)
Uncertainty	不确定(uncertainty, uncertain), 不明确(unclear), 震荡(shock), 动荡(turmoil), 未明(unknown), 不明朗(not clear, unclear), 不清晰(not clear), 未清晰(not clear), 难以估计(hard to estimate), 无法预料(unpredictable), 无法预测(unpredictable), 无法预计(unpredictable), 无法估计(inestimable), 不可预料(unexpected), 不可预测(not predictable), 不可预计(unpredictable), 波动(volatility), 不稳(unstable), 难以预计(unpredictable), 不可估计(inestimable)
Policy	政策(policy), 制度(measures), 体制(system), 战略(strategy), 规章(regulations), 规例(regulation), 条例(regulations), 执政(govern), 政委(political commissar), 国务院(State Department), 人大(National People's Congress), 人民代表大会(People's Congress), 中央(central), 总书记(General Secretary), 国家领导人(national leader), 政治(politics), 政府(government, authority), 国家主席(president), 整改(rectification), 规管(regulation), 监管(supervision), 总理(prime minister), 改革(reform), 整治(regulation), 治理(governance), 统筹(overall planning), 协同(collaborate), 制定(formulate), 实

	施(implement)，相关部委(relevant ministries)，领导小组(leading group)，生态环境部(Ministry of Ecology and Environment)，文件(document)，方案(plan)，政策体系(policy system)，工作格局(work pattern)，协同治理(collaborative governance)，政策法规(policies and regulations)，试点示范(pilot demonstration)，建立健全(establish and improve)，产业结构调整(industrial structure adjustment)，查处(investigate)，依法依规(according to laws and regulations)，专项检查(special inspection)，清单管理(list management)，动态监控(dynamic monitoring)，通报批评(bulletin of criticism)，监管体系(regulatory system)，监督考核(supervision and assessment)，评价指标(evaluation indicators)，组织实施(organization and implementation)，鼓励企业(encourage business)，环境法规(environmental regulations)

The classification of Chinese keywords about the China Climate Policy Uncertainty Index (CPU) is similar to Huang and Luk (2018), but the specific index method is different. Huang and Luk (2018) search the news that contains at least one keyword in these three groups. We made some improvements for a more accurate search. Specifically, we first download all articles that contain the vocabulary of uncertainty. In fact, many climate emergencies will lead to subsequent policy and administrative directives. Therefore, articles containing climate change-related words in their titles were further counted among the obtained articles. Then, many articles related to policies are not truly reflected in the news. For example, when the impact of a typhoon is relatively serious, the reports about the uncertain impact of the typhoon do not involve policy-related vocabulary, but the local government must issue relevant emergency measures to reduce the harm caused by such extreme events. Hence, finally, we conducted an investigation of the articles retrieved in the above process one by one and made a subjective judgment on whether there would be a response policy issued in the future for these articles, and many articles were deleted. Following Huang and Luk (2018), the sample starts in Jan 2000 and ends in Mar 2022.

Considering that the lag of policies and the number of relevant policies are relatively small, a monthly CPU will be adopted in the empirical analysis. The time trends for CPU are reported in Figure 1.

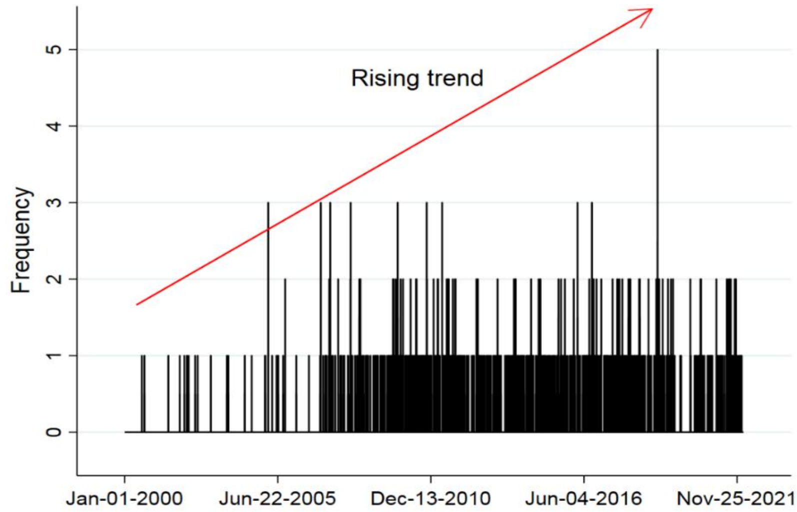


Figure 1 Time trend of China's daily CPU

As shown in Figure 1, the high level of the China's CPU is denser from 2005 to 2022, especially during the last decade, which indicates that the uncertainty of China's climate policy is increasing year by year, and climate change is attracting increasing attention from policy-makers. In this paper, considering the comparison with the condition of the US and the lag time of individual economic responses after policy releases is relatively long, we adopt the monthly China's CPU as the independent variable, which is consistent with the frequency of the variables in Huang and Luk (2018).

3.3 Measuring monthly volatility of Chinese and US stock index

This paper first calculated the log return (r) of the stock market index, and $r_t = \ln(P_t/P_{t-1})$, where P_t represents the closing price in period t. Then, the GARCH model is adopted to obtain the monthly volatility of the Chinese and US stock indices. Although ARCH could describe the volatility and obtain a very good effect, higher orders may be required in actual modeling. This paper adopts the GARCH (1,1) model, which is an important extension of the ARCH model. For a logarithmic series of returns r_t, we assume that its innovation $a_t = r_t - \mu_t = r_t - E(r_t|F_{t-1})$ and $\{a_t\}$ is GARCH(m,s) if $a_t = \sigma_t \varepsilon_t$ and $\sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2$, where $\{\varepsilon_t\}$ is independent identically distributed white noise sequences with zero mean unit variance. $\alpha_0 > 0$,

$\alpha_i \geq 0$, $\beta_j \geq 0$, $0 < \sum_{i=1}^{m} \alpha_i + \sum_{j=1}^{s} \beta_j < 1$. The conditional variance can vary over time. The GARCH model has few grading methods and generally adopts the trial and error method. Considering that GARCH (1,1) can meet the research needs in many cases, this paper adopts the GARCH (1,1) model to estimate the model volatility. The modeling process includes (1) testing the ARCH effect; (2) estimating the parametrics of the GARCH model and obtaining volatility; and (3) testing whether the model has extracted all the effective information, that is, whether the standardized residual conforms to the white noise sequence.

3.4 Measuring monthly correlation between Chinese and US stock index volatilities

To calculate the correlation between the volatilities of the Chinese and US stock market indices, the index of correlation is the Pearson correlation coefficient:

$$\rho(X,Y) = \frac{E[(X-\bar{X})(Y-\bar{Y})]}{\sigma_X \sigma_Y} \in [-1,1] \tag{1}$$

where $\bar{X}$ and $\bar{Y}$ are mean values and σ_X and σ_Y are standard deviations. $\rho(X,Y) =- 1$ and $\rho(X,Y) = 1$ represent perfect negative correlation and perfect positive correlation, respectively. To obtain the time series of $\rho(X,Y)$, the rolling window method is considered. The width is 12 and starts in Dec 2000 and ends in Mar 2022.

