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The Systemic Risk and Structural Evolution of China's Green Energy Industry

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Abstract:

In order to achieve the sustainable development goals, the Chinese government has elevated the development of green energy to the level of a national strategy and has encouraged multiple financial channels to support green energy development. The capital market, especially the stock market, has become the most important factor in promoting the development of the green energy industry. This paper focuses on the analysis of systemic risk in the green energy capital market by selecting 2725 sets of stock market data from China's Green Energy Industry and its sub-industries from 2010 to 2021. The systemic risk level of China's Green Energy Industry and its major sub-industries is investigated by calculating VaR using the FIGARCH model. On this basis, the risk correlation and dynamic evolution of the green energy industry and its sub-industries are investigated by further constructing a multivariate DCC-GARCH model. The study found that (1) the photovoltaic industry has the highest risk level but is followed closely by the wind power and nuclear power industries. It is no longer the most important source of risk for China's Green Energy Industry; (2) the wind power and nuclear power industries have the same level of risk and have replaced the photovoltaic industry as the most important source of risk for China's Green Energy Industry; (3) the hydropower industry has the lowest level of risk and is an important guarantee for the healthy development of China's Green Energy Industry. Finally, based on the results of this empirical study, this paper puts forward some countermeasures and suggestions for the development of green energy.

***Keywords**: China's Green Energy Industry, Capital markets, Systemic risk, Structural evolution.*

I. INTRODUCTION

The world's energy structure is undergoing profound changes, and green energy has become an inevitable choice for countries to achieve sustainable development. China, as one of the world's largest energy consumers, has ample incentive to help its green energy industry prosper, both for the long-term consideration of ensuring its own energy security and for fulfilling its responsibility in energy conservation and emission reduction in line with its "Community of Human Destiny" initiative. To this end, the Chinese government has developed an ambitious green energy development plan. A series of encouragement and support policies have led China to become a major player in the world green energy market.

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What is particularly noteworthy about China's development experience is that, after the initial policy support phase, direct financing has gradually become the most important source of funding for green energy-related enterprises to achieve their own development and technological upgrades through its growing and maturing capital market [1]. In particular, the stock market has played the most crucial role and is the main reason for the explosive growth in China's Green Energy Industry in recent years [2]. At the same time, the riskiness associated with the full involvement of capital markets has received increasing attention from researchers. Especially after the major setback of the photovoltaic industry in 2011, better capturing and predicting the risk level and development trend of the green energy market at the macro level has become a focus of attention [3,4]. This has important theoretical and practical implications for preventing possible systemic crises in this field and thus ensuring its healthy development. However, existing studies have not fully explored the level and structure of macro risks in green energy capital markets and their changing trends.

China has recently proposed the long-term goal of “peak carbon dioxide emissions” and “carbon neutrality”, in which The Energy Greening Strategy will play a more important role. Its green energy industry will still face great developmental pressures and capital demand in the future, and the positive support of market-based capital sources is indispensable. While the capital market continues to play an important role in the resource allocation system of the green energy industry, it should be noted that the uncertainties in the development process of this industry in China have not been effectively curbed for a long time. First, compared with developed countries, China's Green Energy Industry started late, and faced with the pressure to maintain economic growth and to improve people's livelihood, its green energy industry was able to develop rapidly in a short period of time largely due to the strong support of financial subsidy policies. However, as the scale of the green energy industry continues to expand, the marginal effect of supportive policies in promoting the industry's development gradually diminishes, while the irrational investment impulses they lead to and the bad consequences they caused are becoming increasingly evident [5-7]. In addition, although the stock market has contributed to the development of China's Green Energy Industry quickly and conveniently to some extent, the conditions predicted by the efficient market hypothesis for rational arbitrageurs to force irrational noise out of the market are difficult to meet given the reality of high volatility and speculation due to the high proportion of individual investors in the Chinese stock market [8, 9]. Specifically, market shocks triggered by large capital movements in and out of the market in the short term occur from time to time, making the uncontrollable risk of green energy capital markets significantly increase. As the future development trend is continuously bullish, it stimulates speculative capital to enter this industry, which may further lead to the instability of the energy sector itself and even crisis in the long-term healthy development of the whole Chinese capital market.

Based on the above reasons, this study intends to examine the systemic risk of China's green energy capital market from the macro level, starting from the most active and critical stock market. By examining the overall risk and spillover risk of China's Green Energy Industry and its sub-industries and the dynamic trends, this study reveals the risk level, structural characteristics, and general development pattern of China's Green Energy Industry in order to offer targeted risk prevention and governance recommendations,

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to help achieve the goal of risk prevention and control, to smooth development, and to provide a reference for effectively promoting the healthy development of the world green energy market.

This paper measures the systemic risk of China's green energy capital market using finance and econometric methods and analyzes its dynamic correlation with the four main green energy sub-sectors in terms of risk and its trend over time. The specific approach is as follows: first, the systemic risk of China's green energy market and its four submarkets were measured in general by calculating the VaR (Value-at-Risk) using the GARCH family model. Then, we compared and analyzed the systemic risk of China's green energy market in a Long Position and a Short Position to obtain a general impression of the systemic risk of China's Green Energy Market. After that, a multivariate DCC-GARCH model was constructed using the estimation results of the univariate GARCH model of each industry stock index to analyze the risk correlation and evolution trend of the green energy market and each sub-industry and to focus on the key nodes in it. Finally, relevant countermeasures and suggestions were proposed based on the above analysis findings.

The remainder of the paper is organized as follows: Section 2 provides a review of the literature review on green energy risks and the dependences. Section 3 provides the methodology we used to study the systemic risk and structural evolution of China’s Green Energy Industry. Section 4 focuses on the data selection and empirical results. Section 5 is the conclusion, and provides some implications.

II. LITERATURE REVIEW

There is not much literature on the risk of the green energy industry using capital markets as an entry point. Most of the studies have been conducted at the corporate level, focusing on the investment and financing risks of emerging energy projects. To a certain extent, the findings of such studies can provide us with a deeper understanding of the mechanisms that generate macro risks in the green energy industry. Generally speaking, energy projects are typically capital-intensive. This is especially true for photovoltaic and wind power projects, which are major members of green energy compared with traditional energy projects. Their characteristics of being large upfront investments, having a long payback period, and having high uncertainty are more obvious, and the investment risk assessment and prevention of such projects have been emphasized by many researchers [10-12]. Different scholars have analyzed the operational and management risks faced during the rapid development of these industries from the microscopic perspectives of low-level duplication, relative overcapacity, project investment risk evaluation, and corporate credit risk [2,13-15]. The industrial policy is the most concerning factor in this kind of research. Since photovoltaic and wind power do not have price advantages in the initial stages, they rely on industrial policy support. The resulting market distortions and resource mismatches become more apparent in the later stages. This, coupled with the mediating and regulating effects of innovation disincentives and information asymmetries, poses potential risks to the operations of a large number of such enterprises [16,17]. According to a representative study by Tietjen and Pahle et al. (2016), which earlier revealed the impact of increased renewable energy investment on overall energy market risk, this study points out that the continued increase in the share of renewable energy sources is becoming more and

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more evident in its impact on the stability of the overall energy market. In the absence of rapid substitution, the increased uncertainty in the energy sector as a whole will, in turn, backfire on the renewable energy market, leading to a reversal of its returns, although its own investment risk has diminished as the cost of generating electricity has decreased [18]. Based on the findings of the above studies, it is reasonable to infer that the accumulation and superposition of micro risks in the new green energy industry, represented by photovoltaic and wind power, may lead to a more complex and general risk dilemma for the green energy industry and the energy sector as a whole, thus increasing the uncertainty of its long-term development. This situation also requires a higher level of response than traditional energy risk management.

