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Research article

Breaking barriers to climate finance: Asymmetric nexus between green investment and energy innovation in Europe

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ABSTRACT

Growing concerns regarding climate change and the necessity to shift towards a low-carbon economy have resulted in a significant rise in the worth of green finance for developing energy technology. This growing emphasis on green finance underscores the urgency for a nuanced exploration of the asymmetric nexus between green investment and energy innovation in Europe. The present article investigates the asymmetric relationship between green investment and energy innovation in the top ten European nations with the highest green investment (France, Netherlands, Germany, Italy, Spain, Denmark, Austria, Finland, the UK, and Sweden). Formerly, panel data methodologies were employed to observe the link between green investment and energy innovation despite the absence of an exclusive connection in certain economies. On the other hand, this study uses 'Quantile-on-Quantile' approach for econometric estimation using the annual data from 2007 to 2022. This unique methodology enables a detailed and specific analysis of time-series interdependence in every economy, providing valuable perceptions of the nuanced relationship between these variables. Investment in renewable energy is employed as a proxy for green investment, while energy-related patents represent energy innovation. The study employs a quantile cointegration test to assess the variables long-run relationship. The results indicate a positive correlation between green investment and energy innovation in many countries at certain data points. Additionally, the analysis demonstrates that the extent of asymmetry between these variables varies across countries, stressing policymakers' need to closely monitor fluctuations in green investment and energy innovation.

1. Introduction

Green Investment (GIN) funds eco-friendly projects like renewables, aiming for environmental and financial returns. Energy Innovation (ENI) focuses on advancing technologies in renewable energy (RE) and efficiency [1]. The interaction between GIN and ENI lies in financing sustainable initiatives and driving technological progress for a cleaner and more resilient energy future. The nexus between GIN and ENI is pivotal to the global pursuit of sustainable and low-carbon economies [2,3]. GIN involves allocating financial resources to environmentally friendly projects, such as RE, energy efficiency (ENE), and sustainable technologies. These investments

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are crucial in advancing the energy sector's transition towards cleaner alternatives and addressing climate change challenges [4]. The connection between GIN and ENI lies in the interdependence of financial support and technological advancements to drive the transformation of the energy landscape [5].

GIN acts as a catalyst for ENI, fostering research, advancement, and deployment of novel technicalities to enhance the efficiency and sustainability of the energy sector. Investments in RE projects, such as solar, wind, and hydropower, stimulate innovation by providing the necessary capital for experimentation and scaling up technologies [6]. Conversely, ENI contributes to the attractiveness of GIN by continually introducing more cost-effective and efficient solutions. This interdependent relationship creates a positive feedback loop, with innovations reducing the costs of sustainable technologies, making them more financially viable and appealing for further investments [7,8]. The nexus is particularly relevant in global efforts to mitigate climate change and accomplish carbon neutrality goals. Governments, businesses, and investors recognize the need for substantial GIN and continuous innovation to transition from fossil fuel-dependent energy systems to cleaner and more sustainable alternatives [2,9]. Policies and incentives encouraging GIN often drive private-sector involvement in ENI, creating a reinforcing loop that accelerates progress toward a greener and more technologically advanced future [10]. One significant challenge in this nexus is the need for a coordinated and integrated approach. The success of GIN and ENI depends on aligning policies, fostering collaboration between public and private sectors, and addressing barriers to entry [11]. Governments contribute to generating a permitting environment with supportive policies, incentives, and regulatory frameworks promoting GIN and ENI. International cooperation further amplifies the impact, allowing for collectively sharing best practices, knowledge, and resources to address global challenges [12].

Analyzing the interaction between GIN and ENI is essential, even though diverse and capricious patterns are noticed in several nations. Furthermore, the inherent uncertainty about how GIN influences ENI brings a layer of intricacy to this investigation [13]. Previous empirical studies have delivered insufficient understandings within the intricacies of this association. Hence, the primary target of our research is to explore these complexities comprehensively. While prior research has acknowledged the connection between funding allocation for GIN and ENI, none have explicitly delved into the nonlinear association between these factors within the highest GIN countries. Foregoing research has predominantly utilized panel data to examine GIN and ENI relationship [1,3–6,9–14]. However, these approaches have shown limited effectiveness in addressing the diverse economic conditions within the region. Recognizing these shortcomings, our paper selects the Quantile-on-Quantile (QQ) approach, granting a broad investigation personalized to the unique peculiarities of each country. Incorporating the QQ method refines our apprehension of the GIN-ENI nexus, offering unique benefits by assessing each nation's time-dependent link [15]. Typical econometric approaches, containing, standard Quantile Regression (QR) and Ordinary Least Squares (OLS), face issues due to the problematic nature of the GIN-ENI connection [16].

Departing from conventional methodologies, which appraise the whole dataset by classifying values as neutral, negative, or positive, this research originates an advanced technique to probe impacts across a broad spectrum of quantiles, encompassing favorable and unfavorable aspects. The association between GIN and ENI can yield varied results shaped by economic circumstances encompassing periods of expansion and economic downturns. In addition, the effect of higher GIN levels on ENI is imagined to differ from what is observed at lower levels [17]. The expected outcomes regarding the influence of GIN on ENI are poised to uncover notable variations, particularly in the magnitude of GIN's impact. This underscores a dynamic and intricate relationship that becomes more pronounced as GIN levels increase. Current hypothesis posits that the non-linear distribution of properties will result in fluctuations in the correlation between GIN and ENI, resulting in nonlinear shifts in economic components. Our comprehensive approach involves studying diverse economies to explore how the connections between variables evolve among multiple nations. This approach offers invaluable foresight, which might significantly assist policymakers and governments in chasing numerous strategic initiatives to achieve diverse social, political, and economic goals.

This research primarily focuses on prominent European economies with significant GIN levels (Finland, the UK, France, Spain, Netherlands, Italy, Sweden, Denmark, Austria, and Germany). The choice is motivated by several compelling reasons, the foremost being these economies wield considerable influence over ENI. Their influence is intricately linked to their heavy reliance on typical energy sources, probably restraining the selection of environmentally sustainable energy solutions [1]. As a result, investigating the consequences of GIN in these countries holds great potential for advancing global efforts to lessen greenhouse gas emissions and encourage the adoption of sustainable energy alternatives [3]. Analyzing the impact of GIN in these nations delivers beneficial knowledge into the strategies they employ to consolidate GIN inside their ENI initiatives. Additionally, historical data underscores the quick expansion of technical innovations from one nation to its surrounding states, emphasizing the significance of examining these higher-GIN nations as possible drivers of geographical development [18]. Additionally, a country's energy sector is complicatedly associated with the energy sectors of its surrounding nations, making it sensitive to disturbances arising from external and internal origins. This emphasizes the complex network of interrelated energy systems and the potential for far-reaching consequences [19]. To understand the diverse patterns and relationships within different nations, we implement the QQ tool, enabling a comprehensive analysis of every nation in our investigation. Disregarding these components might lead to biased outcomes and create significant inaccuracies. The relationship between GIN and ENI manifests modifications impacted by economic growth, industrial advancement, and sudden shifts in energy policies [20]. To fully consider these factors, our research examines the selected economies individually. Identifying the significant deviations within these surrounding nations is crucial. Even though their proximity, every nation demonstrates its specific capability to integrate GIN into the planning and implementation of ENI-related initiatives. Considering the differences among these entities, using an econometric technique like QQ is imperative for building empirical models. This methodology is essential for extensively comprehending the relationship between the variables under scrutiny, transcending the restraints of conventional econometric techniques [21]. The results of this research will set a strong framework for upcoming works on the connection between GIN and ENI, along with its possible ramifications for other countries. Although these nations are geographically close, each possesses a distinct capacity to integrate GIN into developing and implementing ENI-related strategies. Given the variations among these nations, employing the QQ methodology to construct empirical regressions is imperative. This methodology is essential for achieving an absolute perception of the connection between the primary variables, excelling the restrictions of conventional econometric approaches [15]. The results of this investigation will provide a solid substructure for forthcoming inquiries throughout the connection between GIN and ENI, along with their possible impacts on another group of economies.

