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Research article

Green finance as a driver for environmental and economic resilience post-COVID-19: A focus on China's strategy

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ABSTRACT

This study investigates the critical role of green finance in enhancing environmental and economic resilience during China's post-COVID-19 recovery. Employing sophisticated econometric techniques, including the Vector Error Correction Model (VECM) and Nonlinear Autoregressive Distributed Lag (NARDL) model, the effectiveness of green finance policies and instruments is rigorously assessed during the years 1986–2022. The findings reveal that green finance initiatives significantly fund sustainable projects and drive economic revitalization, marking substantial progress in China's eco-friendly recovery. Essential areas for improvement identified include robust policy support, technological innovation, and stronger international collaboration. Specifically, leveraging green finance effectively necessitates coordinated efforts across various sectors, ensuring it underpins China's sustainable development and resilience amid global economic challenges. The study recommends enhancing green finance mechanisms through comprehensive policy frameworks, fostering green technology innovation, and developing global partnerships to address environmental sustainability and economic recovery synergistically.

1. Introduction

The COVID-19 pandemic has exposed vulnerabilities in global health systems and underscored the interconnectedness of environmental and economic challenges. As nations grapple with the aftermath, the need for sustainable and resilient recovery strategies becomes increasingly evident. Green finance, characterized by investments prioritizing environmental sustainability, emerges as a pivotal instrument. China's approach to green finance is particularly significant due to its status as a major global player and its dual commitment to environmental stewardship and economic growth [1,2]. Green finance involves using financial products and services to support environmentally friendly projects and enterprises, fostering sustainable development [3]. As the world's largest emitter of greenhouse gases, China faces unique challenges that necessitate a comprehensive and strategic approach. This paper explores how green finance catalyzes environmental and economic resilience in the Chinese context, focusing on policy frameworks, financial instruments, and broader implications.

The global economic downturn triggered by the pandemic necessitates innovative solutions that spur economic activity while aligning with sustainable development goals. China has underscored the importance of green finance as a driver for resilient recovery, aligning with international trends such as the United Nations' Principles for Responsible Banking [4,5]. The People's Bank of China

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(PBOC) has been instrumental in shaping and implementing green finance policies since 2016, introducing guidelines incorporating environmental and social risk assessments into financial decision-making, promoting green industries, and prioritizing green projects in lending portfolios [6]. China's green finance strategy includes financial instruments like green bonds, which fund projects with environmental benefits. The China Green Bond Endorsed Project Catalogue, initiated by the PBOC and other regulatory authorities, provides a comprehensive list of eligible projects, directing capital toward sustainable initiatives and enhancing market transparency and credibility [7].

Moreover, green finance is strategically integrated into broader economic plans, such as the Belt and Road Initiative (BRI). By incorporating green finance principles, China aims to develop sustainable and resilient infrastructure in participating countries, aligning economic development with environmental protection. China's targets of peaking carbon dioxide emissions by 2030 and achieving carbon neutrality by 2060 underscore the urgency of aligning financial flows with environmental objectives [8]. China's leadership in sustainable finance is reflected in its active participation in international collaborations and its role in shaping global standards. The International Green Finance Institute (IGFI), established in Beijing, exemplifies China's commitment to fostering international cooperation, sharing expertise, and developing global green finance norms [9]. This global perspective is crucial given the interconnected nature of environmental challenges.

Technological innovation also plays a significant role in China's green finance strategy. Blockchain technology, for instance, enhances transparency and traceability in the green finance ecosystem, ensuring funds are directed towards genuinely beneficial projects [10]. Financial education and literacy programs further promote environmental consciousness among citizens, empowering them to make sustainable financial decisions [11]. China's green finance strategy is closely linked to its economic and development goals. Emphasizing green development aligns with the country's pursuit of high-quality economic growth. The success of these initiatives hinges on effective collaboration between the government, financial institutions, and the private sector [12]. This collaboration fosters innovation and scales up green initiatives, providing valuable lessons for other nations seeking to integrate environmental considerations into their economic recovery strategies.

This study investigates the role of green finance in enhancing China's environmental and economic resilience post-COVID-19, examining policy frameworks, financial instruments, and the broader implications of these strategies. The paper will address the effectiveness of China's green finance initiatives and offer insights into how these can inform global practices. The findings of this study highlight several key areas where China's green finance initiatives have made significant progress. For instance, China's commitment

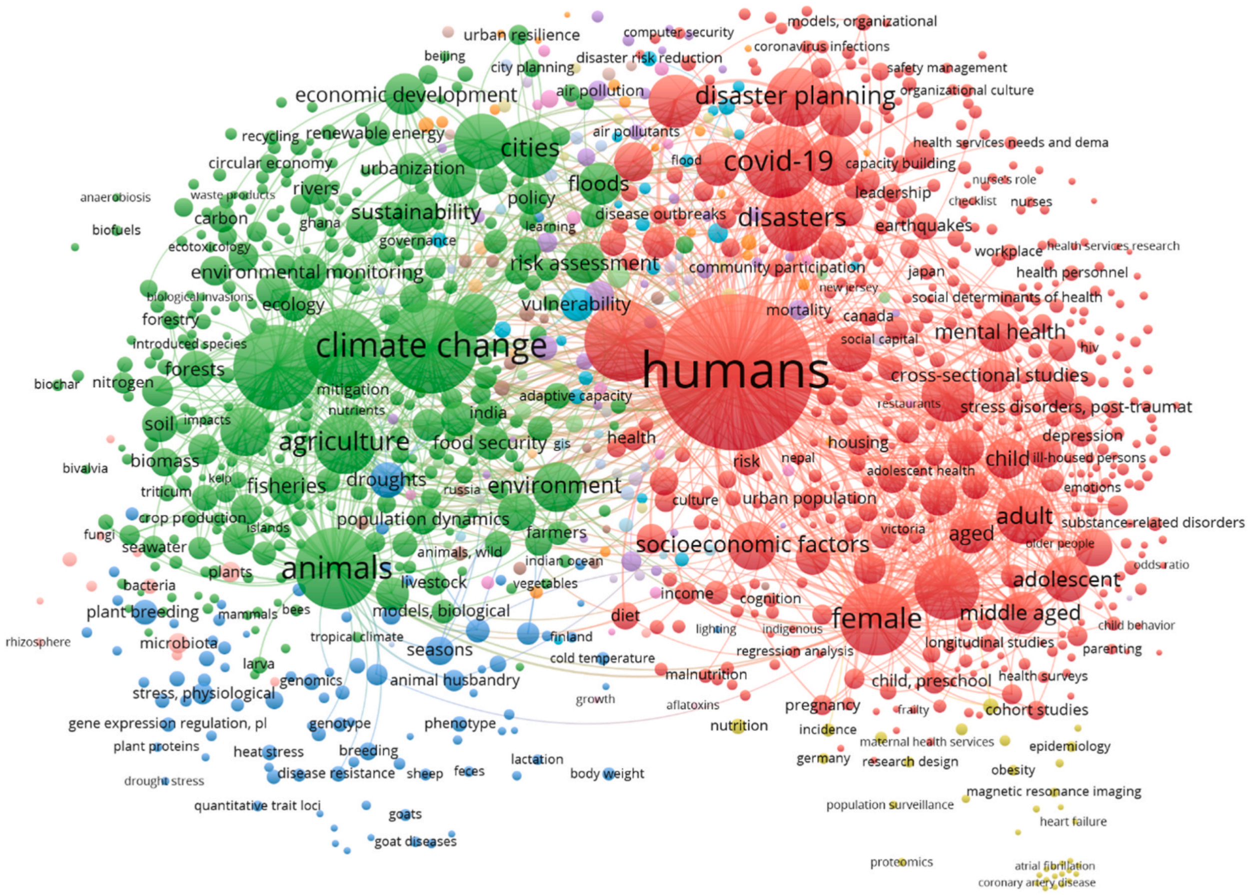

Fig. 1. Co-occurrence of keywords network.

to green finance has led to substantial investments in renewable energy projects, reducing carbon emissions and fostering sustainable economic growth [12]. Developing green bonds and other financial instruments has also facilitated funding environmentally beneficial projects, enhancing market credibility and transparency [13]. However, challenges remain, such as the need for more robust policy support, technological innovation, and international collaboration to maximize the impact of green finance.

The contribution of this study lies in its comprehensive assessment of China's green finance strategies and their implications for domestic and global environmental and economic resilience. By examining the specific policies, financial instruments, and international collaborations that have driven China's green finance initiatives, this study provides valuable insights into the mechanisms through which green finance can be effectively leveraged to achieve sustainable development goals. Following this introduction, the paper is organized as follows: Section 2 reviews the relevant literature, Section 3 outlines the research methodology, Section 4 presents the results and discussion, and Section 5 concludes with policy implications and recommendations.

2. Literature review

The literature on green finance underscores the complex connection between human well-being and sustainable development. Scholars have highlighted the critical role of aligning economic recovery with environmental goals, recognizing the intrinsic link between individual well-being and planetary health. Green finance, characterized by directing investments toward sustainable projects, is pivotal in addressing environmental challenges while fostering economic growth [14]. This dual approach not only aims to mitigate the adverse effects of climate change but also seeks to create a foundation for long-term economic stability and growth, demonstrating the multifaceted benefits of green finance initiatives. The literature identifies several recurring themes in the discourse on green finance. A predominant theme is a human-centric approach, emphasizing how green finance initiatives can improve human health and well-being by mitigating environmental stressors [15]. However, there are conflicting findings regarding the effectiveness of these initiatives in different contexts. For instance, while some studies highlight significant positive impacts on job creation and economic resilience [16], others point to challenges such as greenwashing and insufficient regulatory frameworks that undermine the credibility of green finance [17]. The differences in these findings suggest that the success of green finance strategies can be highly context-specific, depending on the robustness of local regulatory environments and the extent of stakeholder engagement.