Under the development trend of diversification of energy types and complexity of energy structures, many researchers advocate that considering the investment risks and development strategies of various types of clean or green energy in isolation is not sufficient to build a future-oriented energy system and may even lead to unpredictable safety problems. Without changing the basic concept of greening, a holistic perspective on the safe development of energy systems is the best choice [19-21]. Taking this as a starting point, numerous papers from the literature have focused on the issue of external risk spillovers in green energy markets. Such studies have rarely focused on topics related to new energy, renewable energy, and clean energy, etc.

Among such studies, the one that has received the most attention is the issue of risk spillovers between new and traditional energy markets. For example, Reboredo (2015) analyzed the systematic risk and dependence between oil and renewable energy markets using the Copula model and found a significant time-varying average and symmetric tail dependence between international oil price volatility and major global renewable energy indices, with international oil price volatility contributing about 30% to the risk of renewable energy companies [22]. Xia and Ji et al. (2019) further included all major fossil energy sources in the study model. Their study examined the issue of fossil energy and renewable energy market dependence more comprehensively and found that the oil and coal generation markets are the main contributors to the volatility of renewable energy returns and have strong time-varying characteristics with large volatility over time [23]. A study by Reboredo and Ugolini (2018) for the U.S. energy market comes to a similar conclusion. Using a multivariate Vine--Copula to assess the impact of price changes in oil, natural gas, coal, and electricity on clean energy market volatility, they found that oil and electricity prices are the main contributors to the volatility of U.S. clean energy stock returns [24]. Based on this, Yao and Mo et al. (2021) examined the tail correlation between the clean energy market and the crude oil market in more depth using asymmetric multiple fractal detrended cross-correlation analysis (A-MFDCCA) using Chinese market data as a sample [25]. Their study revealed that the overall upward and downward trends of the clean energy market have significant multifractal characteristics and that the efficiency of the clean energy market is negatively affected regardless of the magnitude of the volatility. In addition, the studies by Ahmad (2017),Tiwari and Nasreen et al. (2021) and Jiang and Wang et al. (2021) all provided us with a clearer understanding of the relationship between renewable/clean energy market volatility and conventional energy markets [26-28].

As more and more countries try to use financial instruments as an important option to regulate their energy mix in response to the climate crisis, the relationship between the risk of clean/green energy market and green bonds (GBs), European Emission Allowance (EUA) prices, other commodity markets, and subjective characteristics of market participants is beginning to receive attention.

Liu and Liu et al. (2021) examined the risk spillover between the clean energy market and the green bond market using the conditional value-at-risk (CoVaR) and ΔCoVaR approaches. They found a positive time-varying average and tail dependence between the two, and the risk spillover shows asymmetric characteristics [29]. Hanif and Arreola Hernandez et al. (2021) investigated the frequency between European Emission Allowance (EUA) prices and renewable energy indices, using the European market as an example of volatility spillover, connectivity, and nonlinear dependence [30]. The results of the study showed that the short-term volatility spillover effect between carbon credit price and renewable energy index dominates the long-term volatility spillover effect. The volatility spillover between carbon credit prices and renewable energy indices is significant in both the short and long terms. Meanwhile, Yahya and Ghosh et al. (2020) further extended their research perspective to volatility spillovers and causality between nonferrous metal markets and clean energy markets, using a time-varying Copula model to reveal that the conditional dependence between the two is time-varying and asymmetric, with potential tail dependence [31]. Song and Ji et al. (2019) introduced investor sentiment variables into the study of renewable energy risk. They found that investor sentiment can explain the returns of renewable energy stocks and their volatility to some extent [32]. In addition, a study on private capital entry and investment risk in China's wind power industry and another study on the hierarchical relationship between risk factors in renewable energy generation provided a fuller understanding of the risk profile of some green energy markets and their correlation characteristics with other markets [33,34].

In summary, the existing literature findings can help us form a general impression of the sources of risks and their spillover effects in green energy markets, especially in terms of progressively deeper characterization of their external risk correlations. However, against the background of the increasing scale and proportion of the green energy industry, the overall risk level and internal risk structure of the green energy industry and their relative trends have gradually become important elements in judging the long-term development of the industry due to the significant differences in the starting point and development history of the various green energy industries. The existing literature is still inadequate in this regard and needs to be supplemented:

First, among the components of the green energy industry designed to address the climate crisis, apart from photovoltaic and wind power, hydropower and nuclear power are the most noteworthy in terms of investment scale and application prospects. Both are important options to deal with the uncertainty of photovoltaic and wind power and cannot be ignored [35]. The relative changes in the development of the four major sub-sectors will inevitably have an important impact on the overall risk of the green energy industry, which is important for analyzing the overall risk structure of the green energy industry. However, there is a gap in systematic studies covering the risk profiles of the above four industries. Second, studies on the risk spillover effects of the green energy industry have mostly focused on the external risk spillover

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situation. Still, little has been changed for the internal risk structure and change trends of the industry. However, whether the risk correlation between the green energy industry and its sub-sectors can be accurately described and grasped is crucial for managers to formulate and adjust guiding policies in a timely manner. Finally, China already ranks first in the world in terms of electricity generation and has the world's largest green energy market. At present, China is still developing at a relatively fast pace. The development of its green energy industry plays an important role in both its energy supply and the world energy market. However, there is a lack of research that takes a systematic and developmental view of the risk profile of China's Green Energy Industry. This study takes China's Green Energy Industry as a sample and conducts research on its risk level and organization and on its changing trend. The results will help to complement the abovementioned shortcomings in this research area.

III. METHODOLOGY

3.1 Systemic Risk Estimation Methods

Volatility is one of the most important indicators for evaluating financial market risk. As the mainstream model for financial market risk measurement, the Value-at-Risk (VaR) measurement technique has become the international standard for financial risk management and is now widely adopted. VaR refers to the maximum possible loss of a financial asset or portfolio in a given period of time in the future at a given confidence level within a certain holding period. Its mathematical expression is as follows:

$$\mathrm{Prob}(\Delta P < -VaR) = 1 - \alpha \tag{1}$$

Where Prob denotes the probability and α is the confidence level. This method was proposed by JP Morgan in the 1990s and has become the mainstream method used in the field of risk management.

- FIGARCH model

With continuous research, a large number of empirical analyses found that the return series of financial markets have the characteristics of “leptokurtosis and fat-tail” distribution. To characterize this volatility clustering phenomenon, Engle (1982) proposed the ARCH model [36]. On this basis, Bollerslev (1986) proposed the GARCH model [37]. Subsequently, the GARCH family model formed by continuous expansion gradually became the main method for calculating VaRs and was widely adopted.

The FIGARCH (p, d, q) model applied in this study was proposed by Baillie and Bollerslev et al. (1996) [38] based on the IGARCH model [39]. It replaces the first-order difference term $(1-L)$ in the IGARCH model with the fractional difference term $(1-L)^d$ for 0 < d < 1. For the IGARCH model, the effect of the perturbation term on the conditional variance can persist indefinitely. For the FIGARCH model, the effect of the perturbation term on the conditional variance decays in a slow hyperbolic form, so it is possible to portray the phenomenon that the time series satisfies long memory. Its mathematical expression is as follows:

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$$\varphi L(1-L)^d \varepsilon_t^2 = \omega + \big(1-\beta(L)\big)V_t,\;\; V_t = \varepsilon^2 - \sigma^2 \tag{2}$$

In the above equation, when d = 0, it is the GARCH model. When d = 1, it is the IGARCH model. The conditional variance of FIGARCH (p, d, q) can be written as follows:

$$\sigma_{Pt}^2 = \omega_0(1-\gamma(L))^{-1} + [1-(1-\gamma(L))^{-1}\alpha(L)(1-L)^d]u_{pt}^2 \tag{3}$$

The above equation $(1-L)^d$ can be expanded using Maclaurin's series:

$$(1-L)^d = \sum_{j=0}^{\infty}(-1)^j \binom{d}{j} L^j = \sum_{j=0}^{\infty}\frac{\Gamma(j-d)L^j}{\Gamma(-\mathrm{d})\Gamma(\mathrm{j}+1)},\quad \Gamma(g) = \int_0^{\infty} x^{g-1}e^{-x}dx \tag{4}$$

Where $\Gamma(.)$ is the gamma function and the parameter d (0 < d < 1) is an indicator to determine the long memory of financial time series. Numerous empirical studies have found that the low-order FIGARCH (1, d, 1) model can then fit the high-frequency financial time series data better [40-42].

