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Innovating for a greener future: The role of green bonds in advancing energy innovation

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ABSTRACT

The rise of climate change concerns and the need to transition to a low-carbon economy has led to a surge in the issuance of green bonds and the development of energy innovation. This study explores the asymmetric green bonds-energy innovation nexus in the top ten nations that issue green bonds. Previously, panel data methods were used to obtain consistent outcomes regarding these variables despite the fact that several economies could not illustrate such a relation individually. However, this research adopts the “Quantile-on-Quantile” approach that can examine time-series dependence in every economy by offering detailed and country-specific characteristics. The outcomes revealed a positive linkage between green bonds and energy innovation in most nations at particular quantiles. Furthermore, the analysis indicates that the rank of asymmetries between the variables changes from economy to economy, punctuating the significance of policymakers monitoring modifications in green finance and energy innovation.

1. Introduction

The energy sector is one of the leading contributors to international greenhouse gas emissions. Using fossil fuels like oil, coal, and gas has been identified as a significant contributor to climate change. The increasing concerns regarding climatic variations have led to a universal shift towards a more sustainable and greener economy (Tolliver, Keeley, & Managi, 2020). However, improving renewable energy (REN) sources like wind, hydropower, and solar could considerably lessen greenhouse gas emissions (Irfan, Razzaq, Sharif, & Yang, 2022). The development of these sources of energy requires significant investment in R&D, infrastructure, and technology (Andersen, 2017). Green finance (GF) includes financial services and products to aid sustainable development and environmental goals (Wu, Fareed, Wolanin, Rozkrut, & Hajduk-Stelmachowicz, 2022). One example of GF is green bonds (GB), which are a kind of bonds that are explicitly issued to provide finance environment-friendly ventures or investments (Anh Tu & Rasoulinezhad, 2022; Hacıomeroglu, Danişoğlu, & Güner, 2022). GB can play a substantial role in promoting energy innovation (EIN). By raising capital for sustainable energy projects, GB can support developing and deploying REN technologies. It is receiving appreciation as investors

seek means to back sustainable undertakings (Li, Faridi, & Nazar, 2023; Ye & Rasoulinezhad, 2023).

The global GB market has developed considerably during recent years due to the issuance of GB, attaining a record high of \$269.5 billion in 2020 (Climate Bonds Initiative, 2021). The energy sector is one of the largest recipients of GB proceeds, with REN projects accounting for most energy-related GB issuance. According to the report of IRENA (2018), GB can gather a substantial amount of funds for sustainable energy projects, potentially rising to \$10 trillion by 2050. GB also helps finance a low-carbon economy, which could stimulate innovations in the energy sector. GB's contribution could lead to a reliable and foreseeable source of funds for sustainable energy projects, potentially decreasing the hazards associated with REN projects (Yadav, Mishra, & Ashok, 2023). Second, GB can help reduce the cost of capital for sustainable energy projects by providing access to a larger pool of investors (Li, Li, Huang, & Guo, 2023; Wang, Su, Umar, & Peculea, 2023). Third, GB can help promote transparency and accountability in the energy sector by providing investors with information about their investments' environmental and social impact (Ye & Rasoulinezhad, 2023). However, several challenges are associated with using GB to finance sustainable energy projects. The need for more openness and uniformity in the GB

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market is one of the significant issues. There is no consistent definition of what organizes a GB till now, and the lack of transparency in the market could make it hard for investors to appraise the environmental influence of their investments (Grishunin, Bukreeva, Suloeva, & Burova, 2023).

Investigating the correlation between GB and EIN is challenging. Does the effect of GB and EI display asymmetric behavior? How might the findings differ across diverse economies? Additionally, the potential implications of GB-induced changes in EIN are uncertain. Based on the extant literature, empirical investigations have only examined many unresolved issues superficially. This study aims to enhance previous inquiries by comprehensively scrutinizing these predicaments. During recent years, several investigations have been organized regarding the effectiveness of GB (Hammoudeh, Ajmi, & Mokni, 2020; Li, Faridi, & Nazar, 2023; Tolliver et al., 2020; Yadav et al., 2023). Only a few studies have investigated how GB impacts EIN (Anh Tu & Rasoulinezhad, 2022; Azhgaliyeva, Kapoor, & Liu, 2020; Ye & Rasoulinezhad, 2023). While it is acknowledged that GF policies impact green innovations, there still needs to be more understanding regarding their effectiveness in promoting EIN. In a world where sustainable development and environmental conservation have become paramount, uncovering the nuances of this connection is pivotal. The essence of GB lies in its capacity to drive environmental progress, yet its impact on EIN may follow various paths. Recognizing the possibility of asymmetry is crucial because it allows us to uncover hidden opportunities and potential pitfalls. By doing so, we can tailor financial strategies and policy interventions more effectively, ensuring that GB supports EIN and does so in a manner that aligns with the unique characteristics and needs of different economies. This investigation aims to transcend the surface-level understanding prevalent in the existing literature and bring to light the dynamic and multifaceted nature of the GB-EIN nexus. As per our best awareness, preceding investigations have analyzed the non-linear connection between GB and EIN in countries that support GB. Earlier research has implemented panel data tools to establish the attachment between GB and EIN, even though this connection was not observed in many other nations. This investigation chooses the Quantile-on-Quantile (QQ) tool to produce extensive but economy-specific confirmation of the bond between the variables. The QQ methodology helps examine the time-series correlation of each nation separately (Hung, 2023). The interdependence of GB and EIN displays definite difficulties that cause it challenging to apply customary econometric procedures, like standard quantile regression (QR) and Ordinary Least Squares (OLS).

The typical parametric tools are unprotected to the extreme points of data and cannot account for slope heterogeneities. Consequently, the QQ methodology is utilized to review the effect of GB on EIN, as it is resistant to irregularities and competent in managing heterogeneous slopes (Hung, 2023). It is crucial to use a reliable econometric tool like QQ to assess the influence of GB on EIN. Furthermore, the QQ approach is immune to deviations and could efficiently adapt to slope changes (Sinha, Mishra, Sharif, & Yarovaya, 2021). Prior investigations have examined the complete dataset regarding distinct indicators (neutral, negative, or positive). For instance, these indicators were observed by several studies, like Hu, Wang, and Wang (2021), Irfan et al. (2022), Pan, Zheng, Li, Liu, and Zhang (2018), Liu, Xia, Fan, Lin, and Wu (2017), and Chen (2020). Conversely, this paper exhibits that diverse signs (negative or positive) could be attained through a range of quantiles. The influence of the GB-EIN nexus could differ in the context of an economic downswing versus a period of economic expansion. Highest ranks of GB might have a distinct influence on EIN compared to lower levels. Since the magnitude of GB rises, the bond between GB and EIN may become much trickier and more dynamic. We predict that a non-linear GB-EIN connection would transpire because of the non-linear allocation of characteristics, resulting in asymmetric disparities in macroeconomic signs. As the kinship between variables modifies among different nations, our technique of emphasizing a single nation might present significant recommendations for policymakers and governments to accomplish political, economic, and social objectives among the

variable's upper, medium, or lower segments.

The aim of this inquiry focuses on top GB issuer countries for numerous reasons. Firstly, the chosen economies harm the environment because they rely on typical energy (Fatica & Panzica, 2021). Secondly, due to globalization, these markets possess analogous economic, financial, social, and political frameworks, facilitating the quick circulation of technological progressions from one economy to its closest economies, as proved by historical events. Additionally, a nation's energy industry is influenced by the adjacent countries' energy sectors and economic disturbances (Ren, Li, Wen, & Lu, 2022). Thirdly, we implement the Quantile-on-Quantile (QQ) tool, a time-series instrument that evaluates every economy individually to address cross-sectional interdependence and heterogeneous slopes, which can result in prejudiced outcomes (Sinha et al., 2021). The relationship between GB and EIN is progressively asymmetric because of prompt adjustments to policies and economic development (Yan, Wang, Athari, & Atif, 2022). Accordingly, during the inceptive segment of the present article, we shall concentrate on every economy, aiming to consider the said complexities. Furthermore, regardless of their nearness, these economies repeatedly employ different and separate strategies to regulate GB and EIN. To account for differences among countries, it is essential to form empirical patterns utilizing a proper econometric technique, for example, the QQ technique. Our revelations will provide a more accurate perspective of the correlation between GB and EIN than conventional econometric techniques. Ultimately, the results of this research will establish the groundwork for future investigations of the GB-EIN connection and its impact on other nations.