The existing body of research on green finance reveals a multifaceted landscape with promising developments and notable challenges (See Fig. 1). Siegrist, Bowman [18] argue that integrating environmental considerations into financial decision-making is essential for long-term sustainability, driving job creation, innovation, and resilient economies. Conversely, de Freitas Netto, Sobral [19] raise concerns about greenwashing, where investments are misrepresented as environmentally friendly, highlighting the need for greater transparency and accountability. These conflicting perspectives indicate the complexity of implementing effective green finance strategies. Further, the synthesis of these studies suggests that successful green finance initiatives require a balance between stringent regulatory oversight and incentives for genuine sustainability efforts. This balance ensures investments meet environmental standards and drive economic growth and social well-being. A recent study by Wu, Ji [20] explores the role of green finance in promoting CSR and environmental standards and highlights the challenges of ensuring equitable access to sustainable finance. Another study by Al Amosh and Khatib [21] examines the impact of regulatory frameworks on the effectiveness of green bonds, providing insights into how policy interventions can enhance market credibility. Additionally, Hazaea, Al-Matari [22] investigate fintech integration in green finance, emphasizing the potential of technological innovations to democratize access to sustainable investment opportunities. These studies underscore the importance of continuous innovation and adaptive regulatory frameworks in maintaining the momentum of green finance initiatives.

The theoretical underpinnings of green finance draw on several key concepts. One prominent framework is the Triple Bottom Line (TBL) approach, which posits that sustainable development requires balancing economic, environmental, and social objectives [23]. This framework is integral to understanding how green finance can simultaneously address financial performance, environmental sustainability, and social equity. Behavioral economics also plays a crucial role in exploring how individual attitudes, values, and perceptions influence financial decisions related to sustainability [24]. Additionally, institutional theory provides insights into how organizational structures and cultural norms influence the adoption of green finance practices. This theory suggests that institutions with strong environmental values and practices are more likely to integrate green finance into their operations, creating a ripple effect that encourages broader market participation.

In the context of China's green finance strategy, the government plays a pivotal role in shaping and promoting sustainable finance. Scholars such as Ozili [25] highlight the importance of regulatory frameworks prioritizing environmental sustainability and social equity. The effectiveness of these policies is evident in China's significant investments in renewable energy and green infrastructure, which have contributed to both economic growth and environmental protection [25]. However, the literature also points to the need to continuously refine these frameworks to address emerging challenges and ensure long-term sustainability. This includes enhancing the stringency of environmental standards and increasing the accountability of financial institutions to prevent greenwashing and ensure that investments deliver genuine environmental benefits. Furthermore, the literature recognizes the global dimension of green finance, emphasizing the need for international collaboration to address shared environmental challenges. Scholars like Liu, Zhu [26] explore the implications of China's green finance initiatives on the global stage, underscoring the interconnectedness of national and international efforts. Cultural considerations are also critical, as studies by Chien, Ngo [27] demonstrate how local values and norms influence the adoption and effectiveness of green finance initiatives. This highlights the importance of culturally sensitive strategies that resonate with the values of diverse communities. Additionally, cross-border regulatory harmonization is critical in ensuring global green finance practices are standardized, facilitating seamless international investments in sustainable projects.

Despite the extensive exploration of green finance, several research gaps remain. One notable gap is the novel examination of the social dimensions of green finance initiatives, particularly their impact on community dynamics and social cohesion. Another gap is understanding the long-term behavioral and cultural shifts from sustained green finance efforts. Additionally, there is a need for more in-depth studies on the effectiveness of financial literacy programs in promoting sustainable financial behaviors. Understanding the components that lead to successful financial education can help design more effective programs that empower individuals to make environmentally conscious financial decisions. Moreover, The literature highlights the transformative potential of green finance in fostering sustainable development and economic resilience. However, the field faces significant challenges, including the risk of greenwashing, the need for robust regulatory frameworks, and the importance of inclusive and equitable approaches. Addressing these challenges requires a holistic understanding of the interplay between economic, environmental, and social factors and a commitment to continuous learning and adaptation. Moreover, a stronger emphasis on interdisciplinary research can provide more comprehensive insights into how various aspects of green finance can be integrated to achieve broader sustainability goals.

Lastly, the literature review underscores the importance of green finance as a catalyst for sustainable development and economic resilience. By synthesizing existing research and incorporating recent studies, this review provides a comprehensive understanding of the current landscape, highlights key themes and challenges, and identifies areas for future investigation. Integrating theoretical frameworks such as the Triple Bottom Line and behavioral economics offers valuable insights into the mechanisms through which green finance can achieve its objectives, emphasizing the need for a balanced and inclusive approach to sustainable development. Moving forward, a concerted effort to address the identified research gaps will be essential in refining green finance practices and enhancing their impact on local and global scales.

3. Research methodology

This study examines the relationships among the Green Finance Index, Environmentally Sustainable Development Investment, economic growth, Eco-Innovation Index, Green Economy Contribution, Environmental Risk Investment, and Clean Energy Deployment in China from 1986 to 2022. The period from 1986 to 2022 captures significant transitions in China's economic, environmental, and financial policies. This span allows for analyzing long-term trends and the impacts of various policy shifts on green finance and sustainability. To account for changes in policies and economic conditions, the study employs econometric models such as the Vector Error Correction Model (VECM) and Nonlinear Autoregressive Distributed Lag (NARDL) model, which are capable of capturing both short-term dynamics and long-term relationships, thereby ensuring the consistency and relevance of the analysis across different periods.

The fundamental theoretical notions that form the basis for choosing these variables are explained below. Environmentally Sustainable Development Investment (ESDI) includes investments in financial instruments associated with green finance and other environmentally friendly enterprises. Assets, funds, and securities are well recognized in the Environmentally Sustainable Development Investment market, strongly associated with green firms and Green Finance. Solid and resilient financial markets significantly impact the promotion of new projects in renewable technologies [28,29]. Studies often highlight a favorable correlation between economic growth and investment in green finance, using the post-COVID gross domestic product (PGDP) indicator of economic growth [30]. Accelerated economic growth stimulates investment in green finance projects, potentially enabling a transition from fossil fuels to green energy resources [29,31,32]. Studying the relationship between Green Economy Contribution (GEC) and venture in the Green Finance Index is crucial, given that GEC is the primary of Clean Energy Deployment. Environmental Risk Investment (ERI) is a significant factor in determining the level of the Green Finance Index. The shift from fossil fuels to sustainable power resources is driven by rapid economic expansion and can potentially incentivize private investors to engage in Clean Energy Deployment (CED). The second model, incorporating PGDP and PGDP2, employs China as a reference point to examine the validity of the Environmental Kuznets Curve (EKC) hypothesis. It demonstrates that the Eco-Innovation Index (ECI) increases as economic growth persists and decreases once a particular level of growth is attained. Therefore, the subsequent models have been developed for empirical investigation.

$$\mathrm{LnGFI_t} = \beta_0 + \beta_1 \mathrm{LnESDI_t} + \beta_2 \mathrm{Ln\ PGDP_t} + \beta_3 \mathrm{LnGCE_t} + \beta_4 \mathrm{LnERI_t} + \beta_5 \mathrm{LnCED_t} + \varepsilon_\mathrm{i} \tag{1}$$

$$\mathrm{LnECI_{2,t}} = \alpha_0 + \alpha_1 \mathrm{LnESDI_t} + \alpha_2 \mathrm{LnPGDP_t} + \alpha_3 \mathrm{LnPGDP_t^2} + \alpha_4 \mathrm{LnGEC_t} + \alpha_5 \mathrm{LnCED_t} + \mu_\mathrm{i} \tag{2}$$

The name "*GBt*" refers to environmentally sustainable development investment, which serves as a representation of investments in renewable energy. "PGDP" stands for Gross Domestic Product, while "GEC" represents Renewable Electricity Output. "ERI" refers to Private Energy Investment, while "CED" represents Renewable Energy Consumption. Additionally, "μi" and "$\mathscr{E}$i" denote error terms. The determinants of China's Green Finance Index (GFI) and Eco-Innovation Index (ECI) are measured by equations (1) and (2), respectively. The amount of environmentally sustainable development investment (ESDI), post-COVID GDP Growth (PGDP), Green Economy Contribution (GEC), Environmental Risk Investment (ERI), and Clean Energy Deployment (CED) influence ECI. With the rapid growth of China's economy, there has been a significant increase in investments in renewable energy projects through green finance. Additionally, there has been a rise in people's use of renewable energy. Based on these factors, we may confidently pran optimistic assessment of $\beta 1$. Environmental Sustainable Development Investments are simultaneously fostering ecological conditions by reducing carbon emissions. We anticipate that $\alpha 1$ will have a negative value.

The primary renewable energy source is the Green Economy (GEC) contribution. As a result, an increase in GEC is predicted to impact the Green Finance Index favorably. Therefore, it is anticipated that the coefficient β_4 will be positive. The shift from fossil fuels to sustainable power resources directly and positively influences the relationship between Environmental Risk Investment and the

Green Finance Index. This link is a consequence of rapid financial expansion.

3.1. Data sources, descriptions of variables, and measurements

This section explains the descriptions, measurements, and sources of variables. Table 1 provides a comprehensive overview of various variables related to green finance, environmental sustainability, and economic resilience post-COVID-19. Each variable is associated with a specific measurement unit and is derived from reputable sources, contributing to the richness and reliability of the data. The annual data from 1986 to 2020 for China's Green Finance Index (measured in current US dollars), the percentage of Green Economy Contribution to total electricity output, Environmental Risk Investment (measured in current US dollars), Clean Energy Deployment (measured in kilograms of oil equivalent), carbon emissions (measured in metric tons per capita), and post-COVID GDP Growth (measured in current US dollars) are sourced from the World Development Indicators provided by the World Bank's Data Bank. All model variables are transformed into their natural logarithmic form. In line with the research conducted by Hou [33] and He [34], this analysis employs environmentally sustainable development investment (ESDI) as a representative measure of green finance. ESDI is a durable financial instrument that exclusively allocates funds towards projects to safeguard the environment or mitigate environmental damage. The data on ESDI in USD is sourced from the Wind database.