In order to evaluate the losses caused by long position and short position trading positions, the skewed-Student distribution is introduced into the model considering the restricted short position trading in China, and the VaR of the alpha quantile of long position and short position trading positions can be written as follows:

$$VaR_{Pt,\alpha}^{long} = \hat{R}_{Pt} + St_{\alpha,v}\hat{\sigma}_{Pt} \tag{5}$$

And

$$VaR_{Pt,1-\alpha}^{short} = \hat{R}_{Pt} + St_{1-\alpha,v}\hat{\sigma}_{Pt} \tag{6}$$

Where $\hat{R}_{Pt}$ and $\hat{\sigma}_{Pt}$ are the estimated conditional returns and conditional standard deviations, respectively. v is the degree of freedom of the model estimates. $St_{\alpha,v}$ is the quantile at of the left tail of the skewed student distribution, and $St_{1-\alpha,v}$ is the quantile at α% of the right tail.

After calculating the VaRs, they were tested with the failure frequency test proposed by Kupiec (1995) and the dynamic quantile test (DQ) of Engle and Manganelli (2004) [43,44] respectively, to ensure the accuracy of the conclusions.

3.2 Risk Structure and Evolution Estimation Methods

The risk structure within China's Green Energy Industry and its dynamic evolution process are estimated using a DCC-GARCH model (dynamic conditionally correlated multivariate generalized autoregressive conditional heteroskedasticity model). This model was proposed by Engle (2002) [45] on

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the basis of the CCC-GARCH model, which addresses the obvious disadvantage of the CCC-GARCH model in portraying the time-varying characteristics of time series data correlations by adding a variable conditional coefficient that can better fit the correlations of different time series over time. The DCC-GARCH model is widely used in the study of dynamic correlation of high-frequency time series because of its advantages of adapting to multivariate correlation matrices, fewer parameters to be estimated, and clear economic significance.

The DCC-GARCH model can be written as follows:

Suppose that $r_t = (r_{1,t}, r_{2,t}, \cdots r_{k,t})$ is a sequence of conditional returns on k different financial assets or portfolios obeying a multivariate normal distribution with mean 0 and covariance matrix H_t, i.e.,$r_t|\Omega_{t-1} \sim N(0, H_t)$, where Ω_{t-1} is the information set of return r_t at the moment $t-1$. Then,

$$H_t = D_t R_t D_t \tag{7}$$

R_t is the dynamic conditional correlation coefficient matrix, and D_t is the principal diagonal matrix with the conditional standard deviation as the diagonal element, that is,

$$D_t = diag(h_{11t}^{1/2} \cdots h_{NNt}^{1/2}) \tag{8}$$

h_{iit} can be obtained from a suitable univariate GARCH family model, and

$$R_t = diag(q_{11,t}^{-\frac{1}{2}} \cdots q_{NN,t}^{-\frac{1}{2}}) Q_t diag(q_{11,t}^{-\frac{1}{2}} \cdots q_{NN,t}^{-\frac{1}{2}}) \tag{9}$$

$Q_t = (q_{ij,t})$ satisfies the symmetric positive definite matrix of $N \times N$, and can be written as follows:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1} \tag{10}$$

Where $u_{it} = \boldsymbol{\varepsilon}_{it} / \sqrt{h_{iit}}$, u_t is the standardized residual, $\bar{Q}$ is the unconditional variance matrix of the standardized residual series u_t of the exponential return regression equation, and $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are non-negative scalar parameters and satisfy $\boldsymbol{\alpha} + \boldsymbol{\beta} < 1$.

After transformation, the dynamic correlation coefficient ρ_{12t} between the variables can be written as follows:

$$\rho_{12t} = \frac{(1-\alpha-\beta)\bar{q}_{12} + \alpha u_{1,t-1} u_{2,t-1} + \beta q_{12,t-1}}{\sqrt{((1-\alpha-\beta)\bar{q}_{11} + \alpha u_{1,t-1}^2 + \beta q_{11,t-1})((1-\alpha-\beta)\bar{q}_{22} + \alpha u_{2,t-1}^2 + \beta q_{22,t-1})}} \tag{11}$$

In this study, a FIGARCH model is constructed for each stock index return series considering the long memory of energy market volatility in general. And based on this, a DCC-GARCH model is further constructed to examine the dynamic correlations among the variables under the condition of long memory of volatility. Thus, the estimation results can more accurately reflect the correlation characteristics among

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variables to fully portray the internal structure and evolution trend of capital market risk in China's Green Energy Industry.

IV. DATA AND EMPIRICAL RESULTS

4.1 Data

The financial data involved in this article all comes from the WIND database. We selected The New Energy Generation Index 1 (Code: WI. 882601, abbreviated: GEN), Wind Power Index (Code: WI .884036, abbreviated: WIN), Photovoltaic Index (Code: WI .884045, abbreviated: SOL), Nuclear Power Index (Code: WI. 884046, abbreviated: NUC), and Hydro Power Index (Code: SI .851612, abbreviated: HYD) from January 4, 2010, to March 23, 2021, for a total of 2,725 trading days for analysis, covering the decade of fastest development of Green energy in China.

The daily return of each index is obtained by making a first-order logarithmic difference between the closing prices:

$$R_t = \log(\frac{P_t}{P_{t-1}}) \tag{12}$$

Where R_t is the return of a stock index on day t and P_t is the closing price of a stock index on day t.

After obtaining the returns of five industry indices by the above method, descriptive statistics are first performed, the ARCH effect is tested, and VaR is calculated for each of the five indices in the case of a significant ARCH effect.

Fig1-5 show the volatility of the daily returns of the five industry indices and their distributions, respectively. It can be observed more directly that both the green energy industry as a whole and its major sub-industries have smaller return volatility in some periods and larger return volatility in others, showing obvious characteristics of fluctuation aggregation. This feature was especially evident during the upward cycle of the market. The daily returns of photovoltaic stock index even saw extreme values of over 10% volatility. Further combined with the basic statistical indicators and the results of the Excess Kurtosis test in Table I, obvious characteristics of “leptokurtosis and fat-tail” distribution are shown, and the preliminary judgment is that the GARCH family model is applicable to estimate VaRs.

[1] “The New Energy Power Generation Index” is an industry profile of power providers that use, but are not limited to, bioenergy, geothermal, solar, hydro, and wind energy to generate electricity. It covers the four most widely used green energy sources in China, including wind, solar, nuclear, and hydro energy, and is very representative of the green energy power generation industry.