The remainder of the current research is arranged as follows: Section 2 reviews earlier empirical studies. The data and its depiction are elucidated in Section 3, whereas Section 4 provides the econometric methodology. The results are explained in section 5. Ultimately, Section 6 culminates the work by restating the inferences and propositions for upcoming works.

2. Literature review

Several empirical works have emphasized the role of GB as a green financial tool for EIN. For example, Irfan et al. (2022) examined how exhaustive GF affected green innovation in China. Difference-in-differences and panel vector autoregressive patterns were applied. GF was observed to have a positive and substantial influence on green innovation. Gilbert and Zhou (2017) observed that green financial products, like insurance and green funds, encouraged civilian investment in clean production sectors and promoted green innovation in China. Meanwhile, Jang and Chang (2008) and Chemmanur and Fulghieri (2014) proposed that a varied green financial system could improve the effectiveness of green innovation. In another study, Tolliver et al. (2020) observed a positive association between GB and REN by applying Difference-in-Difference approach.

Hu et al. (2021) observed that the green credit policy had a statistically significant and positive influence on the production of green patents by heavily polluted firms in China, particularly those that face greater financial constraints. Correspondingly, Yu, Wu, Zhang, Chen, and Zhao (2021) assessed the influence of financing limits on the expansion of green innovations among Chinese-listed firms between 2001 and 2017. Results indicated that financing limits impede firms' ability to innovate in green technologies. Anh, Tu, & Rasoulinezhad (2022) explored the role of GB in energy efficiency (ENE) financing for 37 members of the OECD with the help of a panel data framework over the period 2007Q1-2020Q4. The outcomes of the continuously updated-fully modified (CUP-FM) approach revealed the positive influences of GB and regulatory quality index on ENE. Similarly, Ye and Rasoulinezhad (2023) analyzed the impact of GB on the renewable resources' consumption in 15 Asia-Pacific nations between 2011 and 2021. Using the Fully Modified Ordinary Least Squares (FMOLS) tool, it was found that GB has a favorable influence on the proficiency in

renewable natural resource consumption.

According to Azhgaliyeva et al. (2020), implementing GB may effectively advance the ENE in Southeast Asian economies. Hammoudeh et al. (2020) asserted that GB might function as an instrument to boost private sector involvement in developing eco-friendly ventures, which could curtail CO₂ emissions in the USA. Hanif, Aziz, and Chaudhry (2019) identified that the issuance of GB can favor funding REN initiatives that combat air pollution. Similarly, Paraque and Revelli (2019) unveiled the usefulness of GB for financing eco-friendly initiatives and the long-term well-being of our planet and humanity. Li, Sampene, Agyeman, Brenya, and Wiredu (2022) observed the part of the GF-EIN nexus in neutralizing environmental pollution in MINT countries (Nigeria, Mexico, Turkey, and Indonesia). The results of the cross-sectional autoregressive distributed lag (CS-ARDL) tool found that environmental pollution was neutralized through GF and the promotion of EIN. Similarly, Wu et al. (2022) observed that GF and eco-innovation improved ENE in advanced economies.

Contrary to the above studies, some researchers discovered that implementing GF has a detrimental or mixed impact on EIN or environmentally friendly technology. This is due to the allocation of funds being directed towards high-polluting industries, reducing available resources for innovation. Liu et al. (2017) uncovered that implementing GF policies could limit the investment opportunities available to energy-intensive industries, leading to a need for more funds for the R&D of green technology. As a result, companies may need more time to pursue green innovation. In the same way, Andersen (2017) emphasized that GF may cause uncertainty for businesses, particularly for energy-intensive industries that are already financially constrained, which in turn reduces the amount of funding available for R&D. Chen (2020) revealed that the current financial system, led by banks, is insufficient in meeting the requirements for sustainable development. The scarcity of green financing options and the lack of interest incentives may impede the ability of companies to seek financial support for their green innovation projects. Pan et al. (2018) analyzed the performance of GF in encouraging EIN in China and found mixed results. While GF positively impacted EIN in certain regions and industries, it had a limited effect on others.

Most of the prior studies highlight the impact of GF on environmental investment, green economic growth, or green technological innovation while ignoring the role of GF on EIN. Moreover, previous research in the academic sphere has focused on the impact of GB on EIN and has yet to explore the association between specific quantiles of GB and EIN. The study proposes an asymmetric correlation between these variables, and failing to consider this possibility could lead to the loss of critical knowledge and the constitution of incorrect findings (Yan et al., 2022). In addition, preceding investigations have demonstrated a liking for panel data instead of time-series data, regardless of the capable complexities allied with panel data, for example, concerns with generalization, imprecision in measurement, and a mismatched choice of models. In panel data, the relationship between GB and EIN may be ambiguous, making it tough to assess the average impact of GB-induced EIN for each country. So, taking advantage of the QQ methodology is crucial, which assesses each nation autonomously and delivers a much all-encompassing understanding of the correlation.

3. Data

This research appraises the connection between GB and EIN for the ten leading GB issuer nations (UK, Germany, China, Sweden, Spain, France, Netherlands, Japan, Canada, and USA) based on the Climate Bonds Initiative (2021) report. We possess a compilation of data incorporating two variables, where EIN is categorized as the dependent variable and GB as the independent variable. The S&P GB index is implemented to denote the GB market (Ejaz, Ashraf, Hassan, & Gupta, 2022). Monthly series of GB data is obtained from DataStream. In technical innovation, energy patents function as a favored and

extensively employed standard for empirical research (Baloch, Danish, & Qiu, 2022). Unlike other indicators that evaluate innovation, a patent provides particularized knowledge about technology, receives legal protection through country rules, and assists innovators in establishing competitive advantages (Zhao, Zheng, & Fu, 2022). Moreover, a patent, functioning as an innovation outcome, presents notable data accessibility. Hence, we employ energy patents as a proxy for EIN, followed by Zhao et al. (2022) and Baloch et al. (2022). Annual data for EIN is taken from OECD-Statistics,¹ which is eventually transformed into monthly data series by the usage of the quadratic match-sum technique, followed by Sharif et al. (2020) and Razzaq, Wang, Chupradit, Suksatan, and Shahzad (2021). This tool balances data for seasonal oscillations during the shift from bottom to upper frequency by reducing point-to-point inconsistencies.

We have employed the quadratic match-sum technique to increase the temporal resolution of the data. This transformation allows us to capture finer-grained variations in EIN over time, which may reveal important insights and patterns that are not discernible when using annual data alone (Yi, Raghutla, Chittedi, & Fareed, 2023). Our dataset encompasses 157 monthly observations from January 2007 to December 2020 for both GB and EIN. Interpretations of the signs and acronyms referred to in this research are available in Table 1, located at the commencement of this article.

4. Econometric approach

The current segment of the research scrutinizes the econometric techniques applied to calculate the association between GB and EIN. We adopt a quantile-based cointegration test to investigate the long-run interrelationships among our variables. Our statistical analysis utilizes the QQ approach for econometric analysis.

4.1. Quantile Cointegration (QC) test

In this investigation, the Quantile Cointegration (QC) technique, as proposed by Xiao (2009), is employed due to the possible inadequacy of standard cointegration tests that believe on unchanging cointegrating vectors to establish long-run associations among variables precisely. The cointegration degree between the variables could vary during the diverse quantile range of the distribution of the data. In order to bypass potential calculation biases, the QC methodology accommodates secular alterations and the interrelation between the predictor and response variables quantiles when evaluating persistent connections in provi-

Table 1
The taxonomy of abbreviations/symbols.