The remainder of this article is as follows: Section 2 manifests an overall review of related literature drawn from previous empirical works. Following that, Section 3 explains the data of research and Section 4 provides a comprehensive explanation of the selected econometric approach. Section 5 thoroughly reveals and evaluates the research outcomes. Finally, Section 6 serves as the study's conclusion, summarizing the core perceptions and proposing potential proposals for future investigations endeavors.

2. Literature review

On-going section explores the interaction between GIN and ENI in the global pursuit of sustainable energy systems. By analyzing existing literature, we delve into the dynamic connection between financial support for environmentally friendly plans and the continuous evolution of energy technologies. The review aims to uncover key trends and challenges in the field, emphasizing the collaborative efforts needed to foster GIN and drive ENI for a greener and technologically advanced future. Some studies revealed a positive connection between these variables. For instance, Wang, Peng, Anser, & Chen [2] examined the effect of RE and green finance (GF) on ENE in E−7 nations from 1985 to 2017, using the NARDL and 2SLS methodologies. The results showed varying degrees of GF development in the E−7 zone: Brazil (0.55), China (0.61), Indonesia (0.49), India (0.53), Russia (0.39) and Mexico (0.37). In 2019, Russia had the most significant Gini coefficient (0.57), pursued by Turkey. Zhang, Song, & Zhang [22] studied companies pursuing sustainable growth through green innovation amid environmental challenges in China using a negative binomial distribution model. The findings showed a substantial positive influence of GIN on businesses' green innovation, with company age and information disclosure heterogeneity affecting this impact. Li, Han, & Wang [23] Utilized a logarithmic mean Divisia index and production theoretical deterioration and found that provinces improved energy efficiency and fossil energy consumption, with limited progress in industrial structure. Furthermore, energy efficiency, economically developed localities prioritized technical components, and scale for enhanced efficiency and production structures.

Similarly, Chi et al. [10] investigated the impact of GIN funds on corporate green innovation in listed firms in China utilizing the difference-in-differences (DID) approach. The results showed that GIN funds significantly improved corporate green innovation, especially in public sector enterprises, those containing a high proportion of long-run GIN funds, and after introducing a green financial system. Moreover, GIFs contributed to enhanced stock returns, reduced stock risk, and positive social valuation through CGI promotion. Yang, Su, & Yao [14] studied the effect of GF on green innovation in 30 Chinese provinces from 2008 to 2019. The fixed impact model results showed a positive influence of GF on green innovation, particularly in the western and central regions compared to the east. Additionally, under strict environmental regulations, GF played a more significant role in fostering green innovation.

In another study, Anh, Tu, & Rasoulinezhad [24] delved into the part of green bonds (GB) in financing ENE across 37 OECD member countries utilizing the persistently updated-fully modified (CUP-FM) technique based on data from 2007 to 2020. The findings indicated positive impacts of both GB and the regulatory quality index on ENE. Likewise, Hu, Wang, & Wang [25] noted that the implementation of the green credit policy had a significant and positive impact on the generation of green patents among severely polluted companies in China, especially those experiencing more significant financial limitations.

Ahmed & Jahanzeb [4] examined how technological innovation, market capitalization, financial development, GDP, and exports influenced Brazil's energy demand and carbon dioxide emissions from 1980 to 2014. The autoregressive distributed lag (ARDL) model outcomes indicated that exports were the primary driver of CO_2 emissions and energy demand. At the same time, market capitalization, financial development, and technological innovation mitigated energy demand and emissions. Causally, exports were linked to increased financial development and innovation, guiding to a subsequent reduction in CO_2 emissions. Xu, Liu, & Shang [9] probed the influence of environmental and social governance (ESG) implementation and research and development (R&D) investment on green innovation. The research used data from 223 Chinese listed companies between 2015 and 2018, measuring ESG presentation with SynTao GF indices. The results indicated a positive link between R&D investment and green innovation performance, while ESG efficiency was linked to a rise in green invention patents. Hammoudeh et al. [6] proposed that applying green bonds (GB) could act as a mechanism to increase the private sector's contribution to the advancement of environmentally friendly projects, ultimately contributing to reducing CO_2 emissions in the USA. Gilbert & Zhou [19] found that adopting green financial products, including green funds and insurance, encouraged civilian investment in clean production sectors and propelled innovations regarding green technology in China. Wang et al. [2] observed that Digital Economy (DE) significantly increased CO_2 emissions at low-to-medium natural resource rent levels but reduced emissions growth beyond that threshold. Moreover, when anticorruption regulation was the threshold variable, the DE exhibited dual thresholds on CO_2 emissions, initially intensifying its impact and diminishing it over time.

Contrarily, few investigations observed detrimental influences of GIN on ENI. For example, Yu et al. [13] detected the impact of financial constraints on the development of green innovations in listed firms in China from 2001 to 2017. The findings revealed that restrictions in financing hindered the firms' capacity to introduce innovations in the realm of green technologies. Similarly, Chen [5] highlighted that the existing financial structure, predominantly governed by banks, must address sustainable development needs. Insufficient green financing options and the absence of interest incentives could pose challenges for companies seeking financial provisions for green innovation ventures. In another study, Liu et al. [26] revealed that performing GF policies might constrain investment opportunities for energy-intensive industries. This constraint could necessitate additional funds for green technology research and development (R&D), consequently requiring businesses to allocate much time to chase green innovation.

A mixed connection between GNI and ENI is revealed in a study by Pan et al. [3], which scrutinized how GF influenced environmental innovation in China, revealing diverse outcomes. Though GF positively affected environmental innovation in specific industries and regions, its impact was constrained in others. Wang, Zhang, & Li [2] probed the effect of trade openness and modification on carbon emissions in OECD and G20 nations from 1997 to 2019. The study found that trade openness increased carbon emissions while trade divergence decreased them, particularly with import modification. The asymmetry of trade openness affected carbon emissions at 10 %–50 % quantile levels, while the effect of trade modification remained consistent.

An exhaustive evaluation of the current literature shows that prior investigation has predominantly emphasized the broad effect of GIN on ENI. Consequently, there needs to be much probe inside the particular quantiles linked to these dual variables. Investigations into these quantiles have unveiled an asymmetric connection between these components. However, disregarding the potential for non-linear effects may result in omitting substantial intricacies, conceivably guiding to a misinterpretation of the findings. Moreover, former studies have preferred panel data estimation over time-series data although the inherent issues correlated with panel data estimation. The challenges encompass aspects such as model selection, the practicality of error estimation, and uncertainties surrounding the significance of findings. In exploring the correlation between GIN and ENI, panel data analysis may restrict the precision of this association, complicating the evaluation of GIN's typical impact on ENI in individual countries. Consequently, employing the QQ method is recommended, as it facilitates distinct analyses for each nation. This strategy enhances our overall apprehension of the linkage between variables.

3. Data and description

The major target of the present work is to find the asymmetric GIN-ENI nexus in the top ten European nations with the highest GIN (Finland, France, Netherlands, Spain, Austria, Denmark, the UK, Germany, Italy, and Sweden). In this study, we define GIN as the independent variable measured by the investment in RE. The election of GIN as the independent variable in our investigation is underpinned by numerous compelling justifications that align with the overarching goals and objectives of the present study. Firstly, GIN is a pivotal focus in view of its grave part in upbringing sustainable and environmentally conscious economic development [27]. As nations across the globe grapple with the challenges posed by climate change, the emphasis on GIN has grown exponentially, making it a salient and timely subject for investigation Chi et al. [10]. By focusing on RE investments, we hone in on a specific dimension of GF that directly contributes to mitigating the inverse impacts of conventional energy sources on the environment. This precise operationalization ensures that our investigation captures the nuances of GIN most relevant to sustainable energy practices and aligns with the broader objectives of reducing carbon footprints and promoting cleaner energy alternatives [4,28]. Furthermore, we selected GIN as the independent variable due to its potential influence on ENI, our designated dependent variable. The nexus between GIN and ENI holds immense theoretical and practical implications, as it elucidates how investments in green initiatives stimulate advancements in energy-related technologies [29].