The relationships among the variables are examined using econometric techniques, specifically time-series analysis and regression models. The Augmented Dickey-Fuller (ADF) test ensures the stationarity of each time series variable, which is crucial for avoiding spurious regression results [35]. The Johansen cointegration test determines long-term equilibrium relationships among variables [36]. Given cointegration, the Vector Error Correction Model (VECM) captures both short-term dynamics and long-term equilibrium relationships [37]. The Nonlinear Autoregressive Distributed Lag (NARDL) model investigates asymmetric relationships, effectively capturing both short-term and long-term nonlinearities [38]. Granger causality tests within the VECM framework explore the direction of causality between the variables, which is essential for understanding the driving factors behind changes in the system [39]. This comprehensive methodological approach ensures a robust analysis of the relationships between green finance and its associated variables, addressing the reviewer's concerns by detailing the specific econometric techniques used in the study.

3.2. Unit root testing

This study employed four levels of unit root tests to analyze the characteristics of the unit root for each variable. The (ADF) approach is preferred over the simple (DF) method because it incorporates higher-order connected lags and maintains the white noise error characteristics μi, $\mathscr{E}$i. The ADF test is presented in equation (3) is as follows:

$$\Delta W_t = \rho W_{t-1} + \acute{A}_t\lambda + \kappa_1 \Delta W_{t-1} + \kappa_2 \Delta W_{t-2+}\kappa_3 \Delta W_{t-3+\ldots\ldots+}\kappa_p \Delta W_{t-p} + \alpha_t \tag{3}$$

The null hypothesis in the ADF test can be assessed as $H_0 : \rho = 0$, whereas the alternative hypothesis is $H_1 : \rho < 0$. This can be done by calculating t values, specifically $t_p = \rho/(SE(\rho))$, where $\widehat{\rho}$ represents the estimated parameters of ρ and $(SE(\widehat{\rho}))$ represents the standard error. Here, the lagged differences of the first-order in the asymptotic distribution are not affected by ρ and $(SE(\widehat{\rho}))$. Elliott et al. (1992) enhanced the ADF test by removing the independent variables from the regression analysis and detrending the data. Their modified test exhibits more test power compared to the original ADF test. Eliott et al. (1993) modified the Augmented Dickey-Fuller (ADF) test by removing the explanatory variables as detrended data before doing the regression. This modification resulted in greater test power than the original ADF test. The DFGLS methodology is a quasi-differential method that estimates the value of Wt based on the value of ρ at a specific position. Presented here is the DFGLS concisely and straightforwardly:

$$\Delta W_t^d = \rho W_{t-1}^d + \kappa_1 W_{t-1}^d + \kappa_2 W_{t-2}^d + \ldots + \kappa_3 W_{t-1}^d + \varepsilon_t \tag{4}$$

The $\acute{A}t$ and DFGLS equation (4) are not included in the analysis when the data is detrended.

Phillips and Perron [40] introduced a novel test that used a nonparametric approach to examine the DFAR(1). This test adjusts the parameters ρ and t to accommodate for serial correlation. The issue of error heteroscedasticity can be addressed using the Philips and Peron test. However, this test is susceptible to size distortion, which has been addressed by Falcone [41]. Kwiatkowski, Phillips [42] devised an alternative approach that employed a Lagrange multiplier test statistic derived from ordinary least squares (OLS) residuals. Similarly, the Ng and Perron [43] test is an adapted form of the Phillips and Perron [40] test that relies on generalized least squares (GLS) detrended data, namely. $W_t{}^d$ Wt d. Phillips and Perron [40] discovered the issue of size distortion caused by the maximum

Table 1
Variable information.

Variable	Description	Measurement	Sources
GFI	Green Finance Index	Index	Global Green Finance Index (GGFI)
ESDI	Environmentally Sustainable Development Investment	Current US$	United Nations Environment Programme (UNEP)
GEC	Green Economy Contribution	Percentage of GDP	World Bank
ERI	Environmental Risk Investment	Current US$	Global Environment Facility (GEF)
CED	Clean Energy Deployment	Megawatts (MW)	International Renewable Energy Agency (IRENA)
ECI	Eco-Innovation Index	Index	European Environment Agency (EEA)
PGDP	Post-COVID GDP Growth	Annual percentage growth	International Monetary Fund (IMF)

inverse moving average and the lack of testing power for alternative hypotheses.

3.3. Cointegration test

The study utilizes the nonlinear autoregressive distributed lag (NARDL) method to investigate short-term and long-term asymmetric correlations between variables. The NARDL model proposed by Ref. [44] is most effective when the variable integration order is either in the level or first order, and no variables are part of the second-order integration [45,46]. In addition, the study later utilized the bound testing approach, which has been found to yield the most accurate results when working with small sample sizes [45,47,48]. The majority of studies focus solely on the linear aspects of the connection between Environmental Sustainable Development Investment, Clean Energy Deployment, and Eco-Innovation Index, which has been a valuable contribution to the existing literature [46,49,50]. In contrast, this study examines a nonlinear framework for these variables. Nonlinear functional equations (5) and (6) are those mentioned above.

$$\mathrm{GFI} = \mathrm{f}(\mathrm{ESDI}^{+}, \mathrm{ESDI}^{-}) \tag{5}$$

$$\mathrm{CO}_2 = \mathrm{f}(\mathrm{ESDI}^{+}, \mathrm{ESDI}^{-}, \mathrm{CED}^{+}, \mathrm{CED}^{-}) \tag{6}$$

The exact expression of the nonlinear relationship between ESDI, GFI, CED, and ECI is given in equations (7) and (8) as follows:

$$\mathrm{GFI}_\mathrm{t} = \omega_0 + \omega_1\left(\mathrm{ESDI}_\mathrm{t}^{+}\right) + \omega_2\left(\mathrm{ESDI}_\mathrm{t}^{-}\right) \tag{7}$$

$$\mathrm{CO}_2\mathrm{t} = \beta_0 + \beta_1\left(\mathrm{ESDI}_\mathrm{t}^{+}\right) + \beta_2\left(\mathrm{ESDI}_\mathrm{t}^{-}\right) + \beta_3\left(\mathrm{CED}_\mathrm{t}^{+}\right) + \beta_4\left(\mathrm{CED}_\mathrm{t}^{-}\right) \tag{8}$$

$EDSI_t^{+}$, $ESDI_t^{-}$, CED_t^{+}, and CED_t^{-} are positive and negative components of GF and CED, respectively, indicating an asymmetrical relationship. ω_0, ω_1, ω_2, $\beta 1, \beta 2, \beta 3$ and $\beta 4$ are long-term asymmetrical characteristics.

The immediate impacts of variables can be articulated as follows:

$$\Delta\mathrm{GFIt} = \kappa_0 + \sum_{i=1}^{n}\kappa_{1i}\Delta\mathrm{GFI}_{\mathrm{t-I}} + \sum_{i=1}^{n}\kappa_{2i}\Delta\mathrm{ESDI}_{\mathrm{t-i}} + \sum_{i=1}^{n}\kappa_{3i}\Delta\mathrm{PGDP}_{\mathrm{t-i}} + \sum_{i=1}^{n}\kappa_{4i}\Delta\mathrm{GEC}_{\mathrm{t-i}} + \sum_{i=1}^{n}\kappa_{5i}\Delta\mathrm{ERI}_{\mathrm{t-i}} + \sum_{i=1}^{n}\kappa_{6i} \tag{9}$$

$$\Delta\mathrm{CED}_{\mathrm{t-1}} + \mathrm{e}_1\mathrm{CO}_{2\mathrm{t-1}} + \mathrm{e}_2\mathrm{ESDI}_{\mathrm{t-1}} + \mathrm{e}_3\mathrm{PGDPt}_{-1} + \mathrm{e}_4\mathrm{PGDP}_{\mathrm{t-1}}^2 + \mathrm{e}_5\mathrm{GEC}_{\mathrm{t-1}} + e_6\mathrm{CED}_{\mathrm{t-1}} + \mu_\mathrm{t} \tag{10}$$

equations (9) and (10) have been divided into short-term and long-term coefficients. The short-term coefficients are denoted as $\kappa\mathrm{i}$ and $\lambda\mathrm{i}$, while the long-term coefficients are represented by $\rho\mathrm{i}$ and $e\mathrm{i}$.