3.5 Measuring monthly low tail dependence between Chinese and US stock volatilities

In addition to the mean correlation, the impact of climate policy uncertainty on the low tail dependence between Chinese and US stock market volatilities also attracts interest. Low tail correlation is when two financial markets both fall. The linear correlation coefficient mostly reflects the overall correlation, but in financial models, it is the tail correlation that is generally considered. The copula function can accurately construct the joint distribution of multivariate random variables and then be used to calculate the tail correlation of multiple random variables. Specifically, the time series of low tail dependence is calculated with the copula function and rolling window method. The width of the window is 30 and starts in Jun 2002 and ends in Mar 2022. Under each window, we use a bivariate copula to calculate the low tail dependence. A bivariate copula $C(u,v)$ is a bivariate distribution function with standard uniform marginal distributions. $C(u,v) = P(U < u, V < v)$, where U and $V \sim U(0,1)$. In fact, function C: $[0,1]^2 \to [0,1]$. According to Sklar's Theorem, $H(x,y)$ is a bivariate distribution function with marginal distributions $F(x)$ and $G(y)$. There exists a copula C: $[0,1]^2 \to [0,1]$ such that $H(x,y) = C\big(F(x), G(y)\big)$, and $(x,y) \in (-\infty,\infty)^2$. If $F(x)$ and $G(y)$ are continuous, C is unique.

Considering that the distribution of these volatilities may not be a normal distribution, the most copula function should be selected first. Following Okhrin et al. (2021), we use goodness-of-fit tests to determine the copula, and after we find the copula, the low tail dependence can be calculated. The low tail dependence coefficient between X and Y is defined by

$$\lambda_L(X,Y) = P(U \leq u | V \leq v) = \lim_{u \to 0^+} \frac{C(u,u)}{u} \tag{2}$$

If $\lambda_L(X,Y) \in (0,1]$, X and Y have a lower tail dependence. If $\lambda_L(X,Y) = 0$, X and Y are independent in the lower tail.

3.6 The distribution lag nonlinear model (DLNM)

To quantitatively investigate the nonlinear and lag impacts of CPUs on stock market volatilities and their correlation, the DLNM method proposed by Gasparrini et al. (2010) is adopted. The DLNM method has been used widely in assessing the health effects of air pollution and temperature, and it also can be adopted to analyze the nonlinear and hysteretic relationships between variables. It can provide the different coefficients under different levels of CPU and different lag terms. According to Gasparrini et al. (2010), for example, a general model that is used to describe the nonlinear nexus between CPU and $Volatility$ is as follows:

$$Volatility_t = \alpha + \sum_{j=1}^{J} s_j\big(CPU_{tj}; \boldsymbol{\beta}_j\big) + \sum_{k=1}^{K} \gamma_k u_{tk} + \varepsilon_t \tag{3}$$

where u_{tk} represents control variables and has a linear impact on $Volatility_t$, and function s_j could represent the nonlinear impacts of CPU on $Volatility$ when it is defined by a smooth function, such as a spline function or polynomial function. The aim is to transform CPU_t into several time series with different coefficients that could depict its nonlinear impact. By using the smoothed functions, $s(CPU_t;\boldsymbol{\beta}) = \boldsymbol{z}_{t\cdot}^{T}\boldsymbol{\beta}$, the transformation can be shown in Eq. 1:

$$\begin{array}{ccc} \mathbf{1} & & \boldsymbol{J}=\boldsymbol{V_x} \\ \begin{cases} CPU_1 \\ \vdots \\ CPU_t \\ \vdots \\ CPU_n \end{cases} & \Rightarrow S \Rightarrow & \begin{bmatrix} Z_{11} & \cdots & Z_{1j} & \cdots & Z_{1J} \\ & & \vdots & & \\ X_{t1} & \cdots & Z_{tj} & \cdots & Z_{tJ} \\ & & \vdots & & \\ X_{n1} & \cdots & Z_{nj} & \cdots & Z_{nJ} \end{bmatrix} \\ \boldsymbol{CPU} & & \boldsymbol{Z} \end{array} \tag{4}$$

where $\boldsymbol{z}_{t\cdot}$ is the tth row of the $n \times v_x$ basis matrix $\boldsymbol{Z}$. Then, the lag effect also can be introduced into the model. It is assumed that $Volatility_t$ could be affected by CPU_{t-l}, and l is the lag. The $n \times (L+1)$ matrix $\boldsymbol{Q}$ can be obtained, in which:

$$\mathbf{q}_{t\cdot} = [CPU_t, \dots, CPU_{t-l}, \dots, CPU_{t-L}]^T \tag{5}$$

where L is the maximum lag and therefore $\mathbf{q}_{1\cdot} \equiv \boldsymbol{CPU}$, which is the first column of $\boldsymbol{Q}$. Then, a new DLNM can be constructed and $s(CPU_t;\boldsymbol{\eta}) = \mathbf{q}_{t\cdot}^{T}\mathbf{C}\boldsymbol{\eta}$, where $\mathbf{C}$ denotes an $(L+1) \times v_l$ matrix of basis variables obtained by adopting specific basis functions to the lag vector l. For example, if $\mathbf{C} \equiv \mathbf{1}$, it is a moving average model. $\boldsymbol{\eta}$ is the vector of parameters that should be estimated, and the real coefficients $\widehat{\boldsymbol{\beta}} = \mathbf{C}\widehat{\boldsymbol{\eta}}$.

4 Empirical analysis

4.1 Monthly volatility of Chinese and US stock indices

To obtain the monthly volatility of the Chinese and US stock indices, the GARCH (1,1) model is employed. We first calculate the logarithmic returns of four indices, and the results are provided in Figure 2.

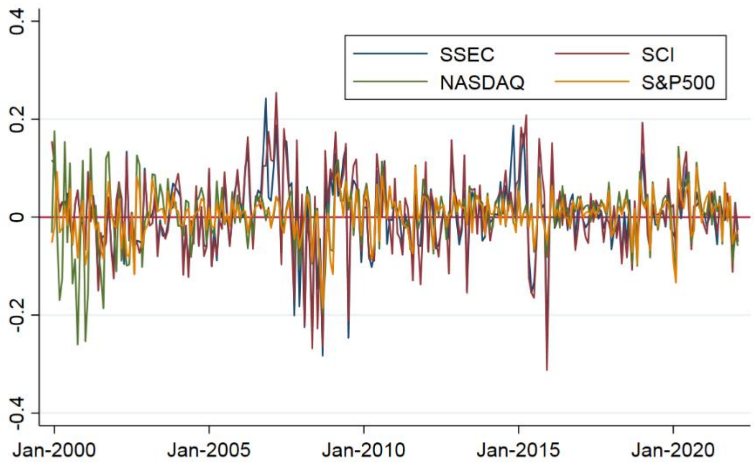


Figure 2 Time trend of log rate of returns of stock market index

As shown in Figure 2, the log rates of returns all fluctuate up and down near 0, showing a smooth character. Before adopting the GARCH model, the stationarity of the variables needs to be tested, and the lag order needs to be determined. The ADF test and PP test are used, and the null hypothesis is that the variable has a unit root. The results of unit root tests of monthly logarithmic returns are reported in Table 1.