Symbol/ Abbreviation	Narration	Symbol/ Abbreviation	Narration
EIN	Energy innovation	ADF	Augmented Dickey-Fuller
GB	Green bonds	μ_0^0	Quantile error term
QR	Quantile regression	J-B	Jarque-Bera
QQ	Quantile-on-Quantile Estimation	τ	τ^{th} quantile of energy innovation
REN	Renewable energy	$\text{Sup}_\tau V_n(\tau) $	Value of supremum norms (α and γ)
GF	Green finance	ρ_q	quantile loss function
ENE	Energy efficiency	h	Bandwidth parameter

¹ Website of Organization for Economic Co-operation and Development (OECD) statistics: <https://stats.oecd.org/>.

sional data distribution. Xiao (2009) originated an unfamiliar process that integrates fractured cointegration errors into lead-lag elements, thereby surmounting the constraints of typical cointegration tests. Sainkonen (1991) indicated that the QC procedure could be demonstrated through a continuous vector $\alpha(\tau)$.

$$X_i = \alpha + \alpha' Y_i + \sum_{k=-s}^k \Delta Y_{i-k} \Pi_k + v_i \quad (1)$$

and

$$Q_\tau^X(X_i M_i^X, M_i^Y) = \beta(\tau) + \alpha(\tau)' Y_i + \sum_{k=-s}^s \Delta Y_{i-k} \Pi_k + F_v^{-1}(\tau) \quad (2)$$

A constant parameter is denoted by the drift parameter $\beta(\tau)$, whereas $F_v^{-1}(\tau)$ signifies the quantile error for the conditional frequency distribution. According to the research conducted by Xiao (2009), the quadratic components of the cointegrating pattern could be declared as below:

$$Q_\tau^X(X_i M_i^X, M_i^Y) = \beta(\tau) + \alpha(\tau)' Y_i + \delta(\tau)' Y_i^2 + \sum_{k=-s}^s \Delta Y_{i-k} \Pi_k + \sum_{k=-s}^s \Delta Y_{i-k}^2 \Pi_k + F_v^{-1}(\tau) \quad (3)$$

The cointegration coefficients derived from the QC test are evaluated by executing the null hypothesis $H_0: \alpha(\pi) = \alpha$, as articulated by Equation (3). As a result, our findings substantiate the $\hat{V}_n(\tau) = [\hat{\alpha}(\tau) - \alpha]$ as the null hypothesis of the supremum rule by practicing $\text{Sup}_\tau |\hat{V}_n(\tau)|$ as the statistics value. By performing 1000 Monte Carlo simulations, we can obtain the critical limits.

4.2. Quantile-on-quantile (QQ) tool

Because of the asymmetric nature of data, we utilize the QQ tool that is acknowledged among supreme replacement for inspecting variables when compared to the customary quantile regression (QR) methodology. Unlike the QR method, which measures the mean effect of the independent variable on the dependent variable's quantiles, the QQ procedure, contrived by Sim and Zhou (2015), surmounts the constraints of the QR model and is remarkably proficient in investigating the interconnection between the independent and dependent variables' quantiles (Li, Faridi, & Nazar, 2023). The current investigation utilizes the QQ tactic that amalgamates non-parametric measurements with the ordinary QR technique to scrutinize the effect of the GB quantile on the EIN quantile and rectify the issue of interdependence. This methodology is applied to bring to light apprehensions in the GB-EIN situation that would be refreshing to identify via ordinary econometric techniques, for example, QR and OLS. The mechanism applies a rudimentary variety of non-parametric regression and is explicated as follows, in compliance with the studies of Hu et al. (2021) and Li et al. (2022).

$$EIN_t = \alpha^\theta(GB_t) + \mu_t^\theta \quad (4)$$

GB_t represents green bonds, while EIN_t stands for energy innovation, respectively in time 't'. The sign θ specifies the θ^{th} GB quantile. The coefficient load $\alpha^\theta(\cdot)$ is deemed ambiguous since the correlation between GB and EIN is still not entirely comprehended. The error of the model is signified by μ_t^θ alongside the θ^{th} quantile.

The assessment of Equation (4) is executed by making use of the local linear regression methodology in the proximity of GB, as illustrated as under, in accordance with the approach recommended by Cleveland (1979).

$$\alpha^\theta(GB_t) \approx \alpha^\theta(GB^\tau) + \alpha^\theta(GB^\tau)(GB_t - GB^\tau) \quad (5)$$

The partial influence of $\alpha^\theta(GB_t)$ on GB_t is denoted by α^θ . The factors θ and τ relate to $\alpha^\theta(GB^\tau)$ and $\alpha^\theta(GB^\tau)$, respectively. $\alpha^\theta(GB^\tau)$ is also known

as $\alpha_0(\theta, \tau)$, while $\alpha^\theta(GB^\tau)$ is denoted as $\alpha_1(\theta, \tau)$. As a result, an updated version of equation (5) can be expressed in the following manner:

$$\alpha^\theta(GB_t) \approx \alpha_0(\theta, \tau) + \alpha_1(\theta, \tau)(GB_t - GB^\tau) \quad (6)$$

To obtain QQ model for our study, we consolidate Equation (6) into Equation (4):

$$EIN_t = \frac{\alpha_0(\theta, \tau) + \alpha_1(\theta, \tau)(GB_t - GB^\tau)}{(*)} + u_t^\theta \quad (7)$$

Equation (7) designates the QQ model to illustrate the bond between the θ^{th} GB quantile and the τ^{th} EIN quantile, where the emblem $(*)$ signifies the provisional GB quantile. The parameters α_0 and α_1 are indexed by θ and τ , apiece, indicating the interdependence between GB and EIN according to their corresponding quantiles. The coefficients α_0 and α_1 could diversify originating from the value of quantiles of EIN and GB. By adjusting the distinct distributions, Equation (7) unveils the instinctive QQ equation for the linkage between GB and EIN.

The QQ technique, which employs a dimensional procedure with a single independent variable, transcends traditional time-series techniques by expertly anticipating the asymmetric link between GB and EIN at the extremities of the distribution. As a result, it provides more reliable and precise forecasts than commonly used methodologies (Razzaq et al., 2021). The bandwidth is critical in highlighting the interrelationship between GB and EIN in the minimization function. To handle this problem, we use the subsequent minimization function proposed by Chu and Marron (1991).

$$\text{Min}_{\delta_0, \delta_1} \sum_{t=1}^n \rho_\varphi[EIN_t - \delta_0 - \delta_1(GB_t - GB^\tau)] L \left[\frac{M_n(GB_t) - \tau}{h} \right] \quad (8)$$

The function of loss of the regression of quantile is symbolized by ρ_φ . In order to measure the efficacy of the pattern, the Gaussian kernel function denoted as $L(\cdot)$ is operated as a weighting component, allocating varied weights to points of data close to GB. The factor related to bandwidth is symbolized as 'h' and the standard indicator function is symbolized by 'I'. Using a narrow bandwidth leads to high variance in the approximations, whereas an extensive bandwidth creates contortions throughout the distribution (Sim & Zhou, 2015). Therefore, obtaining an equilibrium between bias and variance is vital. Following Razzaq et al. (2021) and Chang, Moldir, Zhang, and Nazar (2023), we set the limit for bandwidth as $h = 0.05$.

4.3. Robustness of the QQ tool

The QQ framework presents standard estimated values for quantile regression (QR) by providing accurate forecasts for diverse quantiles of the independent variable (GB). Comparatively the QR tool, which relies on the θ^{th} GB quantile to determine the quantile parameters, the QQ instrument appraises the effect of the θ^{th} GB quantile over τ^{th} EIN quantiles, characterizing the parameters of quantile using each θ and τ , leading to a further intricate review. By averaging the coefficients of QQ with regard to τ , the QR parameters might be calculated. As noted by Sim and Zhou (2015), the QR method's slope coefficients, shown by $\gamma_1(\theta)$, is selected to scrutinized the influence of GB on various EIN quantiles, as depicted under.

$$\gamma_1(\theta) \equiv \bar{\alpha}_1 = \frac{1}{s} \sum_{\tau} \hat{\alpha}_1(\theta, \tau) \quad (9)$$

The number of quantiles is denoted by 's', equal to 19. The range of quantiles is denoted as τ , covering values ranging from 0.05 to 0.95 at spans of 0.05. To examine the robustness of the QQ tool, we may analyze the calculated parameters from QR with the mean QQ values calculated at τ .