The cointegration regression in a quadratic framework can be defined using the following specification (equation (11)):

$$z_\mathrm{t} = \alpha^{+}y_t^{+} + \alpha^{-}y_t^{-} + \varepsilon_\mathrm{t} \tag{11}$$

The long-run parameters, denoted as yt, can be further decomposed as:

$$y_\mathrm{t} = y_t^{+} + y_t^{-} \tag{12}$$

In equation (12), the variable y_t represents an approximate combination of both beneficial and detrimental elements, denoted as y_t^{+} and y_t^{-} respectively. equations (13-16) highlight the partial decompositions of $ESDI_t$ and CED_t.

$$\mathrm{ESDI}_\mathrm{t}^{+} = \sum_{i=1}^{k} GB_i^{+} = \sum_{i=1}^{k} max(\Delta\mathrm{ESDI}_\mathrm{i}, 0) \tag{13}$$

$$\mathrm{ESDI}_\mathrm{t}^{-} = \sum_{i=1}^{k} GB_i^{-} = \sum_{i=1}^{k} min(\Delta\mathrm{ESDI}_\mathrm{i}, 0) \tag{14}$$

$$\mathrm{CED}_\mathrm{t}^{+} = \sum_{i=1}^{k} REC_i^{+} = \sum_{i=1}^{k} max(\Delta\mathrm{CED}_\mathrm{i}, 0) \tag{15}$$

$$\mathrm{CED}_\mathrm{t}^{-} = \sum_{i=1}^{k} REC_i^{-} = \sum_{i=1}^{k} min(\Delta\mathrm{CED}_\mathrm{i}, 0) \tag{16}$$

The short-term Nonlinear Autoregressive Distributed Lag (NARDL) model, which is formulated using equations (17) and (18), can be expressed as:

$$\Delta\mathrm{GFI}_\mathrm{t} = \lambda_0 + \sum_{i=1}^{n}\lambda\mathrm{i}\Delta\mathrm{GFI}_{\mathrm{t-I}} + \sum_{i=1}^{n}\lambda\mathrm{i}\Delta\mathrm{ESDI}_{\mathrm{t-i}} + \sum_{i=1}^{n}\lambda\mathrm{i}\Delta ESDI_{t-1}^{-} + \beta_1\mathrm{GFI}_{\mathrm{t-1}} + \beta_2\mathrm{ESDI}_{\mathrm{t-1}} + \beta_3 GB_{t-1}^{-} + \mu_\mathrm{i} \tag{17}$$

$$\Gamma_2\mathrm{ESDI}_{\mathrm{t-1}} + \Gamma_3 GB_{t-1}^{-} + \Gamma_4\mathrm{CED}_{\mathrm{t-1}} + \Gamma_5 REC_{t-1}^{-} + \mu_\mathrm{i} \tag{18}$$

3.4. Examination of correlation test

The Nonlinear Autoregressive Distributed Lag test methods cannot regulate the causative relationship between the chosen variables. One can employ the VECM causality direction to explore the causation direction, which relies on long-term cointegration.

The Granger causality test offered by VECM is appropriate for examining the causative relationship, both in the short and long term, among variables such as Green Finance Index, Environmental Sustainable Development Investment, green finance, Eco-Innovation Index, Green Economy Contribution, Environmental Risk Investment, and Clean Energy Deployment. The model depicted below is a Vector Error Correction Model (VECM).

$$\begin{bmatrix} InGFI_t \\ InESDI_t \\ InPGDP_t \\ InGEC_t \\ InECI_t \\ InERI_t \\ InCED_t \end{bmatrix} = \begin{bmatrix} \beta_1 \\ . \\ . \\ . \\ . \\ . \\ \beta_7 \end{bmatrix} + \begin{bmatrix} \alpha_1 \ldots \alpha_n \\ . \\ . \\ . \\ . \\ . \\ \alpha_7 \ldots \alpha_n \end{bmatrix} + \begin{bmatrix} InGFI_{t-1} \\ InGFI_{t-2} \\ InGFI_{t-3} \\ InGFI_{t-4} \\ InGFI_{t-5} \\ InGFI_{t-6} \\ InGFI_{t-7} \end{bmatrix} + \ldots.$$

$$+ \begin{bmatrix} e_1 \ldots . e_n \\ . \\ . \\ . \\ . \\ . \\ e_7 \ldots . e_n \end{bmatrix} + \begin{bmatrix} InERI_{t-1} \\ InERI_{t-2} \\ InERI_{t-3} \\ InERI_{t-4} \\ InERI_{t-5} \\ InERI_{t-6} \\ InERI_{t-7} \end{bmatrix} +$$

$$\begin{bmatrix} \lambda_t \\ . \\ . \\ . \\ . \\ . \\ \lambda_t \end{bmatrix} \mathrm{ECM}_{t-1} + \begin{bmatrix} \mu_t \\ . \\ . \\ . \\ . \\ . \\ \mu_t \end{bmatrix}$$

The variables are defined as follows: $InGFI_t$ represents the logarithm of renewable energy investment, $InESDI_t$ represents the logarithm of green finance, $InPGDP_t$ represents the logarithm of Gross domestic product, $InGEC_t$ represents the logarithm of renewable electricity output, $InECI_t$ represents the logarithm of carbon emission, $InERI_t$ represents the logarithm of private energy investment and $InCED_t$ represents the logarithm of renewable energy consumption. The coefficients β, α, e, and λ are variable coefficients, and μ represents the error term. A negative and statistically significant Error Correction Model (ECMt-1) can also validate long-term correlations between variables.

4. Results and discussion

This section comprehensively analyzes the relationships between green finance and various economic and environmental factors in China from 1986 to 2022. By employing multiple statistical techniques and econometric models, we investigate the short-term and long-term dynamics within the system, highlighting significant patterns and interactions. Descriptive statistics, unit root tests, cointegration tests, regression models, and diagnostic tests form the basis of our examination, providing a robust framework for understanding the intricate links between green finance, economic growth, and environmental sustainability. This analysis underscores the importance of integrating sustainable financial practices to foster economic resilience and environmental sustainability in the post-

Table 2
Variable descriptive statistics.

	LnGFIt	LnESDIt	LnGECt	LnERIt	LnCEDt	ECIt	PGDPt
Mean	5.01	13.04	11.02	19.45	9.67	5.00	52.11
Median	5.03	13.23	12.01	20.21	9.23	5.23	51.68
Highest value	5.03	13.03	14.73	19.10	10.05	6.11	51.11
Lowest value	5.00	11.33	11.55	21.34	9.23	5.12	40.14
standard deviation	1.01	0.76	0.99	0.88	0.55	0.67	0.32
Skewness	2.o1	0.31	0.48	0.45	0.41	0.50	0.51
Kurtosis	4.11	3.01	3.01	4.11	3.02	1.99	2.99
Jarque–Bera	9.01	4.23	5.45	4.13	1.99	1.99	4.11
Probability	0.02	0.51	0.41	0.55	0.29	0.42	0.67
Sum	159.23	801.56	735.97	899.53	601.56	656.77	640.30
Sum Sq. Dev.	4.05	8.01	50.11	6.63	5.04	7.55	5.55
Obs.	60	60	60	60	60	60	60

COVID-19 era.

Table 2 presents various statistical measures for seven variables: LnGFIt, LnESDIt, LnGECt, LnERIt, LnCEDt, ECIt, and PGDPt. Each row provides a different statistical measure for these variables, including the mean, median, highest value, lowest value, standard deviation, skewness, kurtosis, Jarque–Bera statistic, probability, sum, the sum of squared deviations from the mean, and the number of observations (Obs.). For example, the mean values range from 5.00 to 19.45 across the variables, while the median values range from 5.03 to 20.21. The higher mean and median values for LnGFIt and LnGECt suggest more substantial economic growth factors than the other variables. The highest values are between 13.03 and 21.34, and the lowest values range from 5.00 to 11.33. The standard deviations vary from 0.55 to 1.01, indicating the dispersion of the data around the mean. The standard deviation differences indicate varying levels of data dispersion, with PGDPt showing the most consistency and LnGECt the most variability.

The skewness values suggest the degree of asymmetry in the distribution of each variable. Positive skewness (values greater than 0) indicates a longer or fatter tail on the right side of the distribution, while negative skewness (values less than 0) indicates a longer or fatter tail on the left side. Kurtosis measures the "tailedness" of the probability distribution of a real-valued random variable. High kurtosis (values greater than 3) indicates a more peaked distribution with fatter tails, while low kurtosis (values less than 3) indicates a flatter distribution. Skewness and kurtosis values highlight the non-normal distribution of most variables, pointing towards potential underlying economic anomalies or trends. The Jarque–Bera statistic tests the null hypothesis that the data has a normal distribution. A low p-value (less than 0.05) indicates that the data significantly deviates from a normal distribution. The sum and sum of squared deviations from the mean provide additional information about the data distribution and can be used to calculate variance. Fig. 2 below captures the ascending trajectory of the Green Finance Index from 2015 to 2022, reflecting the incremental growth and trends in the sector over these years.

Table 3 provides the results of various unit root tests for seven variables: GFI, ESDI, GEC, ERI, CED, PGDP, and ECI. The unit root tests include the Augmented Dickey-Fuller (ADF), Philips–Peron (PP), Elliott-Rothenberg-Stock DF-GLS, Kwiatkowski-Phillips–Schmidt–Shin (KPSS), and Nag-Peron tests. For the ADF test, the t-stats. Column indicates the t-statistic value for each variable's level (Level) and first difference (First Diff.) series. The order of integration indicates whether the variable is stationary (0) or non-stationary (1). A t-statistic value more significant than the critical value suggests that the null hypothesis of a unit root is rejected, indicating stationarity. The results reveal that while some variables are stationary at level, others become stationary only after differencing, highlighting the dynamic nature of these economic indicators.