Table 1 Unit root test of logarithmic returns

	SSEC	SCI	NASDAQ	S&P500
ADF test	-14.598***	-14.425***	-15.064***	-15.172***
	0.0000	0.0000	0.0000	0.0000
PP test	-14.762***	-14.526***	-15.036***	-15.176***
	0.0000	0.0000	0.0000	0.0000

As shown in Table 1, all p values are less than 0.01, indicating that all variables do not contain unit roots. Then, the autoregression models and Akaike information criterion (AIC) are adopted to select the order. The results are provided in *Supplementary Material: Table S1*. According to the results in *Supplementary Material: Table S1*, this paper confirms that both the SSEC and SCI have 4 lag orders and both the NASDAQ and S&P 500 have 1 lag order, and for the sake of the robustness of the conclusion, the lag orders for the NASDAQ and S&P 500 are determined to be 10. Then, the ordinary least squares (OLS) method is used, and the regression results are shown in *Supplementary Material: Table S2*. As shown in *Supplementary Material: Table S2*, the p values of the coefficients of the autoregression models are consistent with the AIC, and then the residuals are extracted and tested for the ARCH effect by using the LM test. The results are shown in *Supplementary Material: Table S3*. From the results of LM tests, ARCH effects have been confirmed. Based on the above tests, this paper selected the mean regression models with 4 lag orders for the stock market index in China and with 1 lag order for the US. The results of GARCH (1,1) are reported in Table 2.

Table 2 Regression results of GARCH (1,1)

	SSEC	SCI	NASDAQ	S&P500
ARCH	0.1992***	0.2123***	0.2038***	0.2010***
	0.002	0.001	0.001	0.001
GARCH	0.7495***	0.7388***	0.7488***	0.7519***
	0.000	0.000	0.000	0.000
$\alpha + \beta$	0.9487	0.9511	0.9526	0.9529

As shown in Table 2, the coefficients of residuals and conditional variances are significant at the 1% level, and their sums are less than 1, indicating that variances exist and are finite for the SSEC, SCI, NASDAQ and S&P 500. Then, the volatilities could be estimated and are reported in Figure 3.

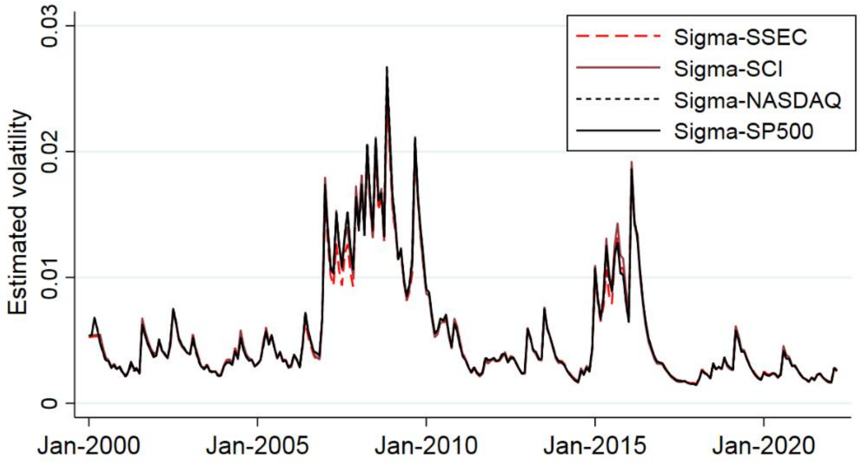


Figure 3 Estimated volatilities of different stock market index returns

To ensure that the model has extracted useful information, the standardized residuals are examined by adopting the portmanteau test, and the results are reported in Table 3.

Table 3 Portmanteau test for white noise

	SSEC	SCI	NASDAQ	S&P500
(Q) statistic	36.9364	38.0164	39.8659	40.6112
P-values	0.6089	0.5599	0.4762	0.4433

According to Table 3, all p values are greater than 0.1, and the null hypothesis that the time series is white noise should be accepted. Therefore, it could be confirmed that all GARCH (1,1) models are reasonable.

4.2 Construction and results of DLNM models

After calculating the CPUs for China and the US and obtaining the volatilities, this paper aims to investigate the nonlinear and lag impacts of climate policy uncertainty on different stock market volatilities and their correlation for China and the US. The impacts on the tail dependence also are considered by using the distribution lag nonlinear models (DLNM), GARCH model and copula function. We selected SSEC and NASDAQ to represent the stock market in China and the US, respectively, and the SCI and S&P 500 also are used in robustness tests for comparison. Specifically, after the unit root test, the empirical analysis can be divided into three parts: (1) GARCH models are adopted to obtain the volatility of the stock market in China and the US, and then the DLNM is used to discuss the nonlinear and lag impacts of the China's CPU and US CPU on stock market volatility. (2) The sliding time window method is used to calculate the time series of Pearson correlation coefficients between Chinese and US stock market volatility, and then the DLNM is adopted for empirical analysis. (3) The different goodness-of-fit (GoF) tests are employed to select the most common copula function to describe the dependency structure of stock market volatility and calculate their tail dependence with a sliding time window. The descriptive statistics of all variables and time trends are reported in Table 4 and Figure 4, respectively.

Table 4 Descriptive statistics

Variables	Obs	Mean	Std.Dev.	Min	Max
China's CPU	267	2.7865	2.8250	0	16
US CPU	267	104.4188	85.0997	1.23	629.02
σ of SSEC	267	0.0054	0.0042	0.0015	0.0239
σ of SCI	267	0.0055	0.0045	0.0015	0.0258
σ of NASDAQ	267	0.0055	0.0045	0.0015	0.0269
σ of S&P500	267	0.0055	0.0045	0.0015	0.0263