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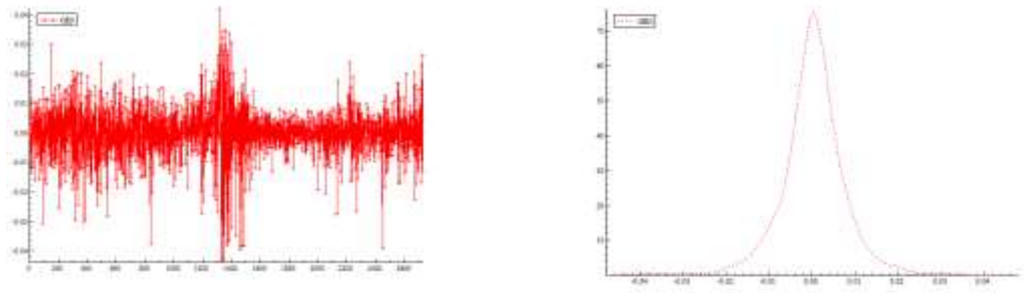

Fig 1: Daily returns of GEN and the distribution

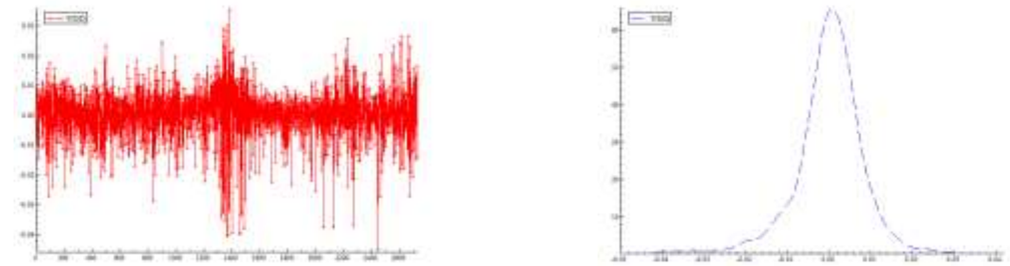

Fig 2: Daily returns of WIN and the distribution

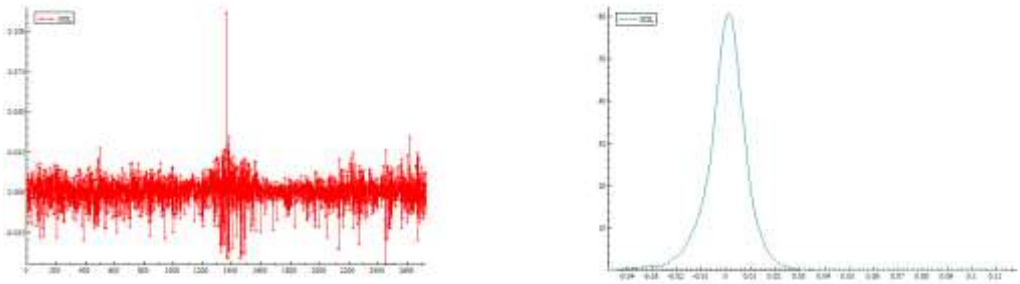

Fig 3: Daily returns of SOL and the distribution

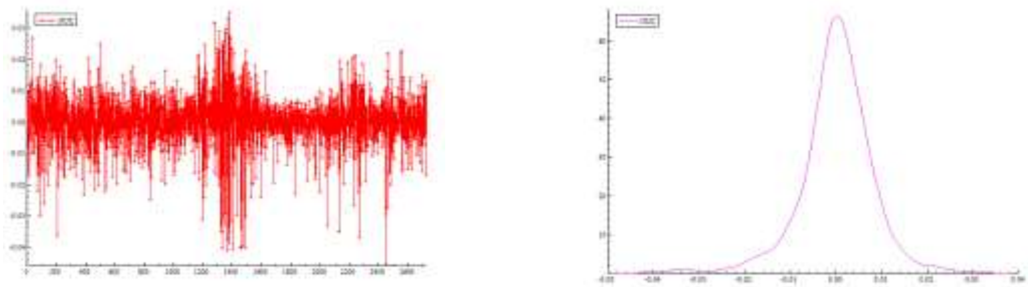

Fig 4: Daily returns of NUC and the distribution

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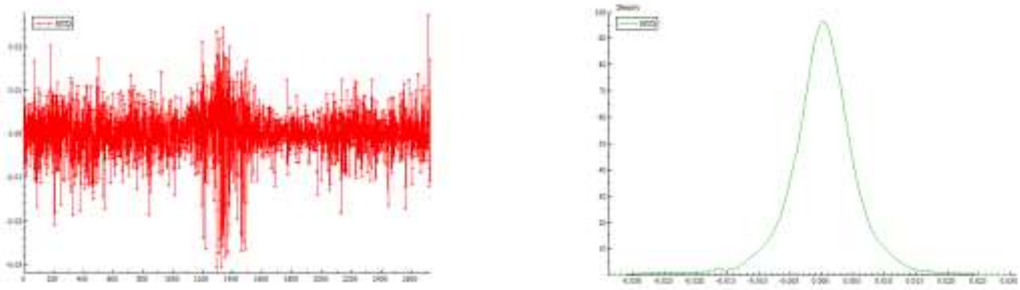

Fig 5: Daily returns of HYD and the distribution

Table I shows the basic statistics and the results of misspecification tests for the daily return series of five industry indices. It can be observed that the volatility of the series for the four major green energy sub-industries is the largest for the photovoltaic industry and the smallest for the hydropower industry, and the overall volatility of the green energy industry is in the middle during the sample examination period. Surprisingly, the nuclear power industry has seen more volatility than wind power, given China's cautious approach to nuclear investment; the industry was the last to open up to social capital and the absolute dominance of state-owned holding companies in it. Combined with the expected returns, the photovoltaic industry is also the best, the wind industry is the second best, the hydropower industry and the nuclear industry are worse, and the overall expected return of the green energy industry is even higher than that of the wind industry. The nuclear industry, with the highest volatility, has the worst expected returns. Overall, the high volatility and high expected returns of photovoltaic and wind power industries and the low volatility and low expected returns of the hydropower industry are in line with expectations from the basic statistics. The high volatility and low expected returns of the nuclear power industry deviate from expectations, and it is possible that China's energy demand and the government's enthusiasm for nuclear power development are sending clearer signals to investors to enter the market.

TABLE I. Basic statistics of returns and misspecification tests

		GEN	WIN	SOL	NUC	HYD
Basic statistics	min	-0.0435	-0.0450	-0.0445	-0.0455	-0.0308
	mean	0.0001	0.0001	0.0002	0.000	0.000
	max	0.0418	0.0352	0.1115	0.0350	0.0272
	St. Dev	0.0080	0.0081	0.0088	0.0083	0.0056
Distribution	Skewness	-0.5604(0.000)	-0.8298(0.000)	0.0218(0.643)	-0.8072(0.000)	-0.6035(0.000)
	Kurtosis	4.9297 (0.000)	3.6892 (0.000)	11.7410(0.000)	4.1494(0.000)	4.1793(0.000)
	Jarque-Bera	2901.9 (0.000)	1858.1 (0.000)	15652(0.000)	2250.9(0.000)	2148.6(0.000)
ARCH	ARCH (2)	189.24 (0.000)	142.15 (0.000)	19.427(0.000)	145.75(0.000)	281.91(0.000)
	ARCH (5)	120.07 (0.000)	92.154 (0.000)	16.634(0.000)	101.19(0.000)	85.840(0.000)

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	ARCH (10)	71.011 (0.000)	50.413 (0.000)	19.824(0.000)	56.810(0.000)	50.413(0.000)
Box-Pierce(Q)	Q(5)	37.9034(0.000)	21.2157(0.001)	30.4539(0.000)	20.0357(0.001)	14.7835(0.011)
	Q(20)	54.2441(0.000)	41.5426(0.002)	45.4519(0.001)	38.1386(0.009)	43.0566(0.002)
	$Q^2(5)$	1011.33(0.000)	773.781(0.000)	106.993(0.000)	845.851(0.000)	1381.16(0.000)
	$Q^2(20)$	3061.77(0.000)	1918.47(0.000)	510.843(0.000)	2522.98(0.000)	3664.12(0.000)
Hurst-Mandelbrot R/S		1.8600	1.6444	1.4162	1.5350	1.5910
Lo R/S		1.7628	1.5816	1.3560	1.4785	1.5603
ADF		-28.1419(0.000)	-28.4777(0.000)	-27.6007(0.000)	-29.1322(0.000)	-30.0818(0.000)
Gaussian(d)		0.0521 (0.000)	0.0298 (0.028)	0.0502(0.000)	0.0299(0.027)	0.0397(0.015)
T		2725				

Note: In Box–Pierce (Q) test, Q represents the original sequence and Q^2 represents the square of the original sequence. The p-values are in parentheses. Gaussian semi-parameter estimation is based on the correlation test of long memory proposed by Robinson and Henry (1999) [46].