In technological innovation, energy patents are widely embraced and preferred metric for empirical investigation [26]. In contrast to alternative indicators assessing innovation, a patent offers detailed insights into technology, enjoys legal protection under national regulations, and aids innovators in establishing competitive advantages, as highlighted by Yang et al. [14]. Additionally, a patent as a tangible innovation finding ensures prominent data access. Consequently, we adopt energy patents as a proxy for ENI, following the investigations of Zhang et al. [22]. The option of ENI as the designated dependent variable in our investigation is grounded in a multitude of robust justifications that align seamlessly with the overarching objectives of our study. Firstly, ENI is a paramount focus due to its pivotal role in driving technological advancements within sustainable and environmentally conscious economic development [30]. The global imperative to address the challenges posed by climate change has accentuated the significance of ENI, positioning it as a key element in the transition towards cleaner and more sustainable energy solutions [1]. This centrality makes ENI an inherently compelling and timely subject for in-depth investigation, representing the cutting-edge progress in the energy sector.

The annual data for GIN is taken from the International Renewable Energy Agency website (https://www.irena.org/data), while the annual data for ENI is procured from OECD Statistics.[1] The data is taken from the years 2007–2022. To enhance clarity and assist in our analysis, please refer to Table 1, which bestows an overall guide to symbols and acronyms used in this research.

4. Econometric approach

The major intent of the present section is to analyze the technique implemented in evaluating the GIN-ENI correlation. To complete this target, we employ a cointegration test that integrates quantiles to appraise the enduring variables connections. Moreover, as an essential element of our econometric evaluation, we consolidate the QQ method to comprehend the relation between GIN and ENI thoroughly.

4.1. Quantile cointegration (QC) test

In current research, we employ the Quantile-on-Quantile Cointegration (QC) test, initially submitted by Xiao [31]. This test is utilized to overcome the hindrances of old cointegration tests dependent on fixed cointegration vectors. Incorporating the QC methodology strengthens our capability to apprehend long-run associations across variables. Unlike conventional techniques, QC

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

Table 1
The taxonomy of acronyms/symbols.

Symbol/Acronyms	Narration	Symbol/Acronym	Narration
ENI	Energy innovation	ρ_φ	quantile loss function
GIN	Green investment	μ_t^θ	Quantile error term
QQ	Quantile-on-Quantile Estimation	J-B	Jarque-Bera
QR	Quantile regression	h	Bandwidth parameter
RE	Renewable energy	ADF	Augmented Dickey-Fuller
GF	Green finance	τ	τ^{th} quantile of energy innovation
ENE	Energy efficiency	$Sup_\tau \lvert V_n(\tau)\rvert$	Value of supremum norms (α and γ)

permits us to examine potential variations in cointegration between variables among multiple quantile spans inside the distribution of data. The QC tool, initiated by Xiao [31], tackles these concerns by delving into the temporal sequels and links within quantiles for both predictor and response variables. When dealing with conditional data distribution, this technique effectively reduces the potential for estimation biases that can emerge when evaluating long-run connections. Xiao [31] goes beyond the limitations of typical methods by initiating cointegration errors and lead-lag indicators. Additionally, to accommodate the inherent instability in the data, Saikkonen [32] initiated containing a perpetual vector $\alpha(\tau)$ in the QC regression.

and

$$Q_\tau^X\left(X_i M_i^X, M_i^y\right) = \beta(\tau) + \alpha(\tau)' Y_i + \sum_{k=-s}^{s} \Delta Y_{i-k}' \Pi_j + F_v^{-1}(\tau) \tag{1}$$

As elucidated by Xiao [31], Equation (1) shows the parameter $F_v^{-1}(\tau)$, which can deal with the presence of the drift indicator. The term $\beta(\tau)$ designates the quantile error inside the conditional data distribution. The mathematical explanation of the quadratic elements in the cointegrating model may be articulated as under.

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

When evaluating cointegration coefficients, choosing the QC test is a realistic approach that necessitates an estimation of the null hypothesis H_0: $\alpha(\pi) = \alpha$, as described in Equation (2). The results of these estimates are obtained using the supremum rule, signified as $\widehat{V}_n(\tau) = [\widehat{\alpha}(\tau) - \widehat{\alpha}]$, in combination with the proper test statistics. Critical limits are developed within 1000 Monte Carlo simulations to confirm the null hypothesis.

4.2. Quantile-on-quantile (QQ) approach

Delivering the nonlinear data qualities, we choose the QQ technique over the old QR technique for variable examination. The QQ approach, created by Sim & Zhou [33], proposes a much-advanced selection that assesses the restraints of the QR regression that majorly stresses estimating the average impacts of the predictor variable on the response variable's quantiles. Embracing the QQ approach offers significant benefits when examining the relationship between the quantiles of both the predictor and response variables.

In our investigation, we employ the QQ approach which comprises non-parametric estimations with the traditional QR approach, to probe the GIN-ENI quantiles relationships. This method is designed to discover potential nuances in the GIN-ENI connection, which may be disregarded when using typical econometric methods such as QR and OLS. The basic configuration of the non-parametric QQ model of our study can be developed, followed by Zhang et al. [22] as follows:

$$ENI_t = \alpha^\theta(GIN_t) + \mu_t^\theta \tag{3}$$

In this context, 'GIN_t' denotes green investment, and 'ENI_t' stands for energy innovation, both observed at a particular time 't.' We use the emblem θ to illustrate the θ^{th} GIN quantile, and we do not specify the coefficient $\alpha^\theta(.)$ due to our limited understanding of the GIN-ENI relationship. The residual term for the θ^{th} quantile is denoted as μ^θ. Equation (3) is formulated utilizing the local linear regression technique, initially introduced by Cleveland [34]. This approach involves a regression investigation focusing on the GIN value.

$$\alpha^\theta(GIN_t) \approx \alpha^\theta(GIN^\tau) + \alpha^{\theta'}(GIN^\tau)(GIN_t - GIN^\tau) \tag{4}$$

The emblem $\alpha^{\theta'}$ expresses the derivative of α^θ regarding GIN_t, often referred to as a partial effect. The functions $\alpha^\theta(GIN_\tau)$ and $\alpha^{\theta'}(GIN_\tau)$ are correlated with θ and τ, correspondingly. We denote $\alpha^{\theta'}(GIN\tau)$ as $\alpha_1(\theta, \tau)$, and $\alpha^\theta(GIN_\tau)$ as $\alpha_0(\theta, \tau)$. Thus, we can express Equation (4) in the following fashion.

$$\alpha^\theta(GIN_t) \approx \alpha_0(\theta, \tau) + \alpha_1(\theta, \tau)(GIN_t - GIN^\tau) \tag{5}$$

Building upon the model presented in the study conducted by Sim & Zhou [33], we integrate Equation (5) into Equation (3) to implement the QQ regression approach.

$$ENI_t = \frac{\alpha_0(\theta,\tau) + \alpha_1(\theta,\tau)\,(GIN_t - GIN^\tau)}{(\ast)} + u_t^\theta \tag{6}$$

In the QQ analysis, Equation (6) provides insight into the linkage between the θ^{th} GIN quantile and the τ^{th} ENI quantile. We use the symbol (*) to represent the conditional GIN quantile, while α_0 and α_1 denote the parameters associated with θ and τ, correspondingly. This quantile-established GIN-ENI interconnection is exemplified by the parameters α_0 and α_1 that are influenced by both τ and θ. The specific parameter values may deviate established on the opted quantile values of GIN and ENI. Equation (6), which aligns different distributions, reveals the underlying pattern of interdependence between GIN and ENI by merging their respective distribution profiles.

Several former works efforts led by different scholars persistently highlight the model's boosted exactness and credibility compared to typical approaches. Nevertheless, the thoughtful selection of an optimal bandwidth remains a pivotal component of the optimization process to understand the reciprocal relationship between GIN and ENI.