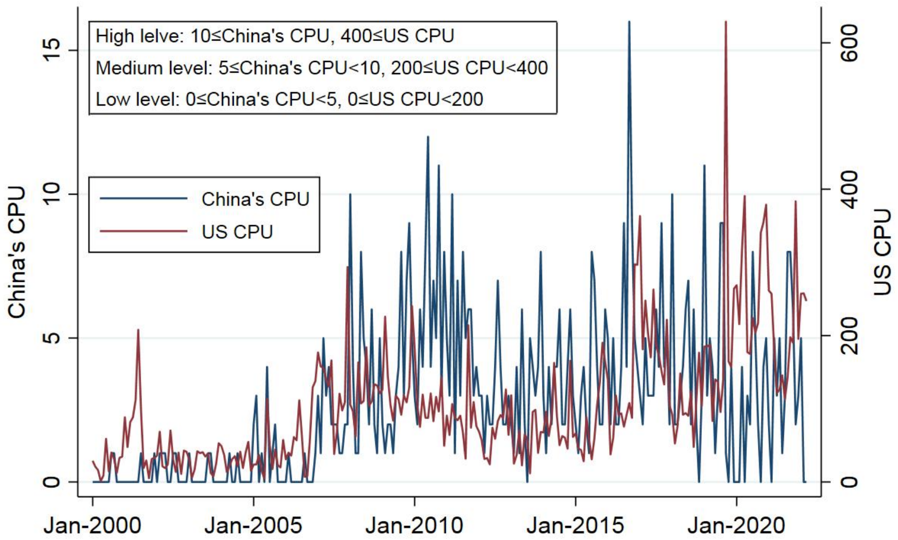


Figure 4 Time trend of China's CPU and US CPU

As shown in Table 4, the mean values and maximums of the China's CPU and US CPU have big differences, but the volatilities of the different stock indices are pretty close. Their time trends are provided in Figure 4 with different Y coordinate systems. During the period of 2000 to 2010, the climate policy uncertainties of China and the US were low, the overall level was rising, and volatility was more violent from 2010 to 2020. This indicates that climate change is receiving increasing policy attention from governments.

Table 5 Unit root test

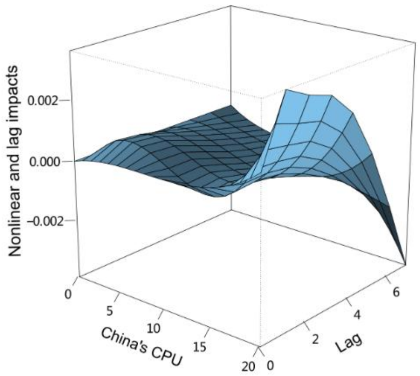
	CPU_{China}	CPU_{US}	σ_{SSEC}	σ_{SCI}	σ_{NASDAQ}	$\sigma_{S\&P500}$
Dickey-Fuller (DF)	-10.130***	-7.227***	-4.054***	-4.144***	-4.045***	-3.986***
	0.0000	0.0000	0.0012	0.0008	0.0012	0.0015
Phillips-Perron (PP)	-10.493***	-7.093***	-3.499***	-3.566***	-3.481***	-3.420***
	0.0000	0.0000	0.0080	0.0064	0.0085	0.0103

From Table 5, according to the results of the DF and PP tests, the p values are less than 0.01, which rejects the null hypothesis of the unit root, and all variables are stationary time series.

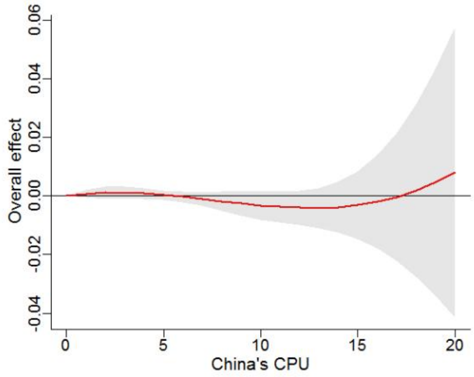
4.2.1 The impacts of CPU on stock market index volatility in China and US

By using the DLNM model, this paper first investigates the nonlinear and lag impacts of the China's CPU on the volatility of the SSEC from Jan 2000 to Mar 2022. These impacts are reported in Figure 5.

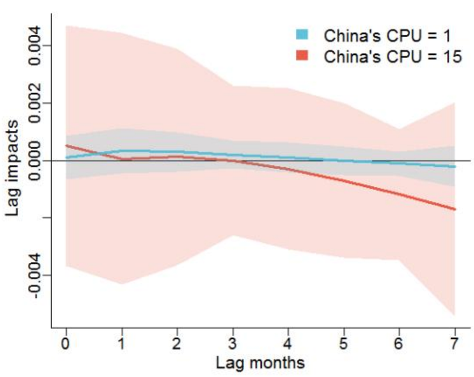
(1) The impacts of China's CPU on the volatility of SSEC



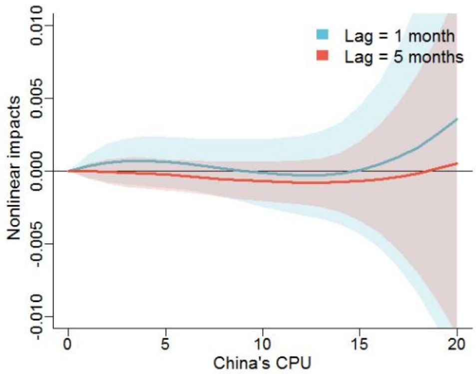
(a) Impacts of China's CPU on SSEC volatility



(b) Overall effects of China's CPU



(c) Lag effects of different China's CPU



(d) Nonlinear effect of lag China's CPU

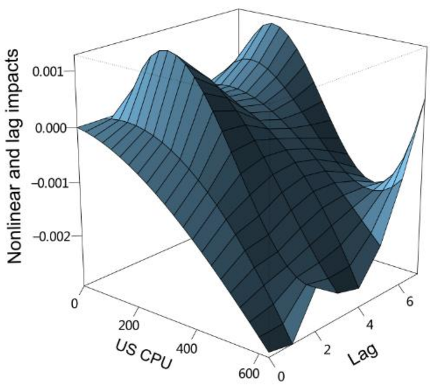
Figure 5 Nonlinear and lag impacts of China's CPU on SSEC volatility

As shown in Figure 5(a), when the China's CPU is less than 15, the coefficients are close to 0, indicating that the impacts of the current period and lag periods are not obvious. When the China's CPU is greater than 15 and less than 20, the increase of the China's CPU from 15 to 20 will make the volatility of the SSEC decrease by 0.2%. Beyond that, the lag impacts also could increase with the change of time. It could be deduced that in China, when climate policy uncertainty is high, the negative impact on volatility will be strengthened and last for more than six months. The same condition also can be found in Figure 5(b), that the overall effect will be obvious when the China's

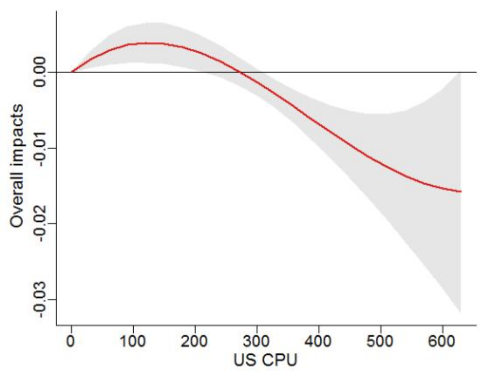
CPU is greater than 15. Figure 5(c) provides the lag impacts of low and high China's CPUs for comparison. Only a high level of climate policy uncertainty could have a negative influence on SSEC volatility. Based on Figure 5(d), lag impacts for both 1 and 5 months have the same change, indicating the same change rules.