5. Outcomes and discussion

In the ongoing section, the preliminary and main results of the

research are provided.

5.1. Preliminary outcomes

A descriptive statistical examination regarding GB and EIN is presented in Table 2. The rising trend of EIN across the chosen economies specifies a significant transition towards EIN (see Table 3).

The average price of the S&P GB index in the USA is the highest at 123.95, ranging between 90.54 and 157.25. China comes in second place, followed by Germany, Sweden, and France, with average GB values of 123.50, 122.45, 121.42, and 118.70, respectively. On the other hand, if we consider EIN, China ranks first with an average monthly count of 1581.45 energy-related patent applications, ranging between 351 and 3177. Japan takes second spot, followed by the USA and the UK. The findings derived by the JB test disclose that the distribution of both EIN and GB is not normal in most nations, excluding Spain, where EIN adheres to a normal distribution. This alteration from normality stresses the significance of applying the QQ methodology, which is suitable for considering non-normally distributed data (Sharif et al., 2020). In most nations, the test of ADF displays that the variables become stationary when converted into their first differences. Consequently, we follow the approach offered by Sharif et al. (2020) and Razaq et al. (2021) and use stationary data by altering them at their first differences.

All nations, except Spain, exhibit a significant positive correlation between GB and EIN. The USA holds the uppermost correlation coefficient of 0.84, accompanied by Sweden (0.82), Netherlands (0.80), and Germany (0.78).

5.2. Main results

Table 4 exhibits the findings derived by the QC test, where τ designates the τ^{th} quantile of EIN. The balance of the variables is illustrated by employing the α and γ (supremum norm coefficients) originated from equation (3).

In each economy, the outcomes attained by the QC test indicate that the long-run correlation between GB and EIN changes during various quantiles. The coefficients display supremum norm values beyond their critical bounds (C1, C5, and C10), representing a strong correlation between GB and EIN in selected nations.

Fig. 1 illustrates the estimated slopes of $\alpha_1(\theta, \tau)$ that describe the effect of the θ^{th} GB quantile on the τ^{th} EIN quantile in several economies

Table 2

Descriptive statistics of GB and EIN.

Country	Mean	Max.	Min.	Std. Dev.	J-B Stats	ADF Level	ADFΔ
Panel A: Green Bonds (GB)							
USA	123.95	157.25	90.54	17.18	262.52*	−0.94	−6.76*
China	123.50	149.45	94.06	11.19	54.27*	−1.48	−4.61*
France	118.70	148.40	92.75	15.97	326.28*	−1.34	−5.80*
Germany	122.45	141.27	92.64	11.44	407.11*	−1.44	−4.31*
Netherlands	112.90	141.10	95.40	11.40	250.30*	−1.70	−5.81*
Sweden	121.42	133.42	91.71	7.77	200.90*	−1.52	−5.63*
Spain	110.62	133.24	88.03	11.40	243.85*	−1.68	−5.02*
Japan	92.53	113.95	75.56	10.03	237.83*	−1.97	−5.79*
Canada	89.70	108.10	81.72	4.68	324.40*	−2.14	−4.53**
UK	95.80	104.56	76.87	3.22	396.72*	−1.68	−4.81**
Panel B: Energy Innovation (EIN)							
USA	456.67	597	350	81	2.83*	−1.66	−5.60*
China	1581.45	3177	351	970	4.80*	−4.32*	−6.70*
France	132.10	174	98	24.43	4.65*	−1.68	−4.40*
Germany	211.50	243	148	30.76	6.70*	−1.53	−5.71*
Netherlands	57.65	72	45	9.87	2.43*	−5.73*	−5.20*
Sweden	22.67	27	17	3.26	12.52*	−1.82	−4.15*
Spain	13.61	16	9	2.24	1.49	−1.85	−3.70**
Japan	475.34	615	352	88.74	5.39*	−1.07	−5.73*
Canada	162.50	228	103	40.75	10.14*	−1.65	−5.75*
UK	276.82	354	208	51.35	4.49*	−1.80	−5.15*

Note: * and ** show the significance rank at 1% and 5%, correspondingly.

Table 3

Analysis of correlation between GB and EIN.

Economies	Correlation	t-Stats	p-value
USA	0.84	10.64*	0.00
China	0.70	7.66*	0.00
France	0.75	9.37*	0.00
Germany	0.78	5.12*	0.00
Netherlands	0.80	5.90*	0.00
Sweden	0.82	6.35*	0.00
Spain	−0.69	−7.93*	0.00
Japan	0.67	9.33*	0.00
Canada	0.75	5.38*	0.00
UK	0.76	5.12*	0.00

Note: ** shows the significance level at 1%.

Table 4

Outcomes of QC test (GB and EIN).

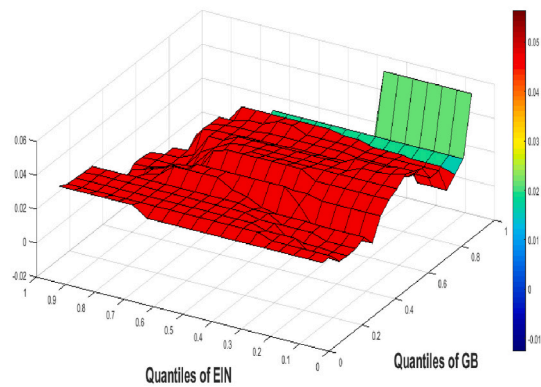
Economy	Coefficients	Sup. V _n (τ)	C1	C5	C10
USA	A	1838.70	1547.79	1046.78	994.89
GB vs. EIN	Γ	962.77	688.61	497.73	346.80
China	α	68581.33	58366.33	57303.24	54880.74
GB vs. EIN	γ	2462.64	1483.21	1446.48	1432.10
France	α	6248.66	5685.95	4686.54	3782.79
GB vs. EIN	γ	3282.90	2695.70	2182.77	1847.48
Germany	α	8326.23	5285.28	3136.06	2524.38
GB vs. EIN	γ	178.66	113.46	56.80	36.36
Netherlands	α	538.43	325.36	292.74	237.58
GB vs. EIN	γ	289.98	197.91	129.73	98.38
Sweden	α	3940.93	3770.27	249.50	205.95
GB vs. EIN	γ	167.72	157.81	49.08	45.78
Spain	α	8754.53	6712.11	4771.12	1476.80
GB vs. EIN	γ	398.17	204.61	103.09	99.11
Japan	α	7114.36	3492.10	3082.11	2225.39
GB vs. EIN	γ	609.45	303.88	213.20	118.13
Canada	α	1245.71	935.79	550.08	208.70
GB vs. EIN	γ	787.82	587.96	497.93	375.70
UK	α	7117.36	3496.14	3086.19	2229.30
GB vs. EIN	γ	606.41	301.86	217.15	118.12

Note: An evenly spaced sequence of 19 percentiles (extending from 0.05 to 0.95) is utilized to compute the t-statistic. The variables' coefficients (α and γ) are exhibited together with their maximal norms and critical values at the 1% (C1), 5% (C5), and 10% (C10) levels of significance.