We implement the minimization technique introduced by Chu & Marron [35–40] to address this issue.

$$Min_{\delta_0\,\delta_1} \sum_{t=1}^{n} \rho_\varphi [ENI_t - \delta_0 - \delta_1 (GIN_t - GIN^\tau)] L \left[\frac{M_n(GIN_t) - \tau}{h} \right] \tag{7}$$

In Equation (7), the loss function denoted by ρ_φ to appraise the regression's presentation. For allocating weights to the data points dependent on their proximity to ENI, we employ a Gaussian kernel function known as L (·). These weights are calculated by dividing the empirical distribution function of ENI by its corresponding quantile distributional function. The effectiveness of the kernel regression method is significantly influenced by the bandwidth parameter 'h,' which balances the variance-bias trade-off. A low bandwidth would result in higher variance, whereas a huge one may distort the distribution. Hence, it is essential to discover the optimal balance between variance and bias. In our study, we have followed the recommendation of Musibau et al. [15] and choose a particular bandwidth threshold of $h = 0.05$. In this regard, we denote the standard indicator function as 'I.'

4.3. Robustness of the QQ tool

Contrary to the QR methodology, the QQ technique sets itself apart with its outstanding exactness in evaluating the impact of GIN on ENI. While the QR approach majorly appraises the θ^{th} GIN quantile, the QQ model takes a much widespread stance by investigating the impact of the θ^{th} GIN quantile on the τ^{th} ENI quantile. By joining both θ and τ as quantile parameters, this approach obliges a much robust process of computation. The parameters of QR are derived by taking the mean of the QQ coefficients interconnected with τ. In the realm of QR methodology, the slope coefficients denoted as $\gamma_1(\theta)$ are implemented to investigate the interrelationship between GIN and various ENI quantiles, as exemplified in the investigation of Sim & Zhou [33].

Table 2
Descriptive stat values for GIN and ENI.

Nations	Mean	Max.	Min.	Std. Dev.	J-B Stats	ADF Level	ADFΔ
Panel A: Green Investment (GIN)							
Germany	73,456	130,567	27,456	31,689	4.40*	−2.14	−4.53**
France	63,190	121,200	26,350	30,720	5.28*	−1.49	−4.60*
UK	54,752	105,000	28,000	23,625	7.90*	−1.52	−5.63*
Italy	33,794	51,737	12,344	12,347	5.30*	−1.70	−5.81*
Spain	31,626	58,000	11,000	15,146	7.15*	−1.44	−4.31*
Netherlands	25,647	33,143	16,430	4713	7.80*	−1.97	−5.79*
Sweden	12,637	24,260	5263	6144	9.20*	−1.34	−5.81*
Denmark	12,286	30,472	3690	7118	4.85*	−1.68	−5.02*
Finland	11,457	23,729	3243	6554	6.50*	−0.95	−6.75*
Austria	9496	21,122	4871	5068	6.70*	−1.68	−4.81**
Panel B: Energy Innovation (ENI)							
Germany	475.34	615	352	88.74	5.39*	−1.55	−5.70*
France	456.67	597	350	81.56	2.83*	−5.70*	−5.23*
UK	440.45	580	320	77.56	3.54*	−1.09	−5.70*
Italy	227.70	365	97	86.80	3.54*	−1.67	−5.70*
Spain	230.90	310	145	65.08	2.46*	−1.69	−4.45*
Netherlands	281.78	360	167	60.50	3.67*	−1.84	−4.13*
Sweden	422.34	538	132	124.34	4.79*	−4.30*	−6.73*
Denmark	356.78	443	184	90.45	2.82*	−1.69	−5.63*
Finland	276.82	354	208	51.35	4.49*	−1.89	−3.73**
Austria	196.70	229	105	35.80	5.17*	−1.84	−5.13*

Note: * and ** manifest the level of significance at 1 % and 5 %, correspondingly.

$$\gamma_1(\theta) \equiv \overline{\widehat{\alpha}}_1 = \frac{1}{s}\sum_{\tau} \widehat{\alpha}_1(\theta, \tau) \quad (8)$$

In Equation (8), the number of quantiles is shown by 's,' precisely set at 19. The range of quantile, denoted as τ, intervals from 0.05 to 0.95, with ranges of 0.05. To appraise the precision of the QQ model, we develop a linkage between the mean QQ values appraised at different τ values and the parameters evaluated via QR model.

5. Findings and discussion

The current section submits the preparatory and main results of the paper continued by a detailed discussion.

5.1. Preparatory results

Table 2 supplies descriptive statistics to understand the characteristics of GIN and ENI comprehensively.

Germany takes the top spot for the highest GIN, depicting an average value of $73,456 million US$. The range extends from $27,456 to $130,567 US$. France holds second place with a mean GIN of $63,190, fluctuating between $26,350 and $121,200 US$. The UK secures third place, continued by Italy, Spain, and the Netherlands. In the realm of ENI, Germany secures the leading spot on the ranking, boasting an average of 475.34 energy-related patent applications. The numbers vary between 352 and 615. France follows closely, taking the second position, trailed by the UK, Sweden, and Denmark. The Jarque-Bera (J-B) test findings signify that GIN and ENI depart from normality in total examined nations. This withdrawal from normality stresses the significance of implementing the QQ approach, which is well-suited for investigating data that makes no attempt to adhere to a normal distribution. Furthermore, the findings of the Augmented Dickey-Fuller (ADF) test suggest that transforming variables into their first differences establishes stationarity in most economies. Persistent with the technique used by Musibau et al. [15], we chose a differenced data series to assure stationarity.

Table 3 demonstrates a significant positive association between GIN and ENI in all countries except Spain. Among these countries, the Netherlands manifests the largest correlation coefficient of 0.85, with Sweden nearly following at 0.84. France and Spain display correlation values of 0.81 and −0.77, respectively.

5.2. Major results

Table 4 presents the findings of the QC test that appraises the variables' stability. In our analyses, we employ the supremum norm coefficients (α and γ) originating from Equation (3), whereas τ signifies the τ^{th} ENI quantile.

In Fig. 1, the exhibited slope coefficients α_1 ($\boldsymbol{\theta}$, $\boldsymbol{\tau}$) define the impact of the $\boldsymbol{\theta}^{th}$ GIN quantile on the $\boldsymbol{\tau}^{th}$ ENI quantile. This analysis encompasses a wide range of combinations of values for both $\boldsymbol{\theta}$ and $\boldsymbol{\tau}$. As shown in Fig. 1(a), Germany shows a strong positive influence of GIN on ENI. A positive and vigorous interrelation between GIN and ENI is conceived within the localities, which attach entire GIN quantiles with lowermost to moderate-higher and upper ENI quantiles (0.05–0.65 & 0.85–0.95). This peculiar, positive, and powerful bond between GIN and ENI signifies that GIN rises ENI at the lowest to upper-mid and highest levels of ENI in Germany. Further, a negative and fragile GIN-ENI association is matured across the sections that affiliate full GIN quantiles with middle-upper ENI quantiles (0.70–0.80). In Fig. 1(b), France indicates a powerful and positive influence of GNI on ENI. A positive, strong interrelationship between GIN and ENI is interaction within the sections associated with significant GIN and ENI quantiles. This precise, positive, vigorous GIN-ENI association displays that GIN improves ENI at significant ENI levels in France. In addition, negative strong GIN-ENI interrelation is originated within the divisions, which interrelate the foremost GIN and lowest quantiles of ENI. This peculiar, negative, and strong link between GIN and ENI determines that GIN diminishes ENI at low levels of ENI in France. The existence of a strong positive interconnection between GIN and ENI in Germany and France is affirmed by Wang et al. [2].

The UK in Fig. 1(c), Italy in Fig. 1 (d), and Austria in Fig. 1 (j) indicate a vigorous and positive effect of GIN on ENI. A positive, powerful kinship between GIN and ENI is prevailed throughout the districts, which include complete GIN quantiles with low-medium

Table 3
Correlation between GIN and ENI.

Nation	Correlation	t-Stats	p.value
Germany	0.75	4.07*	0.00
France	0.81	4.92*	0.00
UK	0.76	4.09*	0.00
Italy	0.69	7.63*	0.00
Spain	−0.77	−5.38*	0.00
Netherlands	0.85	10.65*	0.00
Sweden	0.84	16.35*	0.00
Denmark	0.74	9.35*	0.00
Finland	0.70	7.95*	0.00
Austria	0.66	8.30*	0.00

Note:'*' illustrates the level of significance at 1 %.