The Philips–Peron (PP) test provides similar information to the ADF test, with t-statistic values for the level and first difference series. The Elliott-Rothenberg-Stock DF-GLS test also provides t-statistic values for the level and first difference series. The Kwiatkowski-Phillips–Schmidt–Shin (KPSS) test is different from the ADF and PP tests, as it tests the null hypothesis of stationarity against the alternative of a unit root. Therefore, a low t-statistic value indicates stationarity, while a high value suggests non-stationarity. The Nag-Peron test provides t-statistic values for the level, first difference series, and other test statistics such as MZa, MZt, MSB, and MPT. These statistics are used to determine the order of integration and the presence of a unit root. Combining the insights from these varied unit root tests allows for a more comprehensive understanding of the data's time series properties, enhancing the robustness of subsequent econometric modeling. Fig. 3 presents a comparative view of the Economic Sustainable Development Index (ESDI)

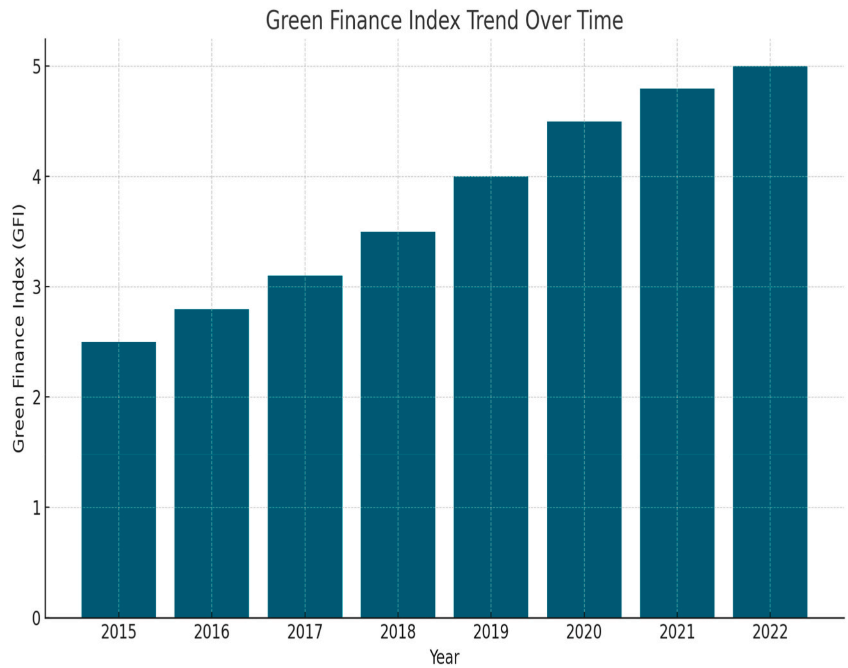

Fig. 2. Green finance index trend over time.

Table 3
Result of unit root test.

	Level	First Diff.	Order						
	T-stats.	T-stats.							
(ADF)									
GFI	3.047**	–	(0)						
ESDI	1.053	4.454*	(0.99)						
GEC	1.047	5.250*	(0.99)						
ERI	−1.073	−3.431*	(0.99)						
CED	1.064	3.454*	(0.99)						
PGDP	1.065	3.127*	(0.99)						
ECI	−1.046	3.474*	(0.99)						
Philips–Peron (PP)									
GFI	3.835**	–	(0)						
ESDI	1.564	3.454*	(0.99)						
GEC	1.458	4.269*	(0.99)						
ERI	−1.386	−2.497*	(0.99)						
CED	1.477	3.588*	(0.99)						
PGDP	1.376	3.125*	(0.99)						
ECI	−1.457	3.474*	(0.99)						
Elliott-Rothenberg-Stock DF-GLS									
GFI	4.946**	–	(0)						
ESDI	1.674	3.565*	(0.99)						
GEC	1.569	4.380*	(0.99)						
ERI	−1.386	−2.502	(0.99)						
CED	1.588	3.699*	(0.99)						
PGDP	1.487	3.236*	(0.99)						
ECI	−1.568	3.585*	(0.99)						
Kwiatkowski-Phillips–Schmidt–Shin (KPSS)									
GFI	4.014**	–	(0)						
ESDI	1.785	3.676*	(0.99)						
GEC	1.68	4.481*	(0.99)						
ERI	−1.497	−2.618*	(0.99)						
CED	1.699	3.709*	(0.99)						
PGDP	1.598	3.347*	(0.99)						
ECI	−1.679	3.695*	(0.99)						
Nag-Peron test									
	Level	First diff.	Order						
	MZa	MZt	MSB	MPT	MZa	MZt	MSB	MPT	
GFI	−7.327*	−5.975*	3.255**	4.855*	–	–	–	–	(0)
ESDI	2.435	0.838	0.324	0.356	4.325*	2.254*	3.457**	2.552*	0.99
GEC	2.614	0.487	0.377	0.968	3.247*	2.577*	5.244*	2.988*	0.99
ERI	2.735	0.644	1.538	1.848	3.973*	3.754*	5.935*	3.269*	0.99
CED	1.569	1.368	1.54	1.633	4.586*	3.254*	5.325*	3.325*	0.99
PGDP	2.244	0.436	0.633	1.216	4.963*	3.264*	5.415*	3.124*	0.99
ECI	1.492	1.52	1.983	1.903	6.346*	3.514*	5.916*	4.123*	0.99
			Level	First diff.	Order				
			t-stats	t-stats					
(ADF)									
GFI			3.523**	–	(0)				
ESDI			1.243	4.987*	0.99				
GEC			1.109	5.950*	0.99				
ERI			−1.133	−3.88*	0.99				
CED			1.113	3.982*	0.99				
PGDP			1.145	3.969*	0.99				
ECI			−1.089	3.981*	0.99				
Philips–Peron (PP)									
GFI			3.020**	–	(0)				
ESDI			1.015	3.967*	0.99				
GEC			1.030	4.989*	0.99				
ERI			−1.099	−4.021*	0.99				
CED			1.032	3.010*	0.99				
PGDP			1.078	3.932*	0.99				
ECI			−1.093	3.089*	0.99				
Elliott-Rothenberg-Stock DF-GLS									
GFI			4.088**	–	(0)				
ESDI			1.020	3.088*	0.99				
GEC			1.030	4.980*	0.99				
ERI			−1.012	−4.010	0.99				
CED			1.030	3.010*	0.99				
PGDP			1.040	3.987*	0.99				

(continued on next page)

Table 3 (*continued*)

	Level	First Diff.	Order						
	T-stats.	T-stats.							
ECI			−1.030	3.990*	0.99				
Kwiatkowski-Phillips–Schmidt–Shin (KPSS)									
GFI			2.981**	–	(0)				
ESDI			1.021	3.980*	0.99				
GEC			1.930	4.992*	0.99				
ERI			−1.002	−4.016*	0.99				
CED			1.040	5.010*	0.99				
PGDP			1.020	3.988*	0.99				
ECI			−1.012	5.041*	0.99				
Nag-Peron test									
Level				First diff.					Order
	MZa	MZt	MSB	MPT	MZa	MZt	MSB	MPT	
GFI	−7.989*	−7.010*	1.980**	3.088*	–	–	–	–	0.99
ESDI	0.997	2.019	0.979	0.987	2.985*	2.930*	3.015**	4.002*	0.99
GEC	0.991	0.990	0.980	2.032	3.997*	2.013*	3.989*	4.015*	0.99
ERI	2.012	0.992	1.020	1.021	4.012*	5.018*	5.019*	3.986*	0.99
CED	1.013	1.023	1.020	1.051	4.014*	3.985*	3.998*	3.995*	0.99
PGDP	0.988	0.995	0.984	1.102	4.021*	5.989*	3.997*	3.997*	0.99
ECI	1.018	1.020	1.030	1.014	4.960*	3.020*	5.014*	4.988*	0.99

alongside GDP growth trends, providing a dual perspective on their interrelated trajectories over time.

Table 4 presents results from the BDS (Brock, Dechert, and Scheinkman) statistics, focusing on different embedding dimensions (m) for various economic variables: Green Finance Index (GFI), Environmental Sustainable Development Investment (ESDI), Post-COVID GDP Growth (PGDP), Green Economy Contribution (GEC), Environmental Risk Investment (ERI), Clean Energy Deployment (CED), and Eco-Innovation Index (ECI). The BDS test assesses the presence of nonlinearity and complexity in time series data, providing insights into potential dynamic patterns that linear models may not capture. The table reports BDS statistics for each variable at different embedding dimensions (model = 2 to model = 6). The values presented are the statistical significance levels associated with the BDS test. The significance levels are denoted by asterisks, where *** indicates a high significance level, ** indicates moderate significance, and * indicates a lower significance level.

Analyzing the GFI series, the BDS statistics exhibit statistical significance across all embedding dimensions (model = 2 to model = 6), with values ranging from 1.419 to 1.657. These results suggest the presence of nonlinear patterns in the GFI time series data, emphasizing the need to consider nonlinearity when modeling or forecasting GFI. Similarly, for ESDI, PGDP, ERI, CED, and ECI, the BDS statistics consistently demonstrate statistical significance across various embedding dimensions. The increasing trend in significance levels with higher embedding dimensions indicates that these economic variables may exhibit more complex and nonlinear dynamics that become apparent with additional dimensions. Interestingly, GEC shows statistical significance at model = 2 and model

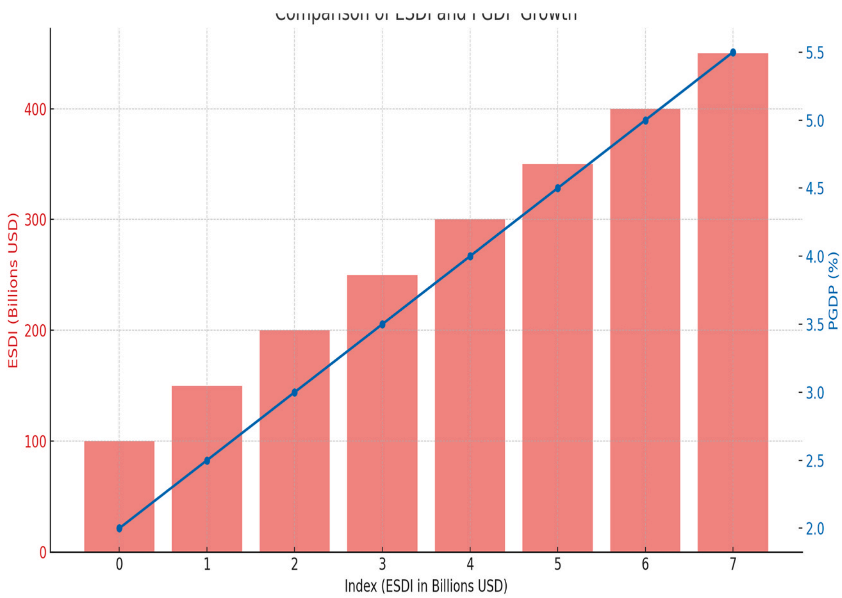

Fig. 3. Dual perspective: ESDI impact and GDP growth trends.