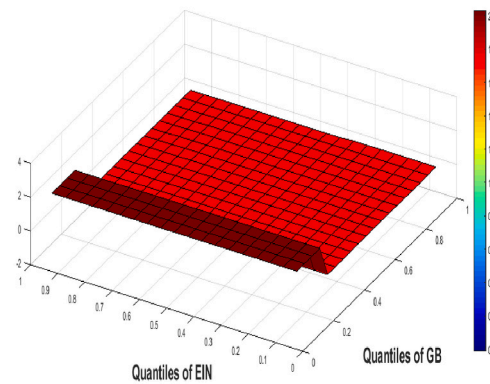
Quantile-on-Quantile (QQ) estimates of the slope coefficient $\alpha_1(\theta, \tau)$

Asymmetric Impact of GB on EIN

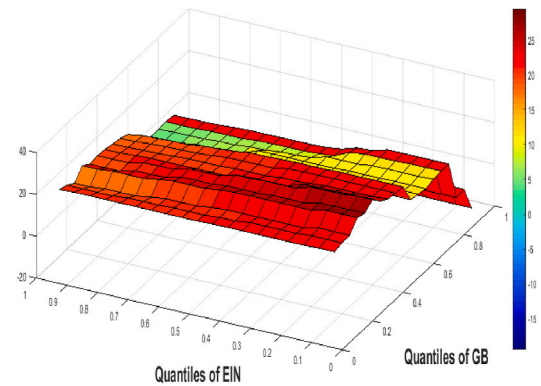
i). USA



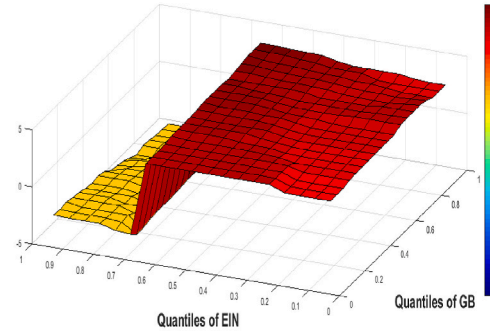
ii). China



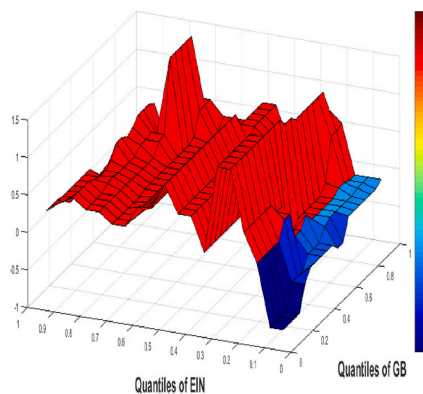
iii). France



iv). Germany



v). Netherlands



vi). Sweden

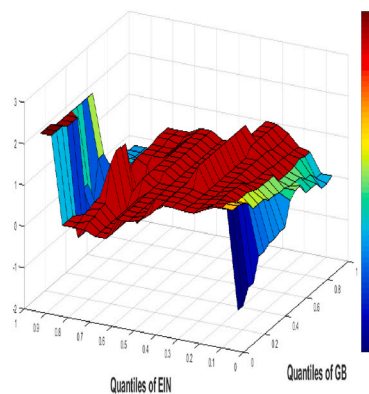


Fig. 1. Quantile-on-Quantile (QQ) estimates of the slope coefficient $\alpha_1(\theta, \tau)$, Note: The graph plots the slope coefficients $\alpha_1(\theta, \tau)$ along the z-axis, with GB quantiles alongside the x-axis and quantiles of EIN on the y-axis. The color bar on the right-hand side represents the slope coefficients, ranging from red (high) to blue (low). A deep blue color specifies a powerful negative affiliation between GB and EIN, while a deep red color designates a positive powerful affiliation. In the same way, a light blue color represents a fragile inverse affiliation, and a light red hue represents a positive fragile affiliation between GB and EIN. This visualization enables the identification of the strength and direction of the relationship between GB and EIN in several scenarios.

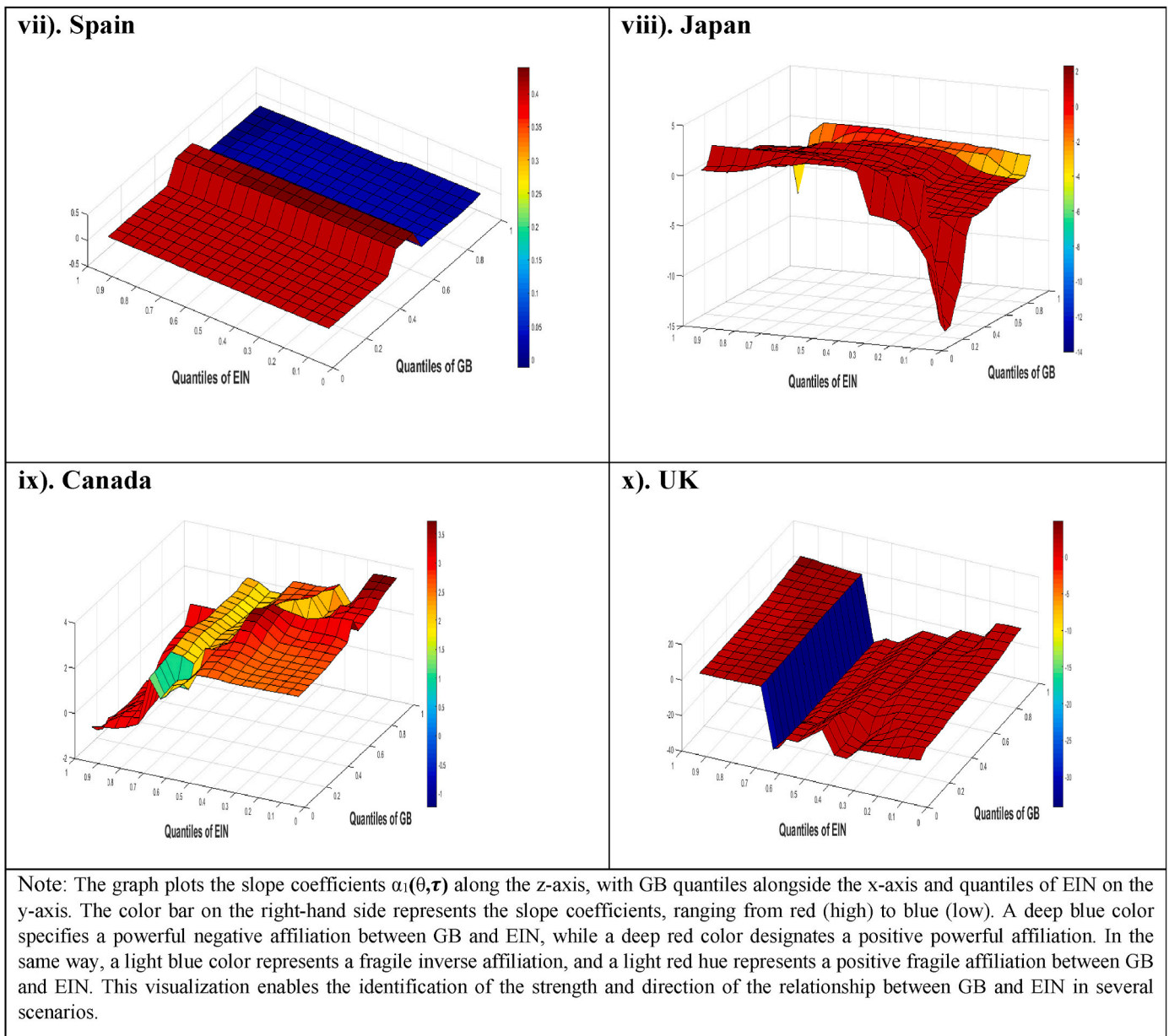


Fig. 1. (continued).

with diverse values of θ and τ . In the **USA** and **Japan**, a strong positive interconnection between GB and EIN persists through the districts that affiliation lowermost to moderately higher quantiles of GB (0.05–0.80) with entire EIN quantiles in both countries. This exclusively strong and positive correlation between GB and EIN exhibits that GB increases EIN at lowermost to higher-middle grades of GB in both the USA and Japan. Furthermore, a weak and positive alliance is also revealed among the domains, which connects higher GB quantiles with whole EIN quantiles in both countries. The positive and powerful influence of GB over EIN is shown in **China**. A positive and powerful bond between GB and EIN prevails between the zones that link mid-low to topmost quantiles of GB (0.20–0.95) with complete quantiles of EIN. This predominantly positive strong bond between GB and EIN proposed that GB raises EIN at the low-mid to upper ranks of GB. In addition, the strongest and positive bond between GB and EIN prevails throughout the parts that blend bottom quantiles of GB (0.05–0.15) with entire quantiles of EIN. The overall positive amalgamation between GB and EIN in our findings is consistent with the studies of [Gilbert and Zhou \(2017\)](#), [Hu et al. \(2021\)](#), and [Ye and](#)

[Rasoulinezhad \(2023\)](#).