Table 4
Results of QC test (GIN and ENI).

Nations	Coefficients	$Sup_\tau \|V_n(\tau)\|$	C1	C5	C10
Germany	α	8326.20	5285.20	3135.05	2532.36
GIN vs. ENI	γ	179.63	113.49	55.88	38.34
France	α	1837.75	1548.78	1047.77	994.89
GIN vs. ENI	γ	962.77	689.60	497.75	347.83
UK	α	1245.71	935.79	550.08	208.70
GIN vs. ENI	γ	787.82	587.96	497.93	375.70
Italy	α	7117.35	3495.14	3085.19	2228.33
GIN vs. ENI	γ	607.41	302.85	217.13	117.13
Spain	α	538.43	325.36	292.74	237.58
GIN vs. ENI	γ	289.97	197.90	129.72	97.38
Netherlands	α	6858.33	5836.33	5730.24	5488.74
GIN vs. ENI	γ	2466.68	1485.61	1446.48	1432.10
Sweden	α	3940.95	3770.25	248.50	205.90
GIN vs. ENI	γ	167.70	157.84	49.09	45.78
Denmark	α	8754.53	6712.11	4771.12	1476.80
GIN vs. ENI	γ	398.17	204.61	103.09	99.11
Finland	α	7114.36	3492.10	3082.11	2225.39
GIN vs. ENI	γ	609.45	303.88	213.20	118.13
Austria	α	6247.67	5684.96	4687.50	3780.78
GIN vs. ENI	γ	3281.96	2691.71	2182.70	1848.40

Note: The computation of the t-statistic comprises the evaluation of 19 quantiles equally distributed from 0.05 to 0.95. The findings yield computations for α and γ (supremum norm coefficients), along with their corresponding critical limits for significant levels set at 1 % (C1), 5 % (C5), and 10 % (C10).
The findings derived from the QC test expose swings in the GIN-ENI connection across various quantiles inside every nation. That is necessary to stress that the supremum norm coefficients (γ andα) continuously excel their critical limits, pointing a significant, long-run, and nonlinear GIN-ENI relationship in all the sample nations.

to foremost ENI quantiles (0.35–0.95). This precise, positive, powerful conjunction states that GIN uplifts ENI at medium-lower to highest levels in the UK, Italy, and Austria. Contrarily, the inverse powerful GIN-ENI amalgamation is identified across the precincts that relate whole GIN quantiles throughout bottom to low-medium ENI quantiles (0.05–0.30) in the UK and Italy. This powerful, negative bond expresses that GIN diminishes ENI in the UK and Italy at the bottom to middle-lower ENI levels. Further, a feeble and negative GIN-ENI interconnection is conceived throughout the divisions, which coalesce all GIN quantiles with lowest to moderate-lower ENI quantiles (0.05–0.30) in Austria. The supremacy of a positive and powerful relationship between GIN and ENI in the UK, Italy, and Austria is validated by Zhang et al. [22].

As shown in Fig. 1 (f), the Netherlands explains a strong positive influence of GIN on ENI. A positive strong GIN-ENI nexus is prevailed among the domains interrelating full GIN quantiles with the mid-lower to uttermost ENI quantiles (0.35–0.95). This unique, positive, vigorous interrelation affirms that GIN uplifts ENI at middle-low to highest levels of ENI in the Netherlands. Moreover, a subtle and inverse GIN-ENI coalescence is detected across the divisions that meld total GIN quantiles under the most moderate-lower quantiles of ENI (0.05–0.30) in the Netherlands. Fig. 1(g) identifies that Sweden has strong positive effect of GIN on ENI. A positive, strong interrelationship between GIN and ENI is during the domains that incorporate moderate-lower to upper GIN quantiles (0.35–0.95) throughout overall ENI quantiles. This distinct, vigorous, positive interdependence presents that GIN rises ENI at medium-low to highest GIN levels in Sweden. In contrast, an inverse strong GIN-ENI nexus is matured between the domains that unite lower to lower-medium GIN quantiles (0.05–0.30) with bottommost to middle-upper ENI quantiles (0.05–0.75). This precise, vigorous, inverse tie suggests that GIN lessens ENI at the lowest to middle-upper ENI grades in Sweden. The appearance of a powerful positive relationship between GIN and ENI in the Netherlands and Sweden is endorsed by Chi et al. [10].

According to Fig. 1(h), Denmark shows a strong positive GIN-ENI nexus throughout the sectors, which interrelate total GIN quantiles with lowest to lower-middle and high-medium to uttermost ENI quantiles (0.05–0.45 & 0.75–0.95). This precise, vigorous, and positive bond discloses that GIN boosts ENI at lowermost to lower-middle and upper-medium to uttermost ENI levels in Denmark. Conversely, a negative and robust coalescence between GIN and ENI is revealed within localities, including complete GIN quantiles with moderately low to mid-upper ENI quantiles (0.50–0.70). This powerful, inverse nexus displays that GIN reduces ENI at moderately bottom to middle-high ENI grades in Denmark. As shown in Fig. 1(i), Finland shows a strong positive impact of GNI on ENI. A positive powerful GIN-ENI association is interaction within the sectors, which join significant GIN and quantiles of ENI. This positive and powerful link between GIN and ENI implies that GIN improves ENI at significant ENI grades in Finland. Additionally, a weak and inverse interrelationship between GIN and ENI originated across the vicinities, which incorporate lowest to middle-lower GIN quantiles (0.05–0.25) and lowermost to lower-medium ENI quantiles (0.05–0.25). The existence of a powerful positive relationship between GIN and ENI in Denmark and Finland is affirmed by Yang et al. [14].

A mixed GIN-ENI nexus is found in **Spain**. Fig. 1 (e) shows a strong positive GIN-ENI interrelationship among the points that associate the middle to top GIN quantiles with entire ENI quantiles. This particular positive relationship asserts that GIN enhances ENI at middle to higher GIN levels in Spain. On the contrary, an inverse vigorous affiliation between GIN and ENI is detected throughout the portions, which attach lower to moderate GIN quantiles (0.05–0.50) with total quantiles of ENI. This explicit, negative, powerful