(2) The impacts of US CPU on the volatility of NASDAQ

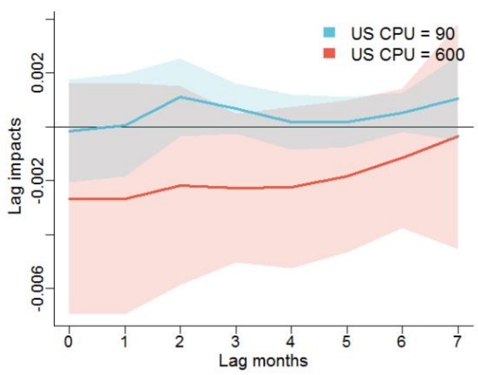
To compare the differences between China and the United States, the nexus between the US CPU and NASDAQ also is considered. The empirical results are provided in Figure 6.



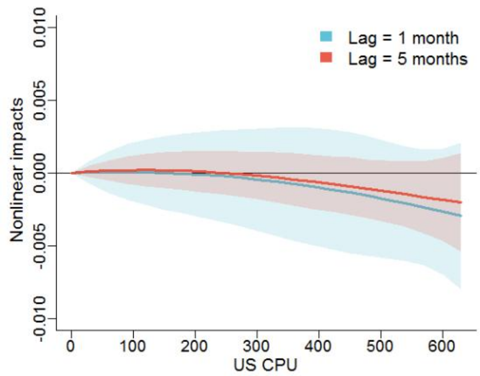
(a) Impacts of US CPU on SSEC volatility



(b) Overall effects of US CPU



(c) Lag effects of different US CPU



(d) Nonlinear effect of lag US CPU

Figure 6 Nonlinear and lag impacts of US CPU on NASDAQ volatility

As shown in Figure 6, the nonlinear and lag impacts of the US CPU on the volatility of the NASDAQ are different from those in China. From Figure 6(a), in the current period, the US CPU has a negative impact on the volatility of the NASDAQ. However, when the US CPU is greater than 0 and less than 200, the US CPU may have a positive lag impact on NASDAQ volatility, and these positive effects will be strengthened after two months and six months. Similarly, the negative lag impacts when the US CPU is greater than approximately 200 will be weakened after two months and six months, indicating that the lag effect has regularity. According to Figure 6(b), the overall effect of the US CPU also is different from that in China. A low level of US climate policy uncertainty could increase the volatility of the NASDAQ, but a high level of US climate policy uncertainty has a negative influence on NASDAQ volatility, which may be strengthened with the increase in the US CPU. From Figure 6(c), a high level of US climate policy uncertainty could have persistent negative effects on stock market volatility, but the impact of a low level of US climate policy uncertainty is positive and weaker than that for a high level of US climate policy uncertainty. Based on Figure 6(d), climate policy uncertainty is more likely to reduce stock market volatility in the future.

4.2.2 The impacts of CPU on the correlation of stock market volatility

The correlation between stock market volatility is calculated by the rolling method, and the rolling window is 12 because this paper adopts monthly data. The time trends of the SSEC and NASDAQ are reported in Figure 7, and the results of unit root tests are reported in Table 6.

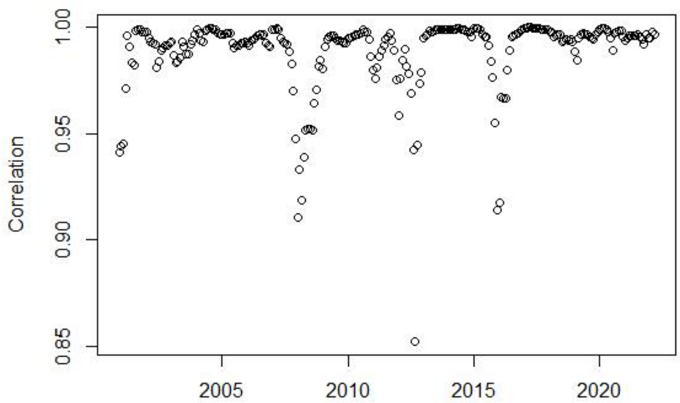


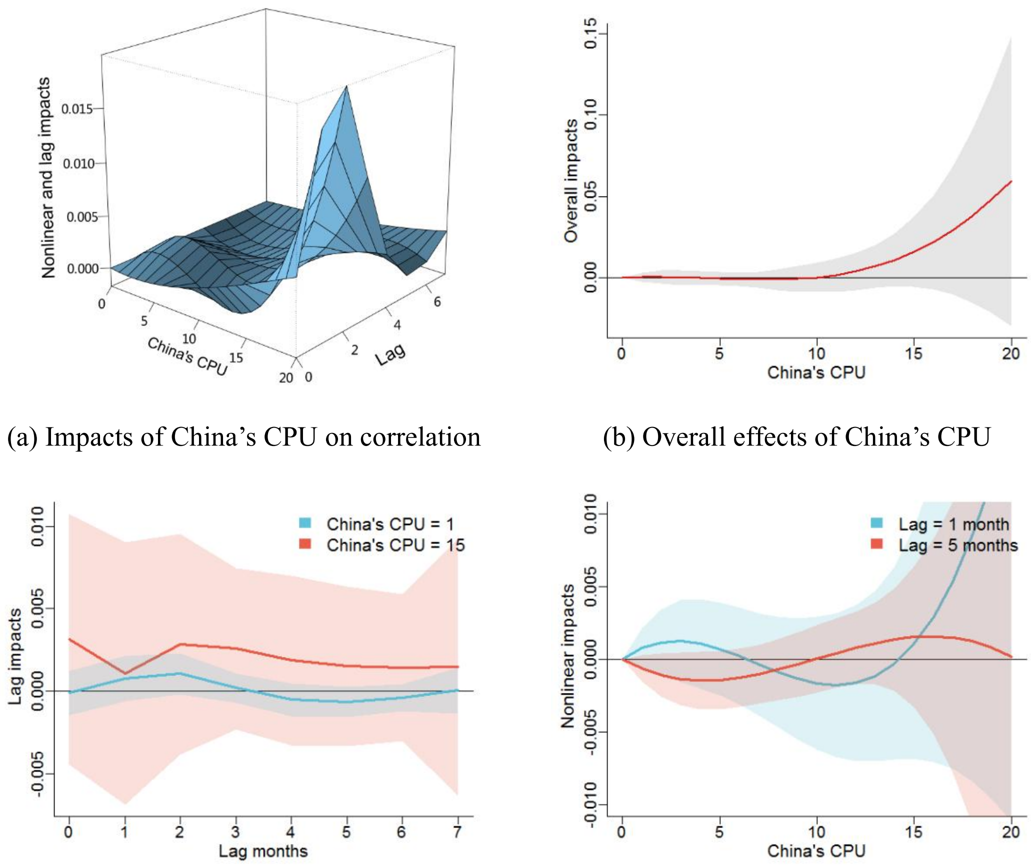
Figure 7 Time trend of the correlation between volatility of SSEC and NASDAQ

Table 6 Unit root tests of the correlations (SSEC-NASDAQ and SCI-S&P 500)

Unit root tests	Correlation (SSEC-NASDAQ)	Correlations (SCI-SP500)
Dickey-Fuller test	-5.556^{***}	-6.758^{***}
	0.0000	0.0000
Phillips-Perron test	-5.661^{***}	-6.790^{***}
	0.0000	0.0000

As shown in Figure 7, there is a significant positive nexus of the volatility between the SSEC and NASDAQ. During most times, the correlation is close to 1. According to Table 6, all p values are less than 0.01, indicating that the time series of correlations do not contain unit roots; therefore, the DLNM models could be used. The correlation between the SCI and S&P 500 will be used for the robustness test.