In **France**, the positive and powerful nexus between GB and EIN is illustrious. A strong positive kinship between GB and EIN is identified across the parts that attach low to mid and upper-mid to higher GB quantiles by entire EIN quantiles. This powerful positive bond between GB and EIN suggested that GB increases EIN at lowermost to median and middle-higher to highest ranks of GB. Furthermore, a positive and weak relation between GB and EIN is presented among the parts that blend upper-mid GB quantiles (0.55–0.70) with all EIN quantiles. In **Germany**, a strong positive affiliation between GB and EIN is detected throughout the vicinities that amalgamate entire quantiles of GB with bottom to middle-higher quantiles of EIN (0.05–0.75). This specifically strong positive kinship between EIN and GB shows that GB increases EIN at lowermost to high-mid grades of EIN. Likewise, a positive but weak/insignificant GB-EIN bond is also observed throughout the districts that combine entire quantiles of GB and upper-middle to utmost quantiles of EIN (0.80–0.95). The obtained outcomes are maintained by the study of [Anh Tu and Rasoulinezhad \(2022\)](#), who observe that GB improves ENE

in OECD economies.

In the **Netherlands**, a strong positive amalgamation between GB and EIN is observed throughout the segments that associate entire quantiles of GB with moderately lowermost to higher quantiles of EIN (0.30–0.95). This precisely positive and vigorous interdependence between GB and EIN indicates that GB uplifts EIN at the low-mid to upper ranks of EIN in the Netherlands. Additionally, an inverse and strong linkage between GB and EIN is detected through the parts that meld whole quantiles of GB with low EIN quantiles (0.05–0.25). This exclusively inverse powerful bond between GB and EIN referred to the fact that GB decreases EIN at low levels of EIN. In **Sweden**, a strong and positive tie between GB and EIN is beheld throughout the domain territories that blend all GB quantiles with lower-mid to moderate-high quantiles of EIN (0.30–0.75). This exclusively strong and positive amalgamation between GB and EIN states that GB boosts EIN at lower-mid to higher-middle grades of EIN. Further, an inverse powerful alliance between GB and EIN is built throughout the sections that join whole GB quantiles with lower and higher EIN quantiles (0.05–0.25 & 0.80–0.95). This particularly negative and powerful union between GB and EIN shows that GB decreases EIN at low to low and upper ranks of EIN. The findings are supported by [Anh Tu and Rasoulinezhad \(2022\)](#), who find that GB improves ENE in OECD economies.

In **Canada**, a powerful and positive union between the quantiles of GB and EIN prevails through the sections that tie entire GB quantiles along with low to mid-high and top EIN quantiles (0.05–0.60 & 0.80–0.95). This especially powerful positive link between GB and EIN indicated that GB increases EIN at low to high-mid and uppermost grades of EIN. In addition, a feeble and positive alliance between GB and EIN is demonstrated across the locations that attach whole quantiles of GB with mid-high EIN quantiles (0.65–0.75). A strong positive association between GB and EIN is presented across the territories that blend complete quantiles of GB with low to middle-higher and high quantiles of EIN (0.05–0.60 & 0.80–0.95) in the **UK**. This exclusively powerful and positive kinship between GB and EIN declares that GB upgrades EIN at low to high-mid and foremost grades of EIN. Moreover, a negative and powerful alliance between GB and EIN is identified between the domains that interconnect entire GB quantiles along with moderately high EIN quantiles (0.65–0.75). This explicitly negative powerful relationship between GB and EIN shows that GB decreases EIN at high-mid levels of EIN. The overall positive bond between GB and EIN in Canada and the UK is maintained by the exploration of [Wu et al. \(2022\)](#), who detected that GF upgraded ENE in developed economies.

In **Spain**, GB and EIN hold a mixed connection. A strong and positive affiliation between GB and EIN is discovered throughout the chunks that merge bottom to mid-GB quantiles (0.05–0.50) with overall EIN quantiles. This specifically positive and powerful union between GB and EIN indicates that GB increases EIN at the low to median grades of GB. Moreover, a strong inverse interconnection between GB and EIN is illustrated across the localities that integrate medium-high to topmost quantiles of GB (0.55–0.95) with full EIN quantiles. This explicitly negative and powerful connection between GB and EIN recommended that GB decreases EIN at the mid-high to upper ranks of GB. The outcome is corroborated by the research of [Li and Li \(2021\)](#), who indicate that GB financing initially has a negative impact on sustainable energy transition before eventually becoming a positive factor. The finding is also accredited by [Pan et al. \(2018\)](#), who witnessed a diversified linkage between GF and EIN.

Table 5 showcases a summary regarding connections between numerous quantiles of GB and EIN in our economies, as demonstrated in [Fig. 1](#). The results indicate a substantial positive bond between GB and EIN in most economies, specifying that GB boosts EIN. Moreover, Spain illustrates a mixed interconnection between GB and EIN.

5.3. Verification regarding robustness of the QQ tool

A comparison has been performed between QQ and QR evaluations

Table 5

Summary of Outcomes (Connection b/w Several Quantiles of GB and EIN).

Economies	Quantiles of GB	Quantiles of EIN	Relation b/w quantiles	Dominant Connection
USA	Low to upper-mid quantiles	Whole quantiles	Powerful and positive	Strong and positive
	Higher quantiles	Whole quantiles	Weak and positive	
China	Lower-middle to higher quantiles	Whole quantiles	Powerful and positive	Powerful and positive
	Bottom quantiles	Whole quantiles	Strongest and positive	
France	Low to mid and upper-mid to high quantiles	All quantiles	Strong and positive	Strong and positive
	Upper-mid quantiles	Whole quantiles	Weak and positive	
Germany	All quantiles	Lower to upper-middle quantiles	Strong and positive	Powerful and positive
	Whole quantiles	Upper-middle to top quantiles	Weak and positive	
Netherlands	Overall quantiles	Low-mid to higher quantiles	Strong and positive	Powerful and positive
	All quantiles	Lower quantiles	Powerful and inverse	
Sweden	Overall quantiles	Low-mid to upper-middle quantiles	Strong and positive	Strong and positive
	Overall quantiles	Low and high quantiles	Powerful and inverse	
Spain	Lower to mid quantiles	Overall quantiles	Strong and positive	Mixed relationship
	Upper-middle to higher quantiles	Whole quantiles	Powerful and inverse	
Japan	Low to upper-mid quantiles	Whole quantiles	Strong and positive	Powerful and positive
	Higher quantiles	Whole quantiles	Weak and positive	
Canada	Whole quantiles	Low to medium-high and top quantiles	Strong and positive	Powerful and positive
	Whole quantiles	Upper-mid quantiles	Weak and positive	
UK	Whole quantiles	Low to upper-mid and highest quantiles	Powerful and positive	Strong and positive
	Overall quantiles	Upper-mid quantiles	Strong and inverse	

to assess if they are similar. [Fig. 2](#) supports the former QQ outcomes and the mean QQ resemblance of the slope coefficients of our selected nations, which illustrate parallel estimates to the QR regression. This demonstrates that both QQ and QR calculations calculate the exact estimations and generate comparable outcomes.

[Fig. 2](#) depicts the positive relationship between GB and EIN for our selected economies, except for Spain. There is a mixed relationship between GB and EIN in Spain. Furthermore, our data show that the relationship between GB and EIN differs among economies. The extent of the coefficients elucidates why GB significantly influences EIN in France, Netherlands, Sweden, Japan, Canada, and the UK while having a relatively weaker effect in Spain and Germany.