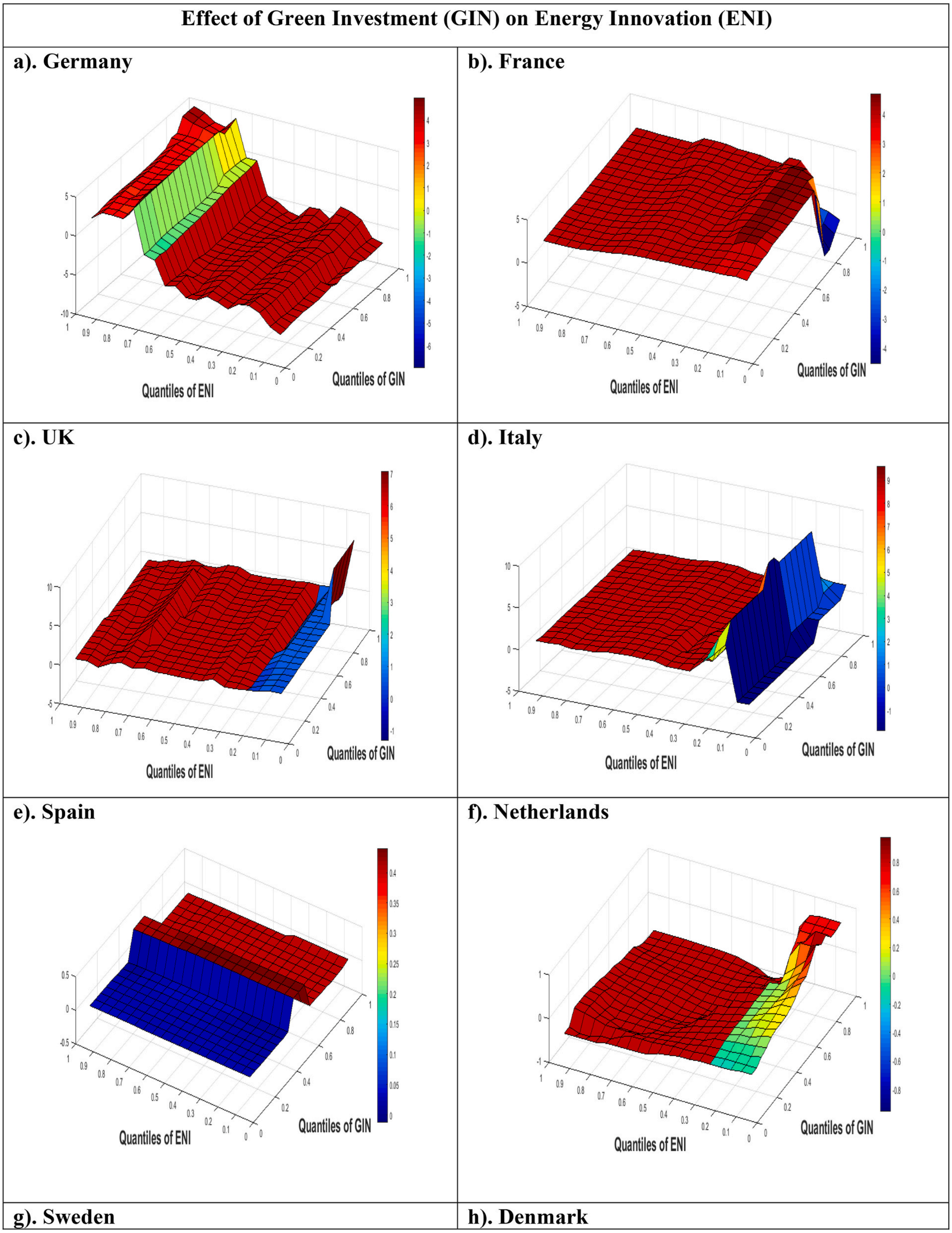
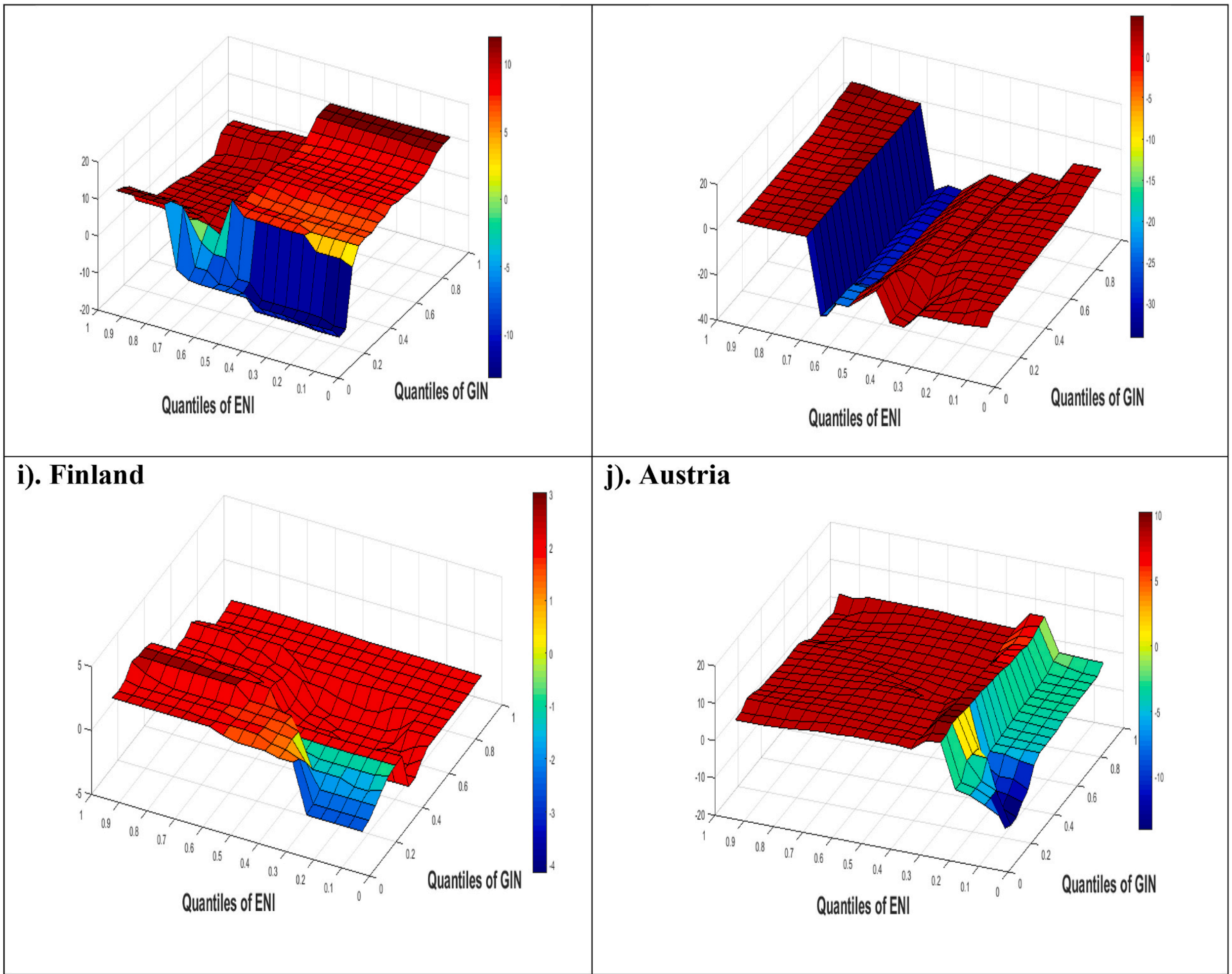


Fig. 1. Quantile-on-Quantile (QQ) estimations of the slope coefficient α_1 (θ, τ).



Note: The visual representations clearly show the estimated slope coefficients α1(θ, τ) positioned along the z-axis. ENI quantiles are plotted on the y-axis, while the x-axis corresponds to GIN quantiles. A color gradient scale is located on the right side of the charts, illustrating the spectrum of slope coefficients, spanning from blue (indicating low values) to red (indicating high values). Deep red expresses a positive strong GIN-ENI correlation, while deep blue indicates a significant inverse correlation. Similarly, a lighter shade of red suggests a moderate positive correlation, and a lighter blue hue implies a weak inverse GIN-ENI relationship. This visible representation simplifies the appraisal of the strength and direction of the GIN-ENI relationship in various circumstances.

Fig. 1. (*continued*).

junction displays that GIN decreases ENI at bottommost to mid GIN levels in Spain. The existence of a mixed connection between GIN and ENI Spain is maintained by Pan et al. [3].

Table 5 briefly overviews the connections between various GIN quantiles and ENI in the sample nations, as depicted in Fig. 1. The findings highlight a significant positive GIN-ENI correlation in most selected nations, pointing out that higher GIN is linked to lower ENI. Nevertheless, it is crucial to note that the GIN-ENI relationship in Spain yields mixed outcomes.

5.3. *Confirming the robustness of the QQ technique*

A comparative assessment is undertaken to appraise the analogy between the QR and QQ analyses. Fig. 2 affirms the former results from the QQ estimation, providing strong evidence of a considerable agreement between the average QQ assessments of slope parameters and the QR estimations in various countries. This analysis implies that both evaluations operate on the same principles and generate analogous analytical findings.

Fig. 2 illustrates a significant positive correlation between GIN and ENI in various economies such as Germany in Fig. 2(a), France in Fig. 2(b), UK in Fig. 2(c), Italy in Fig. 2(d), Netherlands in Fig. 2(f), Sweden in Fig. 2(g), Denmark in Fig. 2(h), Finland in Fig. 2(i) and Austria in Fig. 2(j). However, Spain in Fig. 2(e) diverge from this general trend, presenting a mixed finding. These results underline the discrepancies in the relationship between GIN and ENI between sample economies. Additionally, the coefficients propose a stronger

Table 5
Summary of Findings (Relationship b/w Various Quantiles of GIN and ENI).