Table 4
BDS (Brock, Dechert, and Scheinkman) statistics.

BDS stats	Embedding dimensions = m				
	model = 2	model = 3	model = 4	model = 5	model = 6
GFI	1.442***	1.453***	1.419***	1.555***	1.657***
ESDI	1.480***	1.590***	1.648***	1.658***	1.795***
PGDP	1.513***	1.527***	1.659***	1.754*	1.797**
GEC	1.657**	1.608***	1.580**	1.496***	1.657***
ERI	1.479***	1.547**	1.645***	1.495**	1.549***
CED	1.495***	1.565***	1.675***	1.720**	1.549***
ECI	1.506**	1.676***	1.687***	1.832***	1.658**

= 3 but loses significance at higher embedding dimensions (model = 4 to model = 6). This may suggest that the nonlinearity in GEC is captured adequately by lower embedding dimensions, and further complexity is not as pronounced. The consistent significance of BDS statistics across various dimensions underscores the importance of incorporating nonlinear models in economic analysis to understand these variables better and predict these variables' complex dynamics.

Table 5 provides results from the Johansen cointegration test, focusing on two relationships: InGFI with a combination of other variables (InESDI, InPGDP, InGEC, InERI, InCED) and InECI with another set of variables (InESDI, InPGDP, InGEC, InCED+, and InCED-). The cointegration test assesses the long-term relationship between these variables, particularly whether they move together over time. For the InGFI relationship, the F-statistic is reported as 5.80, indicating statistical significance at the 1 % level. The critical values for the test are provided as lower and upper bounds at different significance levels (1 %, 5 %, and 10 %). The lower–upper bounds help determine the threshold beyond which the F-statistic is statistically significant. In this case, the F-statistic of 5.80 exceeds the critical values, leading to the rejection of the null hypothesis. This result implies cointegration among the variables InGFI, InESDI, InPGDP, InGEC, InERI, and InCED.

Similarly, for the InECI relationship, the F-statistic is reported as 5.94, with statistical significance at the 1 % level. The critical values are again provided for reference. The F-statistic exceeding the critical values leads to rejecting the null hypothesis, indicating cointegration among the variables InECI, InESDI, InPGDP, InGEC, InCED+, and InCED-. The lower–upper bounds further emphasize the significance of the relationship. The cointegration result implies a long-term association among the variables in each relationship. In practical terms, this suggests that changes in one variable are linked to changes in the others over an extended period. The numerical values of the lower–upper bounds and the F-statistic provide a statistical basis for concluding that these relationships are coincidental and demonstrate a meaningful connection. The detection of cointegration among these variables highlights their interdependence over the long term, suggesting that policy measures targeting one variable could have significant ripple effects across the entire economic system.

Table 6 presents the results of two regression models, Model 1 and Model 2, featuring various economic variables and their coefficients. Each variable represents a different aspect of the model, and the coefficients indicate the strength and direction of their relationship with the dependent variable. Additionally, statistical measures such as R-squared, adjusted R-squared, F-statistic, and Wald statistic provide insights into the overall fit and significance of the models. In Model 1, the dependent variable is not explicitly mentioned, but based on the context, it appears to be a composite economic indicator. The independent variables include InESDI+, InESDI−, InPGDP, InPGDP2, InCED+, InCED−, InGEC, and InERI. Each variable's coefficient is accompanied by its standard error in parentheses, indicating the precision of the estimated coefficient. For instance, InESDI + has a coefficient of 1.531***, with a standard error 1.005. This suggests that a one-unit increase in InESDI+ is associated with a 1.531-unit increase in the dependent variable, holding other variables constant. The significance level of '***' indicates high statistical significance.

In Model 2, a similar set of variables is present, but with some differences. Notably, InPGDP2, InCED−, and InERI are omitted, and a new variable, InCED+, is introduced. The coefficients for InESDI+, InESDI−, InPGDP, InCED+, InGEC, and the constant term are presented, along with their standard errors. Comparing the two models, the coefficients and their standard errors differ, suggesting variations in the relationships between the independent variables and the dependent variable. For instance, InESDI + has a coefficient of −1.439** in Model 2, indicating a negative relationship, whereas it was positive in Model 1. The R-squared and adjusted R-squared values indicate the goodness of fit for each model. In Model 1, the R-squared is 1.89, suggesting that the model explains 96 % of the variance in the dependent variable. The adjusted R-squared, accounting for the number of predictors, is 1.77. In Model 2, the corresponding values are 1.88 and 1.72, respectively. These high R-squared values imply robust explanatory power for the models. The F-statistic assesses the overall significance of the models. In Model 1, the F-statistic is 975.32, and in Model 2, it is 794.58. Both values are

Table 5
Johansen cointegration test.

	F-statistics	lowest–highest Bound (1 %)	lowest–highest Bound (5 %)	lowest–highest Bound (10 %)	constant	Result
$InGFI/(InESDI+, \text{InESDI}-, InPGDP, InGEC, InERI, InCED)$	5.80**	3.55–4.63	2.76–3.99	2.57–3.59	6	Cointegration
$InECI/(InESDI+, \text{InESDI}-, InPGDP, InGEC, InCED+, \text{InCED}-)$	5.94***	3.13–4.40	2.43–3.66	2.49–3.54	5	Cointegration

Table 6
Regression models.

Variables	Model 1	Model 2
InESDI+	1.531***(1.005)	−1.439**(−1.032)
InESDI−	−1.440**(−1.022)	1.265***(1.005)
InPGDP	1.484***(1.004)	1.623***(1.003)
InPGDP2	–	−1.255***(−1.008)
InCED+	1.211***(1.006)	−1.263**(−1.024)
InCED−	–	1.286***(1.003)
InGEC	0.269***(0.007)	−0.928**(−0.03)
InERI	0.434***(0.006)	–
Constant	−20.837**(−5.013)	−10.497***(−2.002)
R2	1.89	1.88
Adjusted R2	1.77	1.72
f-stats	975.32	794.58
Wald statistic	1.108(0.254)	1.334(0.263)

substantial, indicating that the models are statistically significant at conventional significance levels. The Wald statistic tests the joint significance of the coefficients for all variables in each model. In Model 1, the Wald statistic is 1.108 with a p-value of 0.254; in Model 2, it is 1.334 with a p-value of 1.263. These p-values suggest that the joint significance of the coefficients is not statistically supported at conventional significance levels. Moreover, Fig. 4 juxtaposes the coefficients of critical variables from two regression models, illustrating their differential contributions to the green economy, as quantified in Table 6.

Table 7 presents the results of two regression models, Model 1 and Model 2, featuring various economic variables and a lagged Error Correction Term (ECTt−1). Each variable has an associated coefficient, representing the magnitude and direction of its impact on the dependent variable. Additionally, standard errors are provided in parentheses, indicating the precision of the estimated coefficients. In Model 1, the dependent variable is not explicitly mentioned, but given the inclusion of InESDI+, InESDI−, InPGDP, InPGDP2, InCED+, InCED−, InERI, InGEC, and ECTt−1, it appears to be a composite economic indicator. The coefficients for each variable convey their respective contributions to the dependent variable. For example, InESDI + has a coefficient of 0.153**, with a standard error of 0.032. This suggests that a one-unit increase in InESDI+ is associated with a 0.153 unit increase in the dependent variable, while the '**' indicates statistical significance at a 5 % level. Conversely, InESDI− has a coefficient of −0.193, with a standard error of 0.722, and is not statistically significant. InPGDP, InPGDP2, InCED+, InCED−, InERI, and InGEC also have associated coefficients and standard errors.

Model 2 follows a similar structure, but some variables differ. Notably, InPGDP2, InCED−, InERI, and InGEC are included, and a new variable ECTt−1 is introduced. The coefficients for InESDI+, InESDI−, InPGDP, InCED+, InGEC, and ECTt−1, along with their standard errors, are presented. Comparing the two models, differences in variable inclusion and coefficients highlight variations in

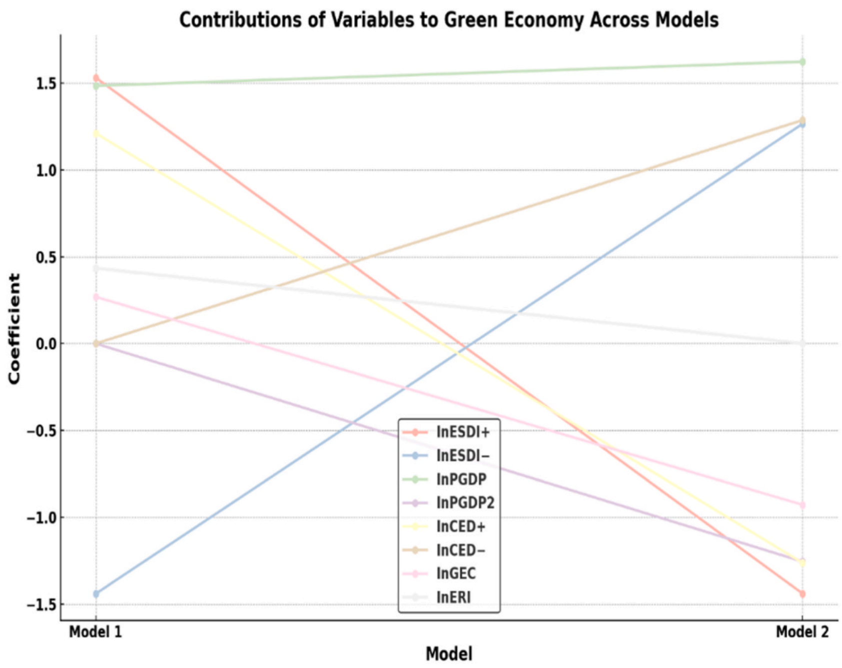

Fig. 4. Dynamic influence: Comparative analysis of variables on green economy.