5.4. Discussion of outcomes

The data reveal a positive alliance between GB and EIN in almost all selected nations. GB has been recognized as a factor that boosts EIN in nine out of ten selected countries, which is corroborated by earlier

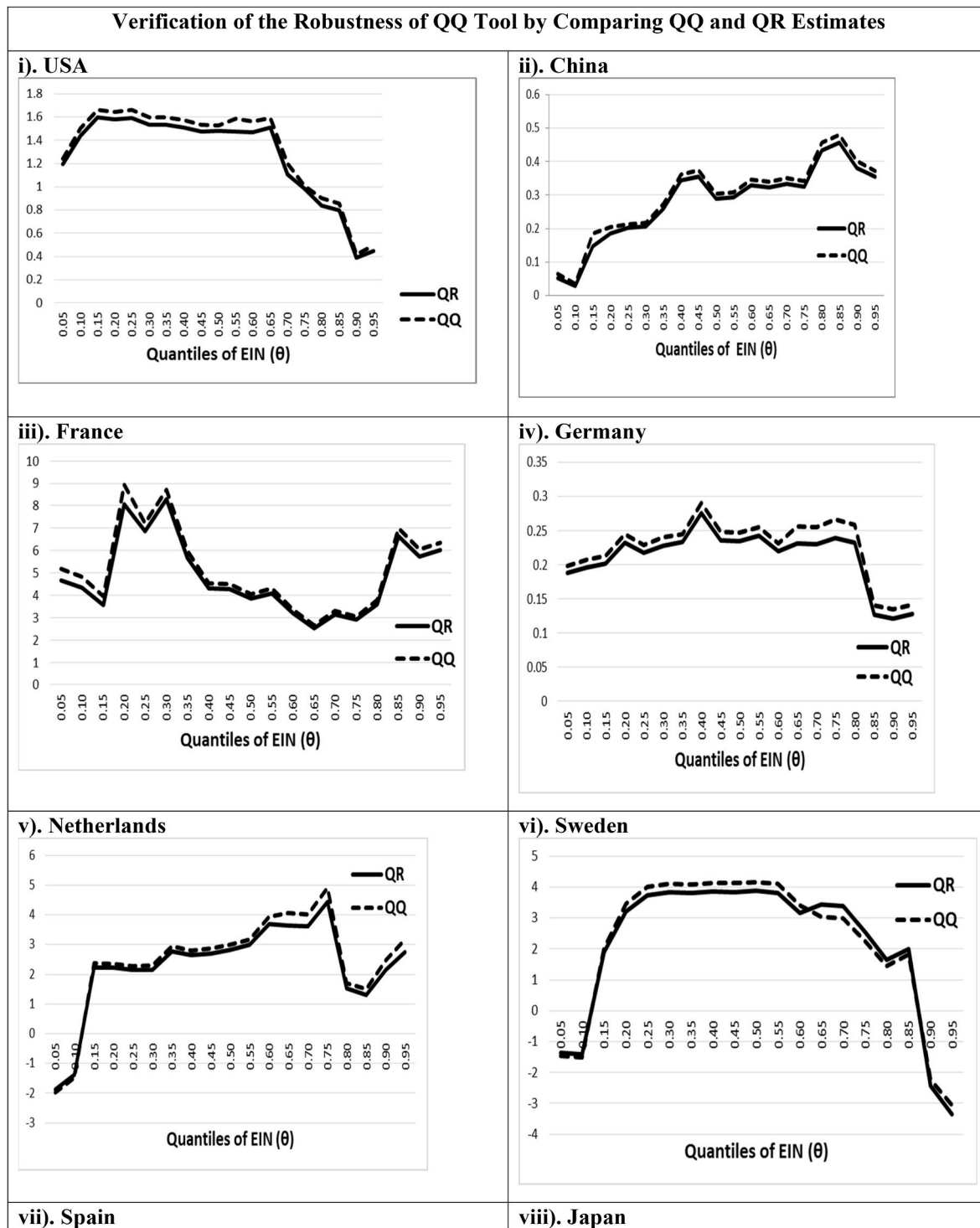


Fig. 2. Verification of the Robustness of QQ Tool by Comparing QQ and QR Estimates, Note: The estimations of usual QR parameters and the averaged-QQ parameters are given against different EIN quantiles.

research findings, like [Azhgaliyeva et al. \(2020\)](#), [Anh Tu and Rasoulinezhad \(2022\)](#), [Ye and Rasoulinezhad \(2023\)](#), which claim that GB boosts EIN. Our discovery of a positive relationship between GB and EIN agrees with the findings of [Irfan et al. \(2022\)](#) for China, [Anh Tu and Rasoulinezhad \(2022\)](#) for OECD economies, [Ye and Rasoulinezhad \(2023\)](#) for Asia-Pacific, [Azhgaliyeva et al. \(2020\)](#) for South-East Asia, [Wu et al. \(2022\)](#) for developed economies, and Hanif, Aziz, & Chaudhry (2019) for developing countries, all of which show that GB promotes

green innovations. Additionally, our findings differ from earlier investigations. Previous research investigated certain properties of GB (inverse, neutral, or positive) during the distribution of data. The current research, in contrast, argues that various inferences (inverse or positive) should be formed from various quantiles throughout the total distribution of data. Furthermore, the findings can help governments and policymakers in individual countries develop policies at numerous ranks of GB and EIN.

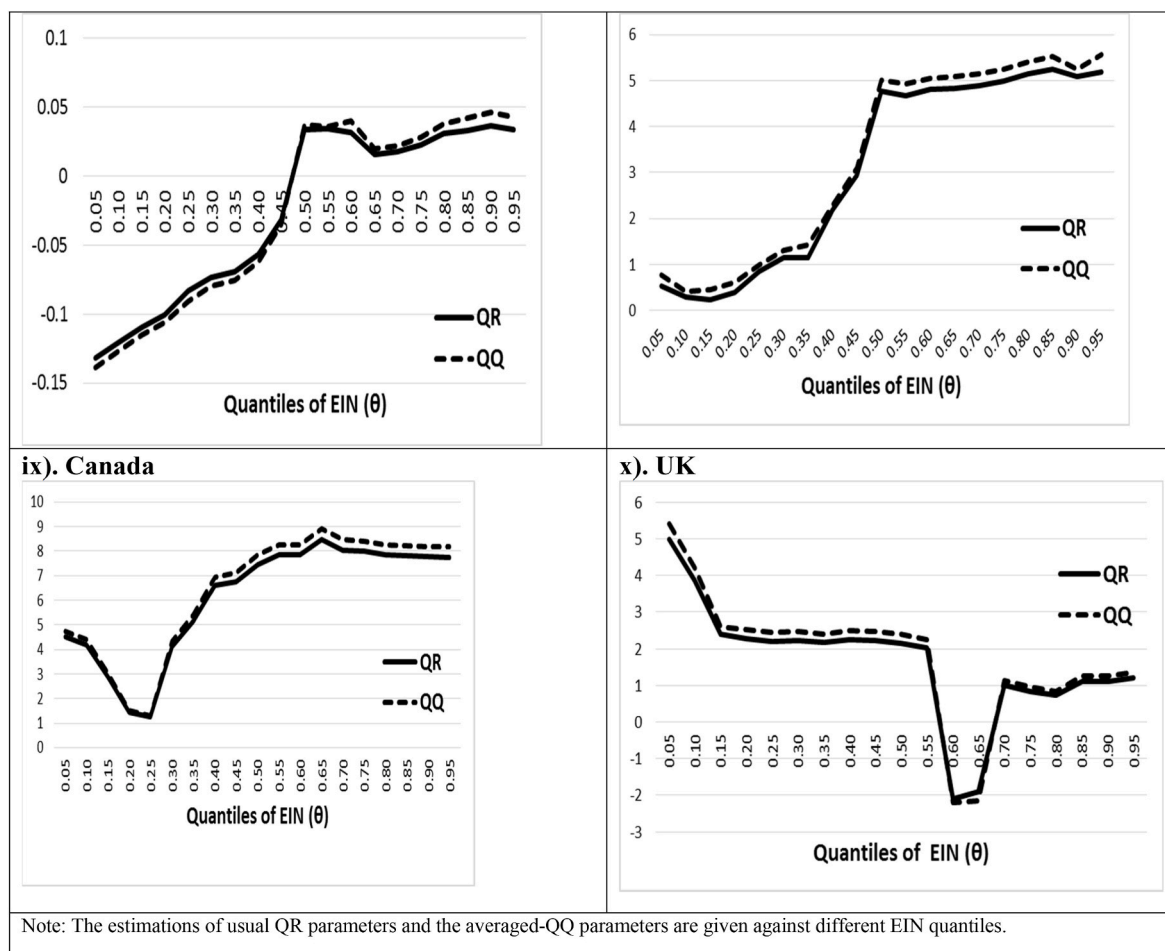


Fig. 2. (continued).