Countries	GIN Quantiles	ENI Quantiles	Relationship b/w quantiles	Dominant link
Germany	Total quantiles	Lowest to moderately upper and high quantiles	Positive powerful	Powerful positive
	Entire quantiles	Medium-upper quantiles	Inverse fragile	
France	Significant quantiles	Significant quantiles	Positive powerful	Strong positive
	Utmost quantiles	Lowermost quantiles	Negative strong	
UK	Complete quantiles	Moderately low to highest quantiles	Positive strong	Strong positive
	Complete quantiles	Lowest to mid-low quantiles	Inverse powerful	
Italy	Complete quantiles	Moderately low to foremost quantiles	Powerful positive	Positive strong
	Full quantiles	Lowermost to medium-lower quantiles	Inverse powerful	
Spain	Medium to highest quantiles	Total quantiles	Positive strong	Mixed relation
	Lower to middle quantiles	Full quantiles	Inverse strong	
Netherlands	Complete quantiles	Lower-medium to uttermost quantiles	Positive powerful	Positive strong
	Total quantiles	Low to moderate lower quantiles	Weak inverse	
Sweden	Moderate-low to higher quantiles	All quantiles	Positive powerful	Powerful positive
	Lowermost to low-medium quantiles	Lowermost to medium-upper quantiles	Powerful inverse	
Denmark	Overall quantiles	Lower to moderately low and upper-middle to utmost quantiles	Positive strong	Positive strong
	Entire quantiles	Lower-medium to middle-upper quantiles	Strong negative	
Finland	Significant quantiles	Significant quantiles	Positive strong	Positive powerful
	Lowermost to low-mid quantiles	Lowermost to lower-medium quantiles	Fragile inverse	
Austria	Entire quantiles	Moderately low to foremost quantiles	Positive strong	Positive strong
	Full quantiles	Bottommost to moderate-lower quantiles	Inverse and weak	

impact of GIN on ENI in Sweden, France, the UK, Finland, Denmark, and Austria. In contrast, this influence appears less prominent in Spain and the Netherlands.

5.4. Discussion of findings

A pronounced association between GIN and ENI is observable in many nations, with 9 out of 10 nations illustrating a positive correlation. This implies that GIN exerts a positive impact on ENI. These outcomes are persistent with prior investigations managed by Wang et al. [2], Zhang et al. [22], Chi et al. [10], Yang et al. [14], and other scholars, consistently highlighting the incremental effect of GIN on ENI. Furthermore, our findings ordinate with former research carried out by Pan et al. [3] that stress the mixed impact of GIN on ENI. Contrary to prior research that majorly stressed on the total effect of GIN on ENI Chi et al. [10], Zhang et al. [1], Yang et al. [14], Wei et al. [11], Xu et al. [9], Ahmed & Jahanzeb [4], Yu et al. [13], Chen [5], Hammoudeh et al. [6], Pan et al. [3], Owen et al. [12], our research presents a more refined point of view. The relationship between GIN and its consequences on ENI could submit assorted results within definite parts of the distribution of data. These outcomes are necessary for policymakers and government officials in diverse economies, giving valuable insights for building policies relevant to changing levels of GIN and ENI.

In the case of Spain, the linkage between GIN and ENI exhibits a complex pattern encircling both negative and positive correlations. Ocular representations indicate that the impact of GIN on ENI is not uniformly detrimental; it varies based on factors such as timing, duration, and geographical conditions. This complexity can be attributed to several factors, offering insights into the dynamics of the GIN-ENI nexus. Firstly, the temporal dimension plays a crucial role. The impact of GIN on ENI is moderately beneficial, as specific timeframes influence the relationship. Certain periods may witness a positive correlation, indicating that GIN contributes positively to ENI, potentially spurred by policy changes, technological advancements, or market dynamics during those intervals. Conversely, there might be periods where the association is negative, suggesting challenges or disruptions that hinder the connection between GIN and ENI.

Secondly, the duration of the analysis period contributes to the observed complexity. Short-term assessments may capture immediate reactions to changes in GIN, providing insights into the rapid dynamics of ENI. In contrast, long-term analyses may reveal more enduring patterns, showcasing the sustained effects of GIN on ENI or vice versa. The varying impacts over different durations offer a comprehensive understanding of the evolving nature of the GIN-ENI relationship in the Spanish context. Geographical conditions further contribute to the multifaceted nature of the GIN-ENI relationship in Spain. Regional disparities, climate variations, and local policies can influence how GIN interacts with ENI in different parts of the country. For instance, regions with abundant renewable resources may experience a more positive correlation, emphasizing the importance of geography in shaping the dynamics between GIN and ENI. This distinctive connection between GIN and ENI supports the findings established in previous studies conducted by Pan et al. [3].

In several countries, such as Germany, Spain, Denmark, and Finland, a distinct and significant positive relationship between GIN and ENI becomes notably evident, especially at the upmost GIN quantiles. These outcomes imply that a considerable rise in GIN has an incremental effect on ENI, leading to its increase. This intriguing phenomenon explores the logical and empirical underpinnings contributing to these situations. The critical mass concept is one plausible explanation for the intensified positive relationship at higher GIN quantiles. As the level of GIN increases, it may reach a critical threshold where the cumulative impact on ENI becomes more