From the results of the misspecification tests, the ADF test indicates that all series are stationary, and the results of the Jarque-Bera test and kurtosis test indicate that all series significantly rejects the normal distribution. The Skewness test results show that, except photovoltaic, all other series show significant left skewness, which to some extent indicates the existence of a long position risk in China's green energy market, so a skewed t-distribution is considered to be introduced into the model. The presence of extreme values of the photovoltaic industry returns observed may affect the test results. Therefore, the test will be continued in the next stage of model parameter estimation. The ARCH effect is significant in the residual of regression equation of each series with its own different lag order as an independent variable. The Box--Pierce test Q-values indicate that all five groups of series are auto-correlated. By combining the results of the Hurst--Mandelbrot R/S test and Lo R/S test, it is clear that the long memory of the mean of each series is insignificant. Additionally, the results of the Gaussian semi-parametric test with all significant d-values indicate the existence of long memory of the variance of each series. However, most of the d-values are below 0.5, indicating that the long memory may be weak.

Combining the above statistical characteristics and test results, considering the possible long-memory characteristics of the variance of all five series, in order to better characterize them, this paper attempts to use the ARMA (p, q)-FIGARCH (p, d, q) model for the estimation of VaR of each industry under a skewed t-distribution. The Shanghai Composite Index (SH.000001) is included in each mean equation in order to eliminate the influence of the broad index volatility on the model fit and the estimation of the results.

4.2 Empirical Results

The empirical results of this paper are divided into two parts. The first part presents the results of the FIGARCH model fitting for each series and the VaRs analysis. The second part presents the results of the DCC-GARCH model estimation and the risk correlation and evolution trend analysis of China's Green Energy Industry with each sub-industry.

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4.2.1 VaRs estimation and analysis

Regarding the estimation of VaRs, after a full comparison of the statistical results of various models (the results of each model fitting are not shown in the main text due to limitations of space), the ARMA (1, 1)-FIGARCH (1, d, 1) model is finally selected in this paper to fit the marginal distribution of all series.

The parameter estimation results are shown in Table II, and the test results are shown in Table III. Taken together, the following summary can be made:

a) The d-values for all five series are significant at the 0.001 significant level with a distribution interval of [0.473, 0.627]. This result indicates the existence of long memory for all series of volatility and shows the reasonableness of the FIGARCH (1, d, 1) model chosen to model each series. The photovoltaic industry has the highest long memory of volatility, the hydroelectric industry has the lowest, and the green energy industry is in the middle overall. The results are as expected.

b) The values of the asymmetric parameter $\log(\xi)$ for each series, including the photovoltaic industry's, are significant at the 0.01 significant level, indicating that the selection of a skewed t-distribution is reasonable.

c) Combining the results of the Kupiect test and the dynamic quantile (DQ) test, it can be found that the p-values both show that the original hypothesis cannot be rejected, indicating that the VaRs estimated using the ARMA (1, 1)-FIGARCH (1, d, 1) model is relatively accurate.

d) In terms of the precision of the estimation results, larger p-values of the Kupiect test and DQ test represent higher precision. It can be found that the estimation results of Long Position are generally better than Short Position, which is consistent with the more market-oriented characteristics of Long Position trading in China (systemic risk is also more concentrated in Long Position). The results are better at the quantile of more extreme values.

In summary, the VaRs calculated by applying the ARMA (1, 1)-FIGARCH (1, d, 1) model provides a set of systemic risk indicators representing China's Green Energy Industry and its sub-industries, which can be used as the next step in the analysis.

TABLE II. Estimation results of the ARMA (1, 1)-FIGARCH (1, d, 1) model

	GEN			WIN			SOL			NUC			HYD		
	Statistic	t-value	P-value	Statistic	t-value	P-value	Statistic	t-value	P-value	Statistic	t-value	P-value	Statistic	t-value	P-value
β_0	-0.0001(0.000)	-1.535	0.125	-0.0003(0.000)	-2.580	0.010	-0.0002(0.000)	-1.596	0.111	-0.0002(0.000)	-2.028	0.043	0.00013(0.000)	1.434	0.152
β_1	0.9706(0.020)	47.59	0.000	1.1383 (0.019)	60.75	0.000	1.1815(0.022)	53.33	0.000	1.1422 (0.022)	52.58	0.000	0.7435(0.013)	57.79	0.000
AR	-0.5322(0.	-2.9	0.00	-0.3558	-1.8	0.06	-0.8622(0.4	-2.1	0.03	-0.8613	-3.9	0.00	-0.6623(0	-3.5	0.00

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	179)	73	3	(0.195)	27	8	07)	17	4	(0.218)	51	0	.188)	20	0
MA	0.5670(0.164)	3.469	0.001	0.467207 (0.197)	2.376	0.018	0.9712(0.409)	2.374	0.018	0.9166 (0.222)	4.133	0.000	0.6472(0.185)	3.506	0.001
$\omega_0 \times 10^6$	116.2734(47.38)	2.454	0.014	53.6619 (20.337)	2.639	0.008	115.6909(56.893)	2.033	0.042	90.7455 (39.128)	2.319	0.021	17.8583(6.364)	2.806	0.005
d	0.5942(0.055)	10.77	0.000	0.5069 (0.069)	7.393	0.000	0.6270(0.096)	6.512	0.000	0.5858 (0.076)	7.674	0.000	0.4729(0.061)	7.702	0.000
α_1	0.1890(0.087)	2.164	0.031	0.3227 (0.073)	4.438	0.000	0.1317(0.050)	2.620	0.009	0.3474 (0.076)	4.584	0.000	0.2901(0.061)	4.739	0.000
γ_1	0.6182(0.118)	5.263	0.000	0.6633 (0.095)	6.997	0.000	0.8197(0.070)	11.62	0.000	0.7339 (0.078)	9.381	0.000	0.6360(0.069)	9.185	0.000
$\log(\xi$	0.0840(0.026)	3.223	0.001	-0.1461(0.028)	-5.320	0.000	-0.1134(0.029)	-3.926	0.000	-0.0728(0.028)	-2.564	0.010	0.1115(0.026)	4.383	0.000
v	5.3104(0.509)	10.44	0.000	5.1773 (0.434)	11.94	0.000	5.0419(0.447)	11.27	0.000	5.7156 (0.582)	9.823	0.000	5.8231(0.535)	10.88	0.000
$LogL$	11053.449	/	0.000	11174.871	/	0.000	10765.201	/	0.000	11139.024	/	0.000	11993.451	/	0.000

Note: St. Dev. are shown in parentheses; See Chung (1999) for more details [47].