The finding of Spain supports this idea, suggesting that GB is detrimental to EIN up to a certain point before becoming beneficial. Overall, the finding of Spain provides empirical evidence to support the idea that GB could have both positive and negative influence over EIN. While GB can provide much-needed funding for environmentally friendly projects, an over-reliance on them may lead to a reduction in private investment in emerging technologies. However, once a certain level of GB funding is reached, the positive effects of increased investment in EIN outweigh the negative effects of reduced private investment. The outcome is corroborated by the work of [Li and Li \(2021\)](#), who indicate that GB financing initially has a negative impact on sustainable energy transition before eventually becoming a positive factor. The finding is maintained by the work of [Pan et al. \(2018\)](#), who witnessed a diverse link between GF and EIN. The finding of Spain also shows that the influence of GB does not continuously affect to boost EIN due to variations in length, time, and place. For instance, the impact of GB on EIN might diverge based on the length of time that the bonds are held. For instance, if a GB is issued for a short period, the impact on EIN may be limited as the funds raised may only be used for short-term projects that do not lead to significant innovation. Additionally, the GB-EIN nexus can vary based on the time and place in which they are issued. For example, if GB is issued at a time when there is already a strong emphasis on environmental sustainability, its impact on EIN may be limited because the financial market is already turning towards more sustainable practices. Similarly, if GB is issued in an area with extensive usage of REN, the impact on EIN may be reduced.

Spain's perplexing GB-EIN nexus can also be ascribed to various components, for example, energy consumption, technological innovation, business cycles, macroeconomic instability, and investment

strategies. On the one hand, the GB may give a significant source of funding for REN projects and other investments in sustainable infrastructure. This increasing investment has the potential to drive innovation and development in the energy industry as businesses and organizations attempt to capitalize on the growing demand for environmentally friendly or green products and services. However, several issues may restrict the favorable influence of GB on EIN. The socioeconomic and geographical aspects of the locations where GB investments are concentrated are essential considerations. Countries with limited resources may need help attracting significant investment in REN or sustainable infrastructure in certain situations. Companies and organizations may be unwilling to engage in initiatives with smaller potential returns, limiting the potential for innovation in these sectors. For example, business cycles and investment plans might influence the availability of funds for REN projects. Macroeconomic instability, such as changes in energy costs, can also have an influence on the attractiveness of green investments and the amount of innovation in the energy industry. Furthermore, energy consumption trends and technological innovation can both have a role in altering the relationship between GB and EIN. For example, if energy consumption patterns shift towards more sustainable sources, such as wind and solar energy, there may be an increased need for new infrastructure and technologies to support these shifts. However, if existing technologies are already highly efficient and effective, there may be limited incentives for further innovation in this area. In Spain, GB decreases EIN at high-mid to higher levels of GB. The inverse relationship between GB and EIN in these regions is corroborated by previous works of [Liu et al. \(2017\)](#) and [Andersen \(2017\)](#).

The impact of GB varies widely across countries and income groups

due to different reasons. There is a powerful correlation between GB and EIN in high quantiles of EIN in the Netherlands, Japan, Canada, the UK, and the USA. This suggests that when EIN ranks are too high, it tends to substantially boost EIN. The fact that the correlation is strongest in these countries at high levels of EIN suggests that these bonds are particularly effective at supporting innovation in contexts where there is already a strong foundation of sustainable practices and policies. In these countries, GB can help accelerate progress towards more ambitious environmental targets and drive innovation in areas like ENE, REN, and sustainable transportation. As mentioned before, the disparities in the influence of GB between numerous nations might be ascribed to a variety of economic aspects. The varying slope coefficients of GB and EIN across economies indicate that macroeconomic disturbances, particularly the economic/financial cycle (expansion or contraction), influence EIN through financial operations. During economic expansions, there is typically more investor demand for GB, as investors have more money to invest in such projects. As a result, the impact of GB on innovation in energy-efficient technology may be greater during these periods. On the other hand, during economic contractions, investors may be more risk-averse, and demand for GB may decrease. This could lead to a reduction in the impact of GB on EIN during these periods. Another factor that could influence the impact of GB on innovation in energy-efficient technology is the regulatory environment. In some countries, governments may incentivize companies to invest in green projects, such as tax breaks or subsidies. This could lead to greater investor demand for GB and, in turn, a greater impact on innovation in energy-efficient technology. Moreover, our chosen countries face specific issues that panel data methods could not tackle. Therefore, we extensively analyzed every economy to understand its distinctive characteristics.

6. Conclusion and policy recommendations

Green bonds are debt securities issued to fund environmentally sustainable projects, whereas EIN encompasses the advancement and implementation of novel technologies aimed at reducing carbon emissions and enhancing energy efficiency. This study has explored the asymmetric connection between GB and EIN in the top ten countries that issue GB. The QQ findings suggest that there exists a positive association between GB and EIN in the most of chosen nations at particular points in the distribution of data.

Our research findings can provide recommendations for policymakers to maximize the impact of GB on EIN for addressing climate change and promoting sustainable economic development. To stimulate accountability and transparency in the issuance of GB, policymakers should establish clear regulatory standards that define what constitutes a GB. These standards should be based on internationally recognized definitions, such as those settled by the International Capital Market Association (ICMA) and the Climate Bonds Initiative (CBI). Mandatory regulations should necessitate that those who issue GBs disclose details on the utilization of funds and the ecological impact of the companies supported by them. Such data must be verified independently to ensure its reliability and precision. Policymakers ought to devise encouragements for both issuers and investors to augment GB investment and issuance. Tax exemptions, reduced regulatory obligations, and superior accessibility to funding sources may be included in incentives for issuers. Incentives for investors may include reduced transaction expenses, tax exemptions, and favored treatment in pension fund investments. GB funds should be established by governments or guarantees provided to support GB issuance, thereby enlarging the availability of finance for sustainable projects and diminishing the risk for investors.

To increase public understanding of green technologies, policymakers should organize educational programs and involve stakeholders. These programs should emphasize the benefits of green technologies for the economy and the environment and provide information on investing in them. Policymakers can work with financial institutions to develop green investment products and provide financing for R&D. This can be

achieved through public funding of research institutions or tax incentives for private investment in R&D. Furthermore, policymakers should finance demonstration programs to test new technologies in real-world settings. They should establish clear regulations that encourage the adoption of green technologies. This might include emission reductions, ENE measures, and REN deployment. Regulatory guidelines should also help emerging technologies integrate into current energy systems. This might include energy storage, grid management, and smart metering standards. To maximize the impact of GB and EIN, the governments of our selected countries should foster collaboration and knowledge sharing between stakeholders. This could include public-private partnerships that bring together government, industry, and academic institutions to work on common goals. Policymakers could also establish platforms for knowledge sharing and best practices exchange, such as industry associations or international networks. This would facilitate the spread of information and expertise and encourage innovation. Educating investors, consumers, and the public about the benefits of GB and REN can help increase demand for these investments and speed up the move to a low-carbon economy. This can contain awareness campaigns and educational programs aimed at schools, universities, and the general public.

In conclusion, the present research has notable shortcomings that provide new opportunities for further exploration in this field. Our main focus is on the relationship between GB and EIN, without considering subcategories of EIN such as wind EIN, solar EIN, and biomass EIN, among others. For future research, these measures could be used to investigate how outcomes change with different energy resources. Another substantial shortcoming of the present research is the usage of the bivariate QQ method, which does not take into account other control variables that affect the GB-EIN nexus. Therefore, in the future, we could amplify our empirical model by implementing inconsistent instruments (for example, Quantile ARDL) that incorporate additional control variables to understand the association fully.

Availability of data

Upon a reasonable request, the author corresponding to this work will furnish the datasets employed in the present study.

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Declaration of competing interest

There are no material financial or non-financial interests to disclose for the authors.

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