Table 7
Regression models.

Variables	M = 1	M = 2
InESDI+	1.153**(1.032)	−1.313**(−1.014)
InESDI−	−1.193 (−1.722)	1.729 (1.164)
InPGDP	1.133 (1.002)	1.322***(1.008)
InPGDP2	–	−1.184*(−1.062)
InCED+	0.182*(0.053)	−0.315*(−0.052)
In CED−	–	0.172 (0.352)
InERI	0.244 (0.242)	–
InGEC	0.126 (0.397)	0.617(0.183)
ECTt−1	−0.782**(0.002)	−0.731***(0.006)

their relationships with the dependent variable. For instance, InESDI + has a coefficient of −0.313** in Model 2, indicating a negative relationship, whereas it was positive in Model 1. The introduction of ECTt−1 in Model 2 suggests considering the lagged error correction term to capture adjustments towards long-run equilibrium. The coefficients and standard errors for the lagged error correction term ECTt−1 in both models indicate its role in adjusting the deviation from the equilibrium in the previous period. In Model 1, ECTt−1 has a coefficient of −0.782**, suggesting a quicker adjustment towards equilibrium, and in Model 2, it has a coefficient of −0.731***, indicating a similar adjustment effect. Fig. 5 contrasts the Error Correction Term (ECT) coefficients from two separate regression models, showcasing the rate at which deviations from long-run equilibrium are corrected in the context of green finance, as indicated by the estimates reported in Table 7.

Table 8 provides the results of several diagnostic tests for assessing the performance and reliability of a regression model. Each test evaluates specific assumptions and aspects of the model, including normality, serial correlation, heteroscedasticity, and ARCH effects. The first diagnostic test is the normality test, specifically the Jarque–Bera test, which assesses whether the residuals of the regression model are normally distributed. In this case, the F-statistic is reported as 10.45, and the associated probability is 1.01. The null hypothesis of normality is not rejected at the conventional significance level of 0.05, suggesting that the residuals follow a normal distribution. The second test addresses serial correlation, examining whether there is a correlation among the residuals over time. The F-stats for the serial correlation test is 10.13, with a probability of 0.83. The non-significant p-value indicates no evidence to reject the null hypothesis of no serial correlation in the residuals.

The third diagnostic test is the Breusch–Pagan–Godfrey test, which assesses heteroscedasticity in the residuals, meaning whether the variance of the residuals is constant across all independent variable levels. The reported F-statistic is 2.05, with a probability of 1.02. The non-significant p-value suggests no substantial evidence to reject the assumption of homoscedasticity. The fourth diagnostic test focuses on ARCH effects, which refer to autoregressive conditional heteroscedasticity in the residuals. The ARCH test reports an F-statistic of 0.591, with a probability of 0.834. The non-significant p-value indicates no evidence of ARCH effects in the residuals. The fifth diagnostic test, the Ramey reset test, assesses the overall model specification by examining whether adding higher-order terms to the model improves its fit. The reported F-statistic is 2.00, with a probability of 1.04. The non-significant p-value suggests no

Fig. 5. Navigating adjustment speeds in green finance.

Table 8
Diagnostic tests for assessing the performance and reliability.

Diagnostic test	F-Stats.	Prob.
Normality (Jarque–Bera) test	10.45	1.01
Serial correlation	10.13	1.03
Breusch–Pagan–Godfrey test	2.05	1.02
ARCH	0.591	0.834
Ramey reset	2.00	1.04

substantial evidence to reject the null hypothesis, indicating adequate model specification. Fig. 6 presents a radar chart that encapsulates the results of several critical diagnostic tests, offering a comprehensive overview of our model's performance and reliability. The comprehensive set of diagnostic tests confirms the robustness and reliability of the regression model, ensuring that the model's predictions are trustworthy and can be confidently used for policy analysis and decision-making.

Table 9 presents a matrix detailing the short-term causal relationships and long-term Error Correction Model (ECM) coefficients among various dependent and independent factors in a dynamic system. Each cell in the matrix represents the strength and direction of the influence of an independent factor on a dependent factor, with associated standard errors in parentheses. Starting with the ΔGFI (Green Finance Index) as the dependent factor, the short-term causal relationships indicate that ΔGF + has a positive coefficient of 0.25*, suggesting a positive impact, while ΔGF− has a higher positive coefficient of 0.69, indicating a stronger positive association. ΔERI (Environmental Risk Investment) also positively influences ΔGFI with a coefficient of 0.35. Other factors such as ΔCED, ΔCED−, ΔPGDP, ΔGEC, and ΔECI also have coefficients suggesting positive or negative short-term impacts on ΔGFI. Moving to the long-term ECM coefficients for ΔGFI, ΔGF + has a coefficient of −0.02, ΔGF− has a coefficient of −0.44, ΔERI has a coefficient of −0.33, ΔCED has a coefficient of −0.16, and so on. These coefficients represent the long-term adjustments toward equilibrium after short-term disturbances. Negative coefficients for ΔGF−, ΔERI, and ΔCED indicate a tendency for the system to correct imbalances over time.

The ΔGF + as the dependent factor shows that ΔGFI has a coefficient of 0.024, suggesting a positive short-term influence, while ΔGF− has a higher positive coefficient of 0.53, indicating a stronger positive association. ΔERI, ΔCED, ΔCED−, ΔPGDP, ΔGEC, and ΔECI also have coefficients suggesting positive or negative short-term impacts on ΔGF+.In terms of long-term adjustments for ΔGF+, the coefficients reveal the system's tendency to correct imbalances over time. For instance, ΔGFI has a coefficient of −0.22, indicating a negative long-term adjustment, while ΔGF− has a coefficient of −0.42, suggesting a negative long-term impact on ΔGF+. This pattern is repeated for other dependent factors, such as ΔGF−, ΔERI, ΔCED, ΔCED−, ΔPGDP, ΔGEC, and ΔECI, with short-term causal relationships and long-term ECM coefficients providing insights into how these factors interact dynamically within the system. The detailed matrix of short-term and long-term relationships underscores the interconnectedness of economic and environmental factors, highlighting the importance of considering both immediate and prolonged effects when formulating policies and interventions.

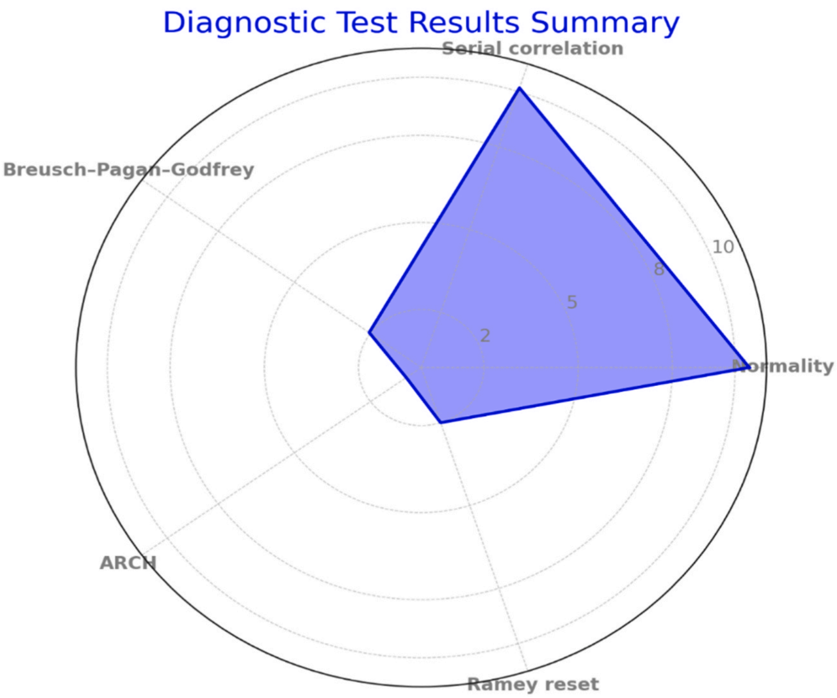

Fig. 6. Model health check: Diagnostic test radar overview.

Table 9
The short-term causal relationships and long-term error correction model (ECM).