(1) The nonlinear and lag impacts of China's CPU on correlation between SSEC and NASDAQ



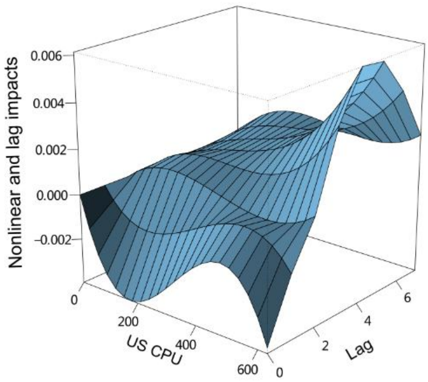
(a) Impacts of China's CPU on correlation (b) Overall effects of China's CPU

(c) Lag effects of different China's CPU (d) Nonlinear effects of lag China's CPU

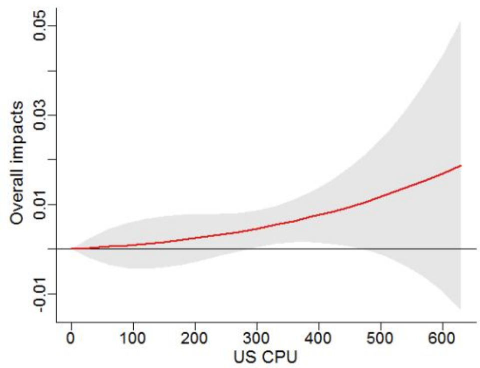
Figure 8 Nonlinear and lag impacts of China's CPU on correlation (SSEC-NASDAQ)

As shown in Figure 8(a), in the current period, only when the China's CPU is high could the correlation between the SSEC and NASDAQ be positively affected. From the perspective of hysteresis effects, a high level could have a positive lag effect on the correlation among 4 months. Based on Figure 8(b), a low level of China's CPU that is less than 10 could not have any impact on the correlation; however, when the China's CPU is greater than 15, climate policy uncertainty could have an increasing overall positive effect on the correlation. From Figure 8(c), the lag effect could be significant only under a high level of China's CPU, such that the China's CPU is equal to 15. Based on Figure 8(d), the lag effects of China's CPU change regularly with the increase of China's CPU, and a longer lag will cause the influence to be weakened.

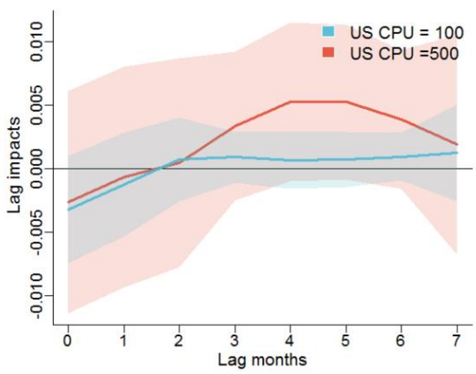
(2) The nonlinear and lag impacts of US CPU on correlation between SSEC and NASDAQ



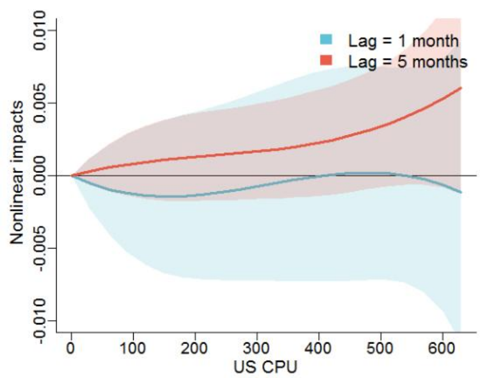
(a) Impacts of US CPU on correlation



(b) Overall effects of US CPU



(c) Lag effects of different US CPU



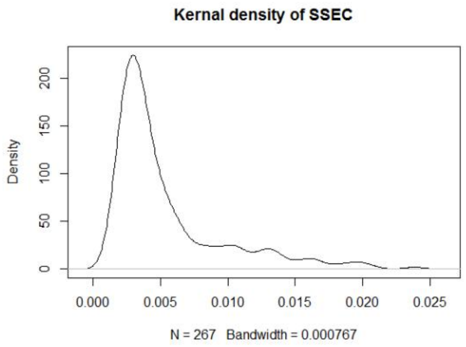
(d) Nonlinear effect of lag US CPU

Figure 9 Nonlinear and lag impacts of US CPU on correlation (SSEC-NASDAQ)

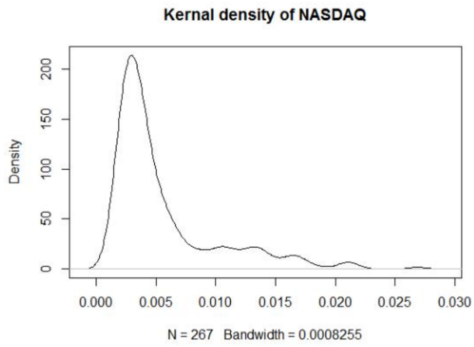
The effects of the US CPU are similar to those of the China's CPU to some extent. According to Figure 9(a), from the perspective of current impact, the US CPU has a nonlinear and negative impact on the correlation between the SSEC and NASDAQ. This negative effect will be strengthened when the US CPU is close to 200 and 600 and will not be obvious in other stages. As shown in Figure 9(b), the overall effect of the US CPU on the correlation is positive and will strengthen with the increase of US CPU, which is similar to that of the China's CPU. However, it is worth noting that this reinforcing effect will appear earlier than the impact of the China's CPU. Based on Figure 9(c), the US CPU could not exert a significant lag effect on the correlation under a low level, but it could have a positive lag effect during three and seven months under a high level. Based on Figure 9(d), the US CPU could have a significant positive impact on the correlation only under a high level and long lag term, such as 5 months.

4.2.3 The impacts of CPU on the tail dependence between stock markets volatility

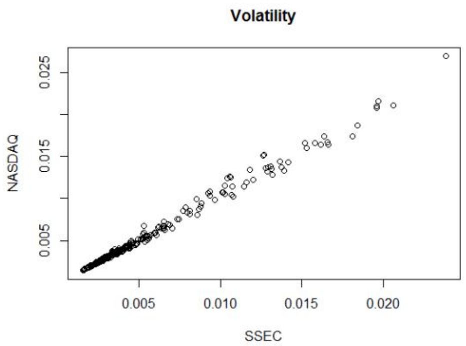
In addition to the discussion about the complex impacts of CPU on the correlation between the stock markets of China and the US, the impact on their tail dependence also is considered, especially the low tail dependence, which has an important impact on the stability of financial markets and the normal operation of financial institutions, and investigating this point could help investors avoid financial investment risks from the perspective of climate policy and economic transformation. We first report the distribution of each volatility and its nexus. Then, different goodness-of-fit (GoF) tests are used to select the most suitable copula to calculate this tail dependence. Similar to Section 4.2, the nexus between the SCI and S&P 500 also is adopted as a robustness test. Then, we conduct unit root tests and use the DLNM for empirical analysis. The kernel densities of the SSEC and NASDAQ and the selection of the copula between these two indices are reported in Figure 10.