TABLE III. Kupiec test and Dynamic Quantile test

	Kupiect test								DQ test					
	Short Position				Long Position				Short Position			Long Position		
	Quantile	Success rate	Kupiec LRT	P-value	Quantile	Faild rate	Kupiec LRT	P-value	Quantile	Statistic	P-value	Quantile	Statistic	P-value
GEN	0.9500	0.9512	0.0822	0.7743	0.0500	0.0473	0.4131	0.5204	0.950	3.9078	0.6892	0.0500	13.983	0.0298
	0.9750	0.9728	0.5057	0.4770	0.0250	0.0253	0.0115	0.9147	0.975	6.3546	0.3847	0.0250	7.3517	0.2896
	0.9900	0.9870	1.1482	0.2839	0.0100	0.0117	0.7920	0.3735	0.990	4.5368	0.604	0.0100	2.7393	0.8408
	0.9950	0.9956	0.2030	0.6523	0.0050	0.0040	0.5443	0.4607	0.995	0.4931	0.9979	0.0050	0.8572	0.9905
	0.9975	0.9978	0.1013	0.7503	0.0025	0.0011	2.7095	0.0998	0.9975	0.1774	0.9999	0.0025	4.8671	0.5610
WIN	0.9500	0.9512	0.0822	0.7743	0.0500	0.0514	0.1077	0.7428	0.950	10.686	0.0986	0.0500	6.7979	0.3399
	0.9750	0.9776	0.7917	0.3736	0.0250	0.0272	0.5057	0.4770	0.975	11.530	0.0733	0.0250	10.921	0.0909
	0.9900	0.9890	0.2714	0.6024	0.0100	0.0106	0.1112	0.7388	0.990	10.477	0.1059	0.0100	5.3703	0.4973
	0.9950	0.9941	0.3939	0.5303	0.0050	0.0059	0.3939	0.5303	0.995	0.8237	0.9914	0.0050	0.8425	0.9909
	0.9975	0.9967	0.6391	0.4240	0.0025	0.0015	0.0015	0.2421	0.9975	0.6854	0.9948	0.0025	2.0102	0.9188
SOL	0.9500	0.9538	0.8476	0.3572	0.0500	0.0491	0.0429	0.8360	0.950	12.627	0.0494	0.0500	3.1019	0.7960

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	0.9750	0.9784	1.3258	0.2496	0.0250	0.0264	0.2162	0.6420	0.975	3.8443	0.6977	0.0250	4.2565	0.6420
	0.9900	0.9897	0.0196	0.8888	0.0100	0.0084	0.7133	0.3984	0.990	2.9753	0.8119	0.0100	1.8241	0.9351
	0.9950	0.9938	0.7737	0.3791	0.0050	0.0037	1.0738	0.3001	0.995	1.2219	0.9758	0.0050	1.5143	0.9585
	0.9975	0.9960	2.1663	0.1411	0.0025	0.0026	0.0049	0.9445	0.9975	1.8245	0.9351	0.0025	0.0962	0.99998
	0.9500	0.9505	0.0121	0.9124	0.0500	0.0492	0.0393	0.8428	0.950	3.6921	0.7183	0.0500	11.492	0.0743
	0.9750	0.9795	2.3541	0.1250	0.0250	0.0217	1.3121	0.2520	0.975	5.1815	0.5208	0.0250	2.5032	0.8681
NUC	0.9900	0.9905	0.0588	0.8084	0.0100	0.0088	0.4079	0.5230	0.990	3.3509	0.7637	0.0100	4.2537	0.6424
	0.9950	0.9941	0.3939	0.5303	0.0050	0.0044	0.2030	0.6523	0.995	0.8425	0.9909	0.0050	0.4931	0.9979
	0.9975	0.9967	0.6391	0.4240	0.0025	0.0037	1.3053	0.2533	0.9975	0.6854	0.9948	0.0025	1.2077	0.9765
	0.9500	0.9439	2.0882	0.1484	0.0500	0.0517	0.1724	0.6780	0.950	2.6375	0.8528	0.0500	7.8438	0.2498
	0.9750	0.9725	0.6894	0.4064	0.0250	0.0275	0.6894	0.4064	0.975	2.8511	0.8273	0.0250	7.5442	0.2734
HYD	0.9900	0.9879	1.1482	0.2839	0.0100	0.0081	1.0937	0.2957	0.990	3.1738	0.7867	0.0100	2.1994	0.9005
	0.9950	0.9934	1.2818	0.2576	0.0050	0.0040	0.5443	0.4607	0.995	1.6908	0.9458	0.0050	0.8572	0.9904
	0.9975	0.9967	0.6391	0.4240	0.0025	0.0018	0.5330	0.4654	0.9975	0.6854	0.9948	0.0025	0.7048	0.9944

Note: In the Dynamic Quantile regression, p = 5.

Fig 6 shows the kernel of estimated VaR for long and short positions for each index. We select the 0.05, 0.025, 0.01 quartiles of the long position and the 0.95, 0.975, 0.99 quartiles of the short position correspondingly for progressive display. It can be found that the skewness of the VaRs distribution of each index and the long position curve is clearly differentiated by the degree of leftward skewness, in order of photovoltaic, wind power, nuclear power, green energy, and hydropower. The rightward skewness of the short position is not as obvious as the long position, but the ranking is consistent with the long position. The degree of the left (right) skew indicates to some extent the magnitude of systemic risk for each industry. It is clear that the photovoltaic industry has the highest systematic risk and that the hydropower industry has the lowest systematic risk. From the concentration of VaRs distribution, the distribution of VaR in the short position for each index is more concentrated towards the mean than the long position, which means that systemic risk for each industry may be more concentrated in the long position.

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Long Position Short Position