Dependent variables	Short-term causal relationship									Long term $ECM_t - 1$
	Independent factors									
	Δ GFI	Δ GF+	Δ GF−	Δ ERI	Δ CED	Δ CED−	Δ PGDP	Δ GEC	Δ ECI	
Δ GFI	–	0.25*	0.69	0.35	0.26	−0.81	0.19*	0.43	−0.43	0.44*
		−0.02	−0.44	−0.33	−0.16	(−0.59)	−0.02	−0.22	(−0.22)	0
Δ GF+	0.024	–	–	0.19	0.28*	−0.83	0.84**	0.053	−0.28	0.62*
	−0.22			−0.27	−0.02	(−060)	−0.03	−0.17	(−0.33)	0
Δ GF−	0.53	–	–	−0.28	0.17	0.166	0.87	−0.30	0.64	0.74
	−0.22			(−0.22)	−0.42	−0.94	−0.72	−0.42	−0.24	−0.28
Δ ERI	0.042	0.14	0.06	–	0.46	0.88	0.24*	0.08	−0.42	0.26
	−0.32	−0.17	−0.38		−0.25	−0.75	−0.02	−0.22	(−0.33)	−0.33
Δ CED+	0.29**	0.16*	0.06	0.19	–	–	0.26	0.26	−0.22	0.35*
	−0.03	0	−0.22	−0.27			−0.27	−0.25	(−0.28)	−0.02
Δ CED−	0.28	0.36	−0.24	−0.49	–	–	−0.33	−0.466	0.76	0.54
	−0.22	−0.28	(−0.26)	(−0.25)			(−0.40)	−0.43	−0.55	−0.52
Δ PGDP	0.27*	0.22*	0.33	0.25	0.44**	0.24	–	0.77	−0.63	0.32*
	0	0	−0.27	−0.33	−0.05	−0.25		−0.70	(−0.16)	0
Δ GEC	0.042	0.39	–	0.19	0.05	0.03	0.39	–	0.22	0.33***
	−0.22	−0.15		−0.32	−0.16	−0.25	−0.14		−0.42	−0.08
ECI	−0.35	−0.25	0.26	0.32	−0.24**	–	0.08	−0.33	–	0.32*
	(−0.14)	(−0.20)	−0.25	−0.27	(−0.04)		0.33	−0.27		0

5. Discussion

The findings presented in this study offer a novel understanding of the complex relationships within the dynamic system under investigation, specifically focusing on green finance, environmental sustainability, and economic resilience post-COVID-19, with a spotlight on China's strategy. This section explains the implications and significance of the identified patterns, enhanced by comparisons to previous literature and established theoretical frameworks. The short-term causal relationships among crucial factors paint a complex picture of interdependencies. Notably, the Green Finance Index (ΔGFI) emerges as a pivotal variable, showcasing sensitivity to both positive and negative short-term influences. The positive impact of ΔGF+ and ΔERI suggests that increased environmental sustainable development investment and reduced environmental risk investment tend to elevate the Green Finance Index in the short run. This finding aligns with Yin [51], who emphasizes integrating environmental considerations into financial decision-making to drive sustainable economic growth. Cao and Tao [16] also support this by highlighting the positive impact of green finance initiatives on job creation and economic resilience. However, the stronger positive association with ΔGF− indicates that a more comprehensive approach involving reductions in both environmental sustainable development investment and environmental risk investment has a more pronounced positive effect on the Green Finance Index in the short term. This contrasts with Nieuwenhuijsen [52], who raises concerns about greenwashing and insufficient regulatory frameworks, suggesting that mere investment reductions may not always yield the desired environmental benefits without robust policies.

Furthermore, the interplay of economic factors such as ΔPGDP, ΔGEC, and ΔECI reveals complicated relationships with the Green Finance Index, reflecting the multifaceted nature of economic resilience and its alignment with sustainable financial practices. The short-term impacts of these economic factors suggest their immediate influence on the Green Finance Index, balancing economic growth, environmental considerations, and innovative eco-friendly practices. These findings resonate with the Triple Bottom Line (TBL) framework, which posits that sustainable development requires balancing economic, environmental, and social objectives [23]. Investigating the long-term adjustments portrayed by the Error Correction Model (ECM) coefficients unveils a crucial aspect of the system's self-correction mechanism. The negative coefficients associated with ΔGF−, ΔERI, and ΔCED in the long term underscore the system's inclination to correct imbalances over time, promoting a sustainable and resilient economic ecosystem. The persistence of these negative adjustments implies a gradual convergence towards equilibrium, emphasizing the importance of addressing environmental risks and adopting sustainable financial practices for long-term economic stability. This finding aligns with institutional theory, suggesting that organizations with strong environmental values and practices are more likely to integrate green finance into their operations, promoting market stability [53].

The positive long-term ECM coefficient of ΔECI suggests a lasting positive influence on economic innovation in the context of green finance, signifying the potential of eco-innovations to contribute significantly to the equilibrium-seeking dynamics of the system over the long term. This is supported by Acquah, Baah [54], who highlight the role of green finance in promoting circular economies and enhancing market credibility. In the broader context of China's strategy, the positive short-term and long-term impacts of environmentally sustainable development investments (ΔGF+) align with China's commitment to green finance and sustainable development. However, the stronger positive association with reduced environmental risk investment (ΔGF−) suggests a more holistic strategy for achieving economic and environmental balance. This finding is consistent with China's dual goals of environmental stewardship and economic growth, as highlighted by Zoungrana [2].

5.1. Policy implications

The findings hold significant policy implications for governments, financial institutions, and environmental regulators, especially in China's post-COVID-19 context. The identified short-term and long-term relationships highlight the need for targeted policies that align economic resilience with environmental sustainability through green finance initiatives. The positive short-term impact of sustainable development investments on the Green Finance Index emphasizes the need to promote green investments. Policymakers should incentivize businesses and financial institutions to integrate environmental considerations into their decision-making processes through financial instruments, tax incentives, and supportive regulatory frameworks.

Conversely, the stronger positive association with reduced environmental risk investment suggests the benefits of managing and mitigating environmental risks. Implementing robust regulatory frameworks and incentives can encourage practices that reduce environmental impact, supported by institutional theory, which stresses the importance of regulatory frameworks in promoting sustainability [25]. Long-term adjustments from the Error Correction Model (ECM) coefficients stress the need for sustained efforts toward economic and environmental equilibrium. Policies should develop comprehensive strategies that integrate green finance principles into national plans, ensuring continuous improvements to address emerging challenges and ensuring long-term sustainability (Chen & Wang, 2021).

In China, reinforcing policies supporting green finance and innovation in sustainable practices aligns with the country's goals. Policymakers should ensure effective enforcement of environmental regulations to promote long-term economic stability, supported by China's investments in renewable energy and green infrastructure [6]. Economic innovation as a positive influence on the Green Finance Index suggests fostering an environment conducive to eco-friendly technologies. Investments in research, innovation hubs, and collaboration among government, industry, and academia can drive advancements in green finance, aligning with the behavioral economics framework that explores how values and perceptions influence sustainable financial decisions [24].

5.2. Conclusion

This study provides insights into environmental sustainability, economic resilience, and green finance dynamics. Analyzing short-term and long-term adjustments offers valuable perspectives for policymakers, particularly within China's post-COVID-19 strategy. Short-term causal relationships highlight the pivotal role of the Green Finance Index (ΔGFI) in responding to various influences. Environmental Sustainable Development Investment (ΔGF+), reduced Environmental Risk Investment (ΔGF−), and economic factors such as Post-COVID GDP Growth (ΔPGDP), Green Economy Contribution (ΔGEC), and Eco-Innovation Index (ΔECI) impact the Green Finance Index, underscoring the need for a balanced approach to green finance, integrating economic growth and environmental considerations, supported by the TBL framework. Long-term adjustments, indicated by the ECM coefficients, emphasize the system's tendency to correct imbalances over time. Negative coefficients associated with ΔGF−, ΔERI, and ΔCED highlight the importance of addressing environmental risks and adopting sustainable financial practices for long-term stability, aligning with institutional theory's emphasis on long-term regulatory stability.

The findings align with China's strategy's commitment to green finance and sustainable development. The positive impacts of Environmental Sustainable Development Investment (ΔGF+) support China's transition towards a sustainable economy. Considering both reduced Environmental Risk Investment (ΔGF−) and economic innovation (ΔECI), a comprehensive approach can enhance China's strategy in the post-COVID-19 era, supported by the TBL framework and previous literature. The policy implications emphasize targeted interventions that align economic resilience with environmental sustainability. Policymakers should consider incentives, regulatory frameworks, and strategic planning to foster green finance initiatives. The long-term adjustments highlight the need for sustained efforts toward economic equilibrium, advocating for national strategies that integrate economic and environmental objectives. This study contributes to the discourse on green finance, economic resilience, and environmental sustainability in a post-COVID-19 world, guiding policymakers toward a more resilient and sustainable economic future.

5.3. Limitations and future research

While this research has provided valuable insights into the complex interplay of green finance, environmental sustainability, and economic resilience, it is essential to acknowledge certain limitations inherent in the study. These limitations shape the boundaries of the research and provide context for interpreting the findings.

Firstly, the study's reliance on quantitative data and statistical analyses may limit the depth of understanding in capturing qualitative nuances. Future research could benefit from incorporating qualitative methodologies like case studies or interviews. Another limitation lies in the scope of the study, which focused primarily on China's strategy. This specificity may limit the generalizability of findings to other regions with distinct economic, political, and environmental landscapes. Future research could explore comparative analyses across multiple nations.

The study's temporal scope, centered around the post-COVID-19 period, introduces a limitation regarding the generalizability of findings to periods unaffected by significant global disruptions. Longitudinal studies that span pre- and post-pandemic periods could offer deeper insights into the persistent effects of global disruptions on green finance. The reliance on pre-existing indices and data sources, such as the Global Green Finance Index and World Bank indicators, introduces potential data accuracy, reliability, and timeliness limitations. Continuous data verification and updates in future research are essential. The variables used in this study primarily represent environmental and economic effects. Future research could expand the scope by including more comprehensive variables that capture financial and social effects, such as social equity, financial literacy, and community impact. Finally, while this study provides valuable insights into the Chinese market, it is essential to acknowledge potential cultural and institutional biases. Future research should address these biases by incorporating a diverse range of contexts to enhance the applicability of the findings.

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Data availability statement

The datasets used and/or analyzed during the current study are available on reasonable request.

CRediT authorship contribution statement

Jianjiang Shen: Writing – review & editing, Visualization, Validation, Resources, Funding acquisition. **Jiaojiao Yu:** Writing – review & editing, Validation, Supervision, Project administration. **Wali Muhammad Khoso:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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