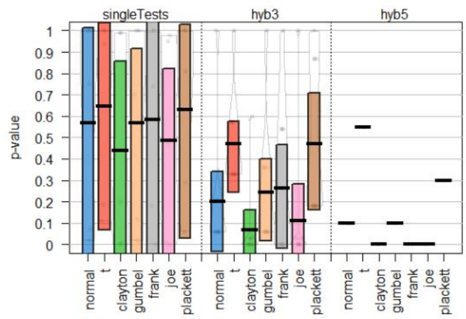
(a) Distribution of volatility of SSEC



(b) Distribution of volatility of NASDAQ



(c) Nexus between the volatilities



(d) Comparison of different GoF tests

Figure 10 Nexus and GoF results for the volatilities of SSEC and NASDAQ

As shown in Figure 10, both distributions of the volatilities of the SSEC and NASDAQ are not Gaussian distributions; therefore, the bivariate normal distribution function is inappropriate. Based on the results of different GoF tests, the most suitable copula is clayton for the nexus between the volatilities of the SSEC and NASDAQ. Then, we estimate the parametric of this copula and calculate the low tail dependence. The rolling window method is adopted with a width equal to 30. Therefore, this time series starts in Jun 2000 and ends in Mar 2022.

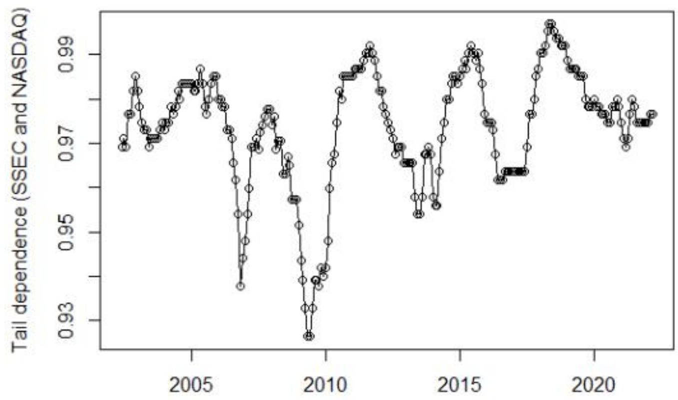


Figure 11 Time trend of tail dependence between SSEC and NASDAQ

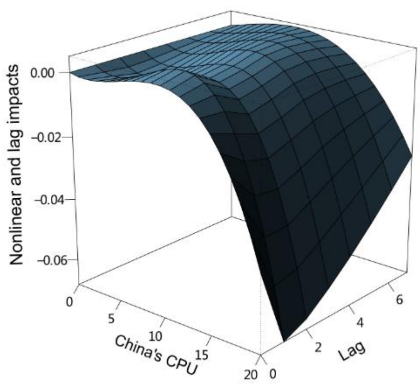
Table 7 Unit root tests for tail dependence of SSEC-NASDAQ

Unit root tests	Tail Dependence (SSEC-NASDAQ)
Dickey-Fuller test	-4.330***
	0.0004
Phillips-Perron test	-3.070**
	0.0289

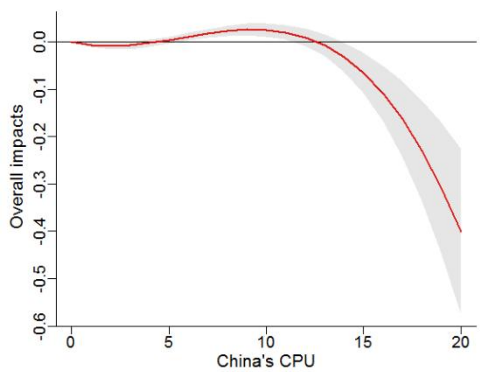
Note: DF-GLS test is used to select the most suitable lag (lag=10).

As shown in Figure 10 and Table 7, all p values are less than 0.05, indicating that the time series of tail dependence does not contain a unit root. Therefore, the DLNM method could be used.

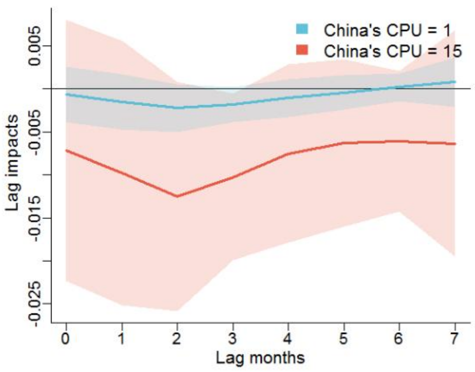
(1) The nonlinear and lag impacts of China's CPU on tail dependence between SSEC and NASDAQ



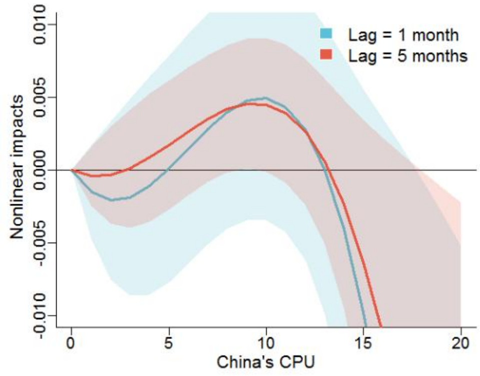
(a) Impacts of China's CPU on tail dependence



(b) Overall effects of China's CPU



(c) Lag effects of different China's CPU

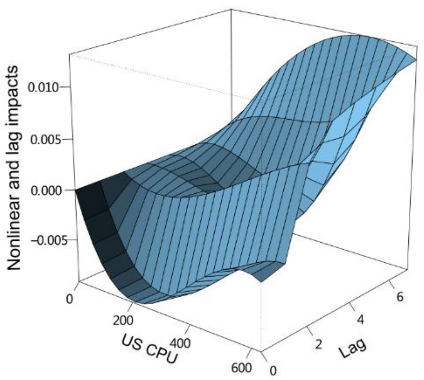


(d) Nonlinear effects of lag China's CPU

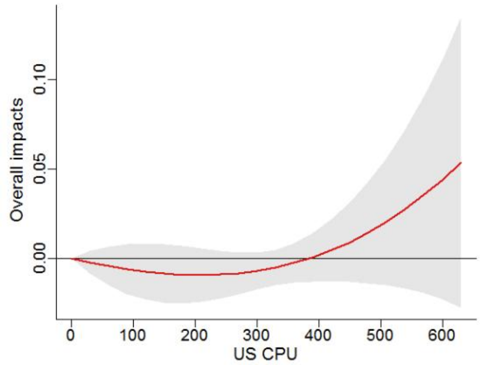
Figure 12 Nonlinear and lag impacts of China's CPU on tail dependence (SSEC-NASDAQ)