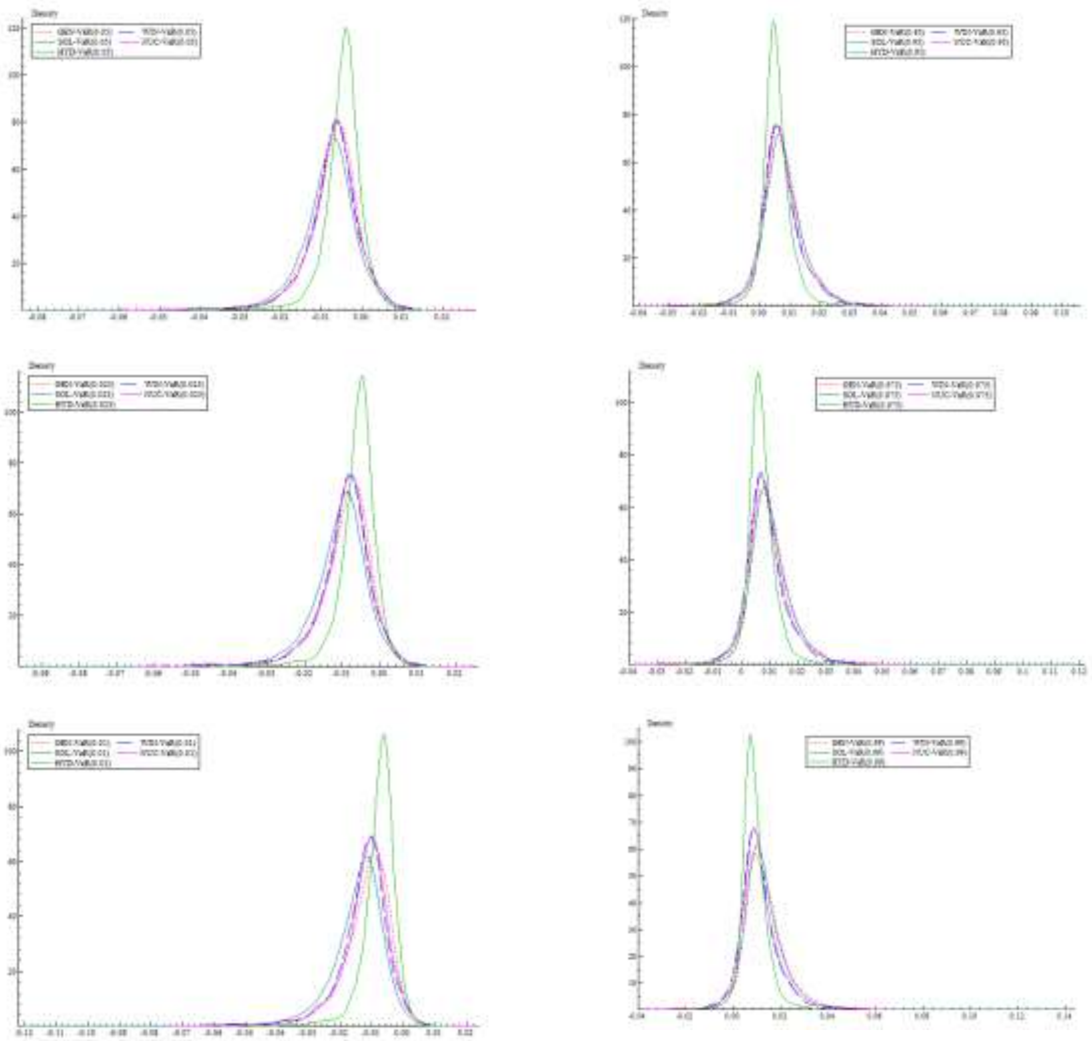

Fig 6: Kernel of VaR for long and short positions for each index

Fig 7 shows the VaRs of China's Green Energy Industry and its sub-industries, with regards to the long position at the α= 0.05, 0.01, 0.0025 quantiles and the short position at α= 0.95, 0.99, 0.9975 quantiles, respectively. There is an overlay of short position values and long position values for both the Green Energy Industry and its four sub-industries. That is, Short Position VaRs are negative when certain long position VaRs are positive. This implies that the risk of equity capital in the Chinese green energy industry is somewhat controllable, which may be due to the strict regulatory policies of the Chinese capital market.

4.2.2 DCC-GARCH estimation and analysis

Following the general estimation procedure of the DCC-GARCH model, the residual series obtained by constructing the univariate ARMA-FIGARCH model for each index in the previous section are used to obtain five standardized residual series after standardizing them separately. Then, the GARCH (1, 1)

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models were constructed separately to examine the dynamic conditional correlation among 5 industries.

Table 4 shows the parameters of the univariate GARCH (1, 1) model for the standardized residual series of each index. It can be seen that both the ARCH term coefficient (α) and the GARCH term coefficient (β) reach a significant level and that the sum of both is less than 1, satisfying the model constraints.

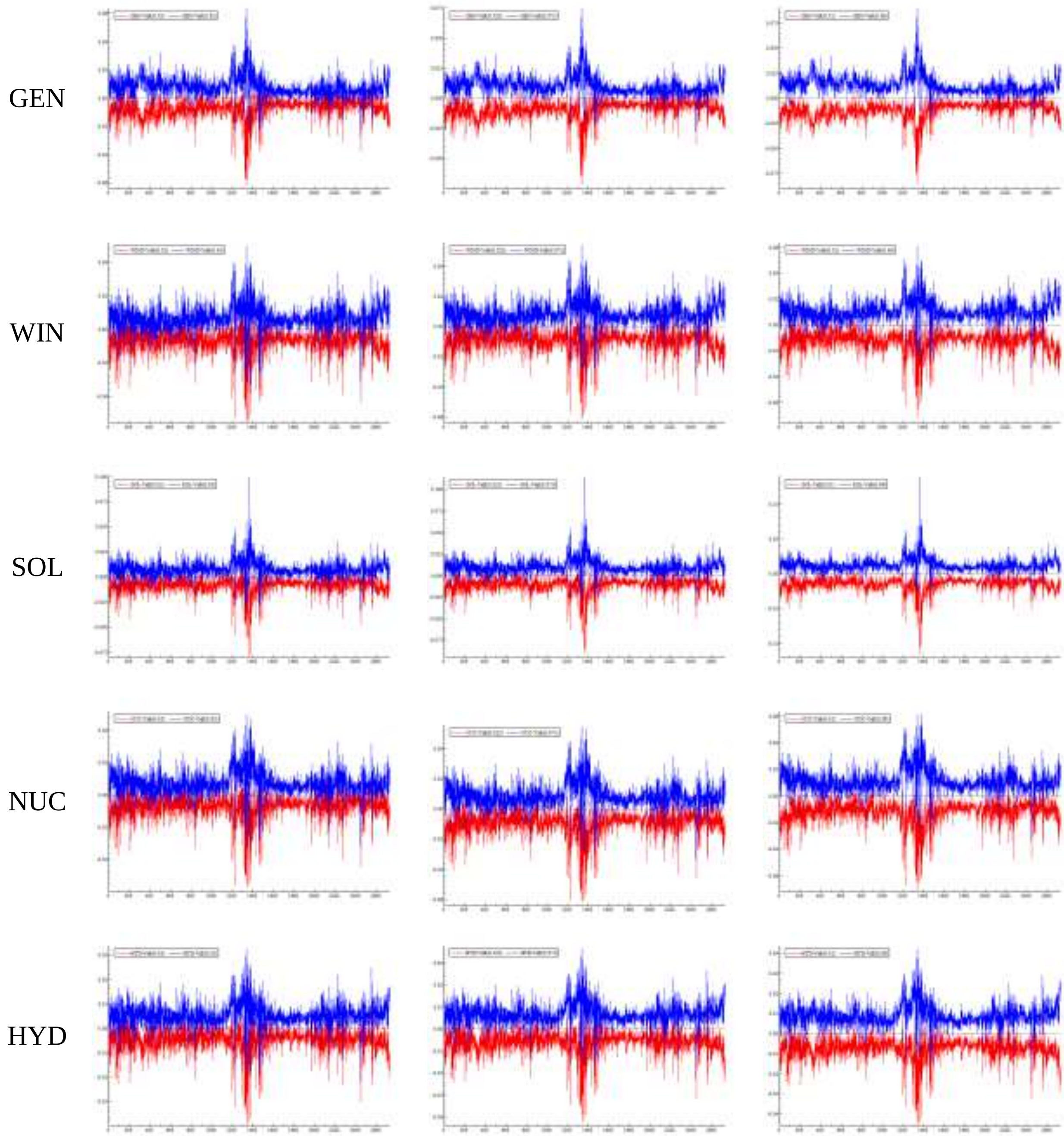

Fig 7: VaR for each index with the long positions and the short positions

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TABLE IV. Standardized residuals' GARCH (1, 1) model parameters

		Coefficient	t-value	t-value	α+β
GEN(std)	α	-0.0157 (0.004)	-3.576	0.000	0.794
	β	0.8099 (0.048)	16.72	0.000	
WIN(std)	α	-0.0262 (0.001)	-20.18	0.000	0.808
	β	0.8337 (0.057)	14.68	0.000	
SOL(std)	α	-0.0044 (0.000)	-10.86	0.000	0.970
	β	0.9747 (0.022)	44.56	0.000	
NUC(std)	α	-0.0197 (0.009)	-2.185	0.029	0.857
	β	0.8767(0.042)	21.10	0.000	
HYD(std)	α	-0.0276 (0.010)	-2.740	0.006	0.704
	β	0.7319 (0.148)	4.934	0.000	

Table V shows the estimation results of the conditional correlation coefficients between the green energy industry and the four sub-industries. It can be seen that the conditional correlation coefficients between the green energy industry and each sub-industry are all reach a significant level of 0.01. $\alpha > 0$, $\beta > 0$, and $0 < \alpha+\beta < 1$, and all are significant at the 0.01 significant level, satisfying the model constraints. Table 6 shows the results of the multivariate mixed parameter tests using the Hosking test and Li-McLeod test [48,49], indicating that the estimation results of the DCC-GARCH model parameters are reliable.

TABLE V. Estimated results of conditional correlation coefficients

	Mean	t-value	p-value	Min	Max	std.dev
GEN-WIN	0.5052(0.023)	22.06	0.000	0.1855	0.7257	0.0678
GEN-SOL	0.4620(0.034)	13.66	0.000	0.0711	0.7199	0.0738
GEN-NUC	0.4765 (0.023)	20.37	0.000	-0.0187	0.6727	0.0750
GEN-HYD	0.3608 (0.0270)	13.35	0.000	0.0595	0.6059	0.0833
WIN-SOL	0.7192 (0.051)	14.19	0.000	0.2566	0.8631	0.0533
WIN-NUC	0.7115 (0.016)	44.41	0.000	0.4230	0.8682	0.0549
WIN-HYD	0.2068 (0.032)	6.433	0.000	-0.2231	0.5841	0.0990
SOL-NUC	0.5955 (0.050)	12.04	0.000	0.0832	0.8125	0.0651
SOL-HYD	0.1676 (0.031)	5.498	0.000	-0.1913	0.5271	0.0651
NUC-HYD	0.1994 (0.032)	6.303	0.000	-0.1227	0.5271	0.0943
α	0.0367(0.012)	3.138	0.002	/	/	/
β	0.8836(0.061)	14.60	0.000	/	/	/
Log-Lik	-16548.932					

TABLE VI. Hosking test and Li-McLeod test

	H	H^2	Li−McL	Li−McL^2
Q(5)	144.660 (0.110)	114.048 (0.706)	144.674 (0.110)	114.077 (0.706)
Q(10)	261.115 (0.302)	220.720 (0.893)	261.146 (0.301)	220.808 (0.892)
Q(20)	506.590 (0.410)	422.866 (0.994)	506.700 (0.408)	423.233 (0.993)

Note: H and H^2 , Li-McL and Li-McL^2 are the multivariate portmanteau statistics of Hosking test and Li-McL test, respectively, with a maximum lag of 20 orders and p-values in parentheses.

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According to the information provided in Table V, if we examine the correlation between the green energy industry and the constituent industries in terms of the mean value of the conditional correlation coefficient, the ranking is wind power, nuclear power, photovoltaic power, and hydroelectric power, in that order. In terms of the volatility of the conditional correlation coefficients, the ranking is hydroelectric, nuclear, photovoltaic, and wind power, in that order. Combined with the VaRs above, the wind power industry has the highest correlation and the lowest volatility with the green energy industry, indicating that the risk impact of wind power on the green energy industry is likely to be stable and continuous. The correlation between hydropower and the green energy industry is the lowest, and volatility is the highest, indicating that hydropower's risk impact on the green energy industry is somewhat uncontrollable. The correlation between nuclear power and the green energy industry and its volatility are both slightly higher than photovoltaic, which is also surprising. This may imply that China's photovoltaic industry is embarking on a new development mode after its initial laissez-faire development, while the development of the nuclear power industry does not seem to be as prudent and steady as generally believed. The above speculations are to be further explored in the context of the time-varying characteristics of the conditional correlation coefficient. Second, from the correlation between each sub-industry, the conditional correlation coefficients between the wind power industry and the photovoltaic industry, and the nuclear power industry and between the photovoltaic industry and the nuclear power industry are high and less volatility. Combined with their VaRs, these three industries may constitute the main force of systemic risk in China's Green Energy Industry. The conditional correlation coefficients between the hydropower industry and the other three industries are small, and volatility is large, indicating that the specific direction and choice of investors may have changed significantly when investing in China's Green Energy Industry.

Fig 8-11 show the volatility of the DCCs of between China's Green Energy Industry and the wind power, photovoltaic, nuclear power and hydropower industries, respectively. It can be seen visually that the correlation between the green energy industry and each sub-industry shows a significant time-varying and dramatic volatility during the period examined in this paper. Among them, (1) the volatility plot of the DCC between the green energy industry and wind power industry shows that the correlation between these two has been at a high level, and the volatility is strong. The strong volatility appears from October 2013 to December 2014. After 2020, the correlation shows a significant upward trend, and the volatility tends to weaken. (2) The volatility plot of the DCC between the green energy industry and photovoltaic industry show more obvious time period differences. Between 2010 and 2015, volatility was stronger. Since 2015, volatility has gradually decrease. From 2018 to the present, the correlation between the two shows a gradually decreasing trend. (3) The volatility plot of the DCC between green energy industry and nuclear power industry shows that the correlation between the two is low and volatility is high before 2015. However, after 2015, the correlation between the two is significantly higher, and volatility is significantly lower. (4) The volatility plot of the DCC between the green energy industry and the hydropower industry shows that, from 2010 to 2014, the correlation is high and volatility is low. Between 2014 and 2015, the correlation decreases while volatility increases significantly. From 2015 to the present, the correlation is significantly lower and volatility is at a high level.

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Fig 8: Volatility plot of DCC between GEN and WIN

Fig 9: Volatility plot of DCC between GEN and SOL

Fig 10: Volatility plot of DCC between GEN and NUC

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Fig 11: Volatility plot of DCC between GEN and HYD

V. CONCLUSION

By comparing the VaRs of the China's Green Energy Industry and its sub-industries and further analyzing their dynamic correlations, a more comprehensive understanding of the systemic risks and structural evolution of China's green energy industry over the past decade can be gained, and there are several issues that deserve our attention: Firstly, hydropower industry with the largest share of installed capacity and the highest total market value has the lowest overall systemic risk. Compared with the other three sub-industries, it has an obvious advantage in terms of stability, which may be related to its large investment scale and long construction cycle, resulting in a higher share of government funds in the construction process. Its low systemic risk is accompanied by a low expected return, indicating that its positioning as a public service project has very limited acceptance and attractiveness to social capital. Combined with the DCC data, its contribution to the overall risk of the green energy industry also shows a significantly lower trend after July 2014. Secondly, the systemic risk of the photovoltaic industry has improved significantly over the selected observation period, although it has experienced severe overcapacity and low-level expansion during its development. This is clearly related to the increasing technology and decreasing cost of power generation in it[50]. It is worth noting that the systemic risk of the wind power industry is almost the same as the photovoltaic power industry although its scale is still relatively weak. Thirdly, the systemic risk of nuclear power industry has approached that of the wind power industry, though governments and markets are generally cautious about developing the nuclear power industry due to safety concerns. Its correlation with the green energy industry has increased significantly after June 2015, and its volatility has decreased, which implies that the nuclear power industry has become one of the main sources of systemic risk for China's Green Energy Industry, and its share may be higher than generally believed. Fourthly, the systemic risk level of the photovoltaic industry has gradually become mediocre during the period examined in this paper. Since August 2015, its correlation with the green energy industry has significantly decreased. Its volatility has become lower, indicating that its risk spillover effect on the green energy industry is also converging. Combined with the technological breakthroughs achieved in China in areas such as ultra-high voltage transmission and photovoltaic efficiency, and the continued reduction of costs due to the scale effect[50,51], this could mean that China's photovoltaic industry has changed from its previous crude development mode to a new intensive and sustainable development stage. Finally, both for China's Green Energy Industry in general and for its major sub-industries, the period around 2015 was an important demarcation point. During this period, the Chinese stock market experienced a historic level of violent shocks, the absolute value of systemic risk for each index reached its highest level during the period under examination. And the level of risk spillover between China's Green Energy Industry and its sub-industries increased and experienced dramatic volatility. After 2015, the systemic risk and structure of China's Green Energy Industry entered a new stage of evolution.

The above empirical results and related analysis provide a more in-depth and comprehensive understanding of the development of China's Green Energy Industry. The lessons learned are worthy of reference for other countries in greening their own energy systems to a certain extent.

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