As shown in Figure 12(a), from the point of view of the current period, a low level of China's CPU could not have a significant impact on the tail dependence between the volatilities of the SSEC and NASDAQ. A high level of China's CPU, such as during the period where the China's CPU is greater than 10, could have a negative impact on the tail dependence, and this negative impact could be strengthened with the increase of China's CPU. In terms of the duration of the lag effect, the lag impact of a low level of China's CPU is not significant, and only a high level of China's CPU could have a lag and negative impact on low tail dependence, which also could be strengthened under a higher level of China's CPU. According to Figure 12(b), only a high level of China's CPU has a negative and significant impact on the tail dependence of the SSEC and NASDAQ volatilities, and the total negative effect could be enhanced with the increase of China's CPU. From Figure 12(c), only a high level of China's CPU could have a significant, lag and negative impact on low tail dependence, and this effect will be exerted over the long term, even more than 7 months. Based on Figure 12(d), the lag effects of both low and high levels of China's CPU have similarity, and the impact will turn out to be negative with the increase of China's CPU.

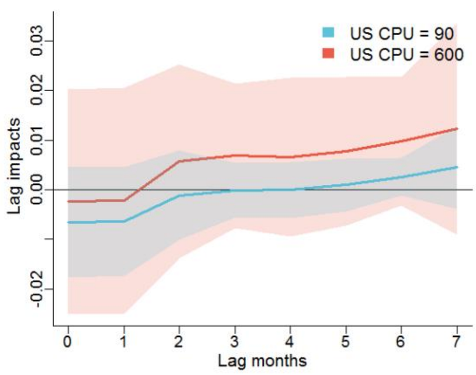
(2) The nonlinear and lag impacts of US CPU on tail dependence between SSEC and NASDAQ



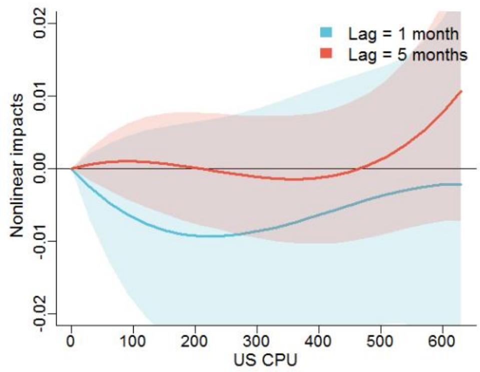
(a) Impacts of US CPU on tail dependence



(b) Overall effects of US CPU



(c) Lag effects of different US CPU



(d) Nonlinear effect of lag US CPU

Figure 13 Nonlinear and lag impacts of US CPU on tail dependence (SSEC-NASDAQ)

The nonlinear and lag impacts of the US CPU on tail dependence (SSEC-NASDAQ) are different from those of the China's CPU. As shown in Figure 13(a), from the point of view of the current period, only when the US CPU is close to a medium level could it have a negative impact on low tail dependence. Even if the US CPU level is high, it will not have any impact in the current period. However, the US CPU with a high level could have a lag and positive impact on low tail dependence, and this impact will be strengthened with the increase of lag terms and the US CPU. According to Figure 13(b), the overall impact of the US CPU is the complete opposite of that of the China's CPU. A US CPU under a low level could not exert a significant impact on low tail dependence but will turn out to have a positive impact when the US CPU is greater than approximately 400, and this impact will be strengthened with the increase of US CPU. From Figure 13(c), as the lag increases, the US CPU will first have a negative impact and turn to exert a positive impact on low tail dependence. The critical point is an approximately four-month lag.

Based on Figure 13(d), compared with a US CPU under a low level and short lag terms, a high level US CPU with long lag terms will have a positive impact on low tail dependence.

To confirm the robustness of the empirical results, the SSEC and NASDAQ are replaced by the SCI and S&P 500, and the same empirical methods are conducted again. All the regression results were basically consistent.

5 Conclusions

This paper first calculates the daily and monthly indices of climate policy uncertainty in China from January 2000 to March 2022. The calculation process is based on the textual analysis method and refers to the methods of the climate policy uncertainty index and economic policy uncertainty index of the US. Then, according to this index and the US CPU, we use the DLNM model to compare and analyze the nonlinear and lagged effects of the CPU in China and the US on stock market volatility, volatility correlation and low tail dependence. We not only find that the time trends of CPU indices in China and the US from 2000 to 2022 are very similar but also confirm the significant differences between the nonlinear and lag impacts of these two CPU indices on stock markets.

(1) The magnitude of climate policy uncertainty in China and the US is different due to the different news media and text criteria selected in the statistical process, but they show a similar upward trend from January 2000 to March 2022. According to our assessment, China's climate policy uncertainty was low from 2000 to 2006, a period when climate change and its impacts were not widely considered by the government or residents. In 2009, the 15th Conference of the Parties (COP 15) to the United Nations Framework Convention on Climate Change (UNFCCC) was held in Copenhagen, Denmark, letting climate change and low-carbon development once again become a priority for all countries. China has actively formulated and implemented a series of climate change strategies, regulations and policies. For example, the Chinese government has formulated and released implementation plans for peaking carbon emissions in energy, industry, urban and rural development, transportation, agriculture, rural areas and other sectors and actively planned

measures for carbon sequestration, energy transformation, pollution reduction and carbon reduction. Therefore, the uncertainty of China's climate policy began to rise in approximately 2009, and the high level of climate policy uncertainty has continued until now.

For China: (1) Low climate policy uncertainty does not affect volatility in the domestic stock market. However, higher climate policy uncertainty increases stock volatility in the current period, and the positive effect lasts for approximately five months, after which it decreases stock volatility. (2) Only when there is a high degree of uncertainty about China's climate policy does the correlation increase, and the effect gradually increases over time, peaking approximately 2-3 months before dissipating around April. (3) When climate policy uncertainty is low, it does not affect the correlation of extreme volatility in the Chinese and American stock markets. Only when the level of uncertainty is high can it reduce the correlation of low tail volatility. The higher the uncertainty is, the stronger the reduction effect.

For the US: (1) As climate policy uncertainty increases, stock market volatility decreases during the period. When climate policy uncertainty is low, a lag of approximately two and six months increases volatility in the country's stock market. When climate policy uncertainty is high, the effect diminishes to zero after a lag of more than 6 months. (2) As the uncertainty of US climate policy increases, the impact on the correlation of the Chinese and US stock markets is always negative, but this negative effect is not obvious when the uncertainty is very low or high, and the lag time of the effect of US climate policy is longer. (3) The uncertainty of US climate policy does not improve the low tail correlation of the Chinese and US stock markets in the current period, but it has a significant positive effect after more than 2 months, and the higher the uncertainty is, the stronger the positive effect is, and it even lasts for half a year.

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