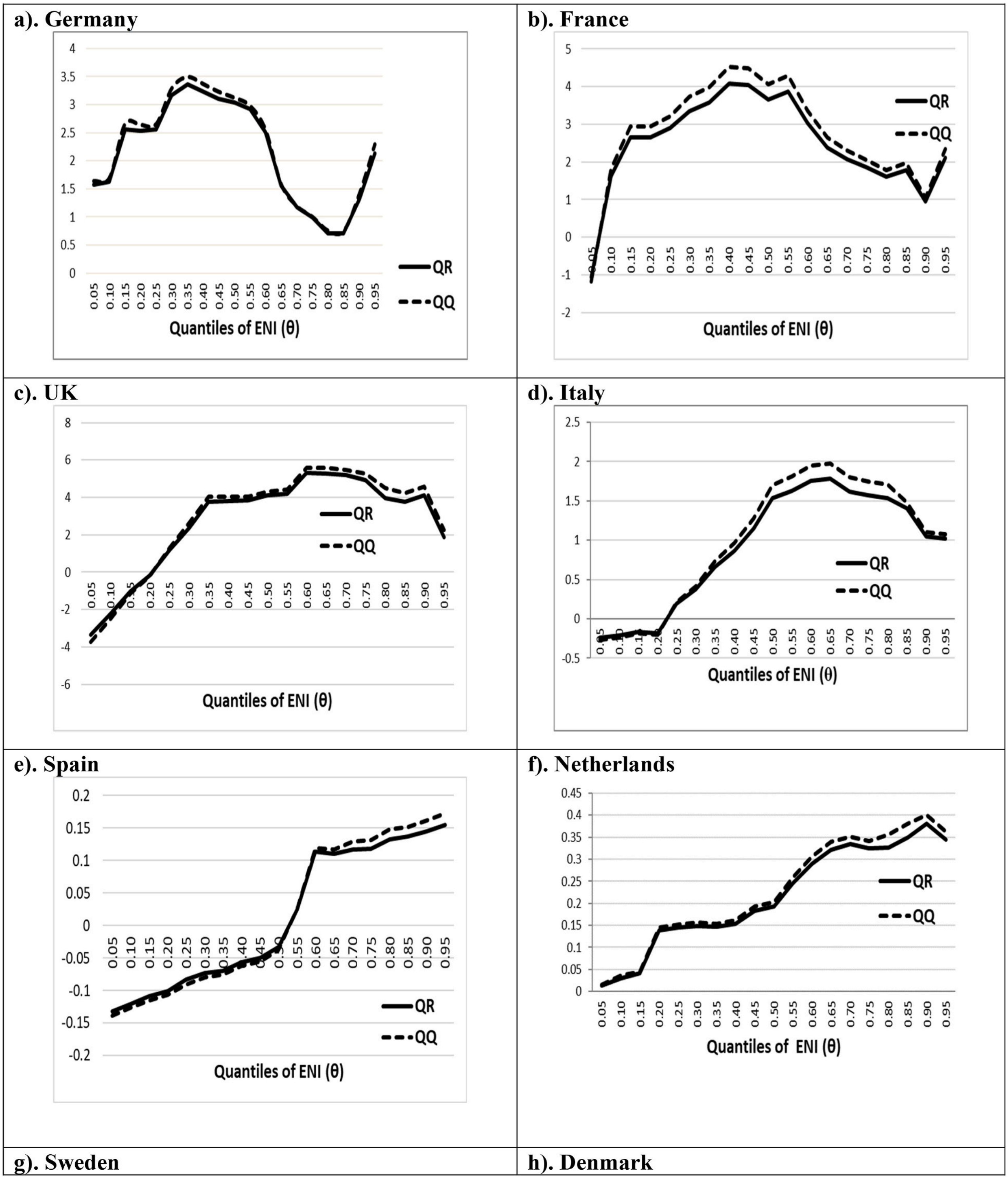
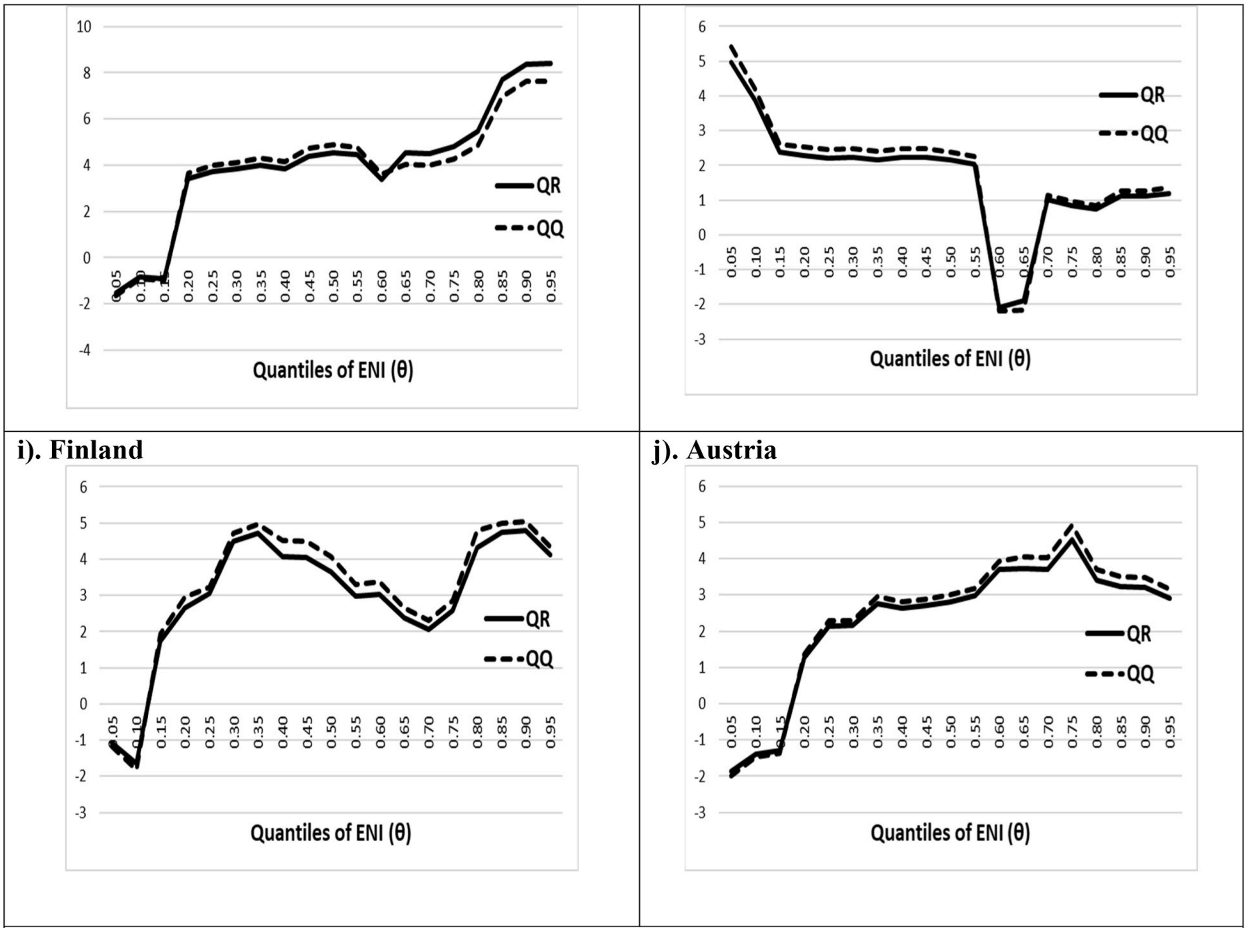


Fig. 2. Verifying the robustness of the QQ approach by comparing QQ and QR method.

pronounced. This phenomenon could be attributed to the economies of scale and interactions that emerge when financial resources are directed towards environmentally sustainable projects. At higher quantiles, the cumulative effect of GIN may trigger a more substantial response in ENI, fostering a positive feedback loop.

Strengthening the relationship at higher quantiles may also indicate strategic policy interventions and regulatory frameworks.



Note: The analysis encompasses conventional QR computations and mean QQ evaluations for multiple ENI quantiles.

Fig. 2. (*continued*).

Governments in these countries might have implemented targeted policies, incentives, or subsidies that specifically encourage higher levels of GIN. Such strategic measures could amplify the positive impact on ENI, creating an environment where a substantial increase in GIN is closely linked with a proportional rise in innovative solutions within the energy sector. Furthermore, the nature of the positive relationship at higher quantiles may also be linked to the maturity of the RE market in these countries. As the GIN landscape evolves and matures, the incremental effect on ENI may become more noticeable, reflecting a greater capacity for transformative change in response to heightened financial support.

In numerous economies, namely Italy, the Netherlands, the UK, Austria, France, and Finland, a distinct and significant positive relationship between GIN and ENI becomes notably evident, specifically at uppermost GIN quantiles. These outcomes propose that a substantial boost in GIN has an incremental influence on ENI, leading to its increase. This intriguing pattern prompts an investigation into the logical and empirical factors contributing to these instances' heightened negative correlation. A self-reinforcing innovation cycle is one plausible explanation for the increased positive relationship at higher ENI quantiles. As the energy sector progresses and attains higher quantiles of innovation, it may foster an environment conducive to more transformative changes. The connection between GIN and ENI in these countries could be characterized by a positive feedback loop, where heightened innovation generates greater demand for GIN, reinforcing positive impacts on both fronts.

Furthermore, enhancing the relationship at higher quantiles may be associated with the cumulative effects of successful ENI initiatives. As countries reach higher quantiles of ENI, they may be more adept at recognizing and leveraging GIN opportunities. Boosting knowledge of the potential economic and environmental benefits of RE and sustainable technologies likely fuels this positive cycle. In addition, strategic policy frameworks and regulatory support may contribute to the observed pattern. Governments in these countries may have implemented policies incentivizing innovation in the energy sector, fostering an environment where increased ENI aligns with a more substantial positive impact from GIN. Such policies encompass research and development grants, tax incentives, or subsidies to promote RE and sustainability innovation.

However, Spain presents a distinctive scenario in which the negative link between GIN and ENI is observable merely up to a certain threshold, after which it transitions inside a positive correlation. This intriguing transfer may be rationalized by considering various logical and empirical factors that influence the dynamics of the GIN-ENI relationship. One logical explanation for the change in the relationship at a specific threshold could be associated with the concept of initial resistance or inertia. Initially, as GIN increases, resistance or delays in adapting to these changes within the ENI landscape might occur. This resistance could be due to infrastructure constraints, technological inertia, or regulatory hurdles. However, once a certain threshold is surpassed, the cumulative effects of sustained GIN may overcome these initial barriers, leading to a positive correlation with energy innovation.

Furthermore, transitioning to a positive correlation beyond a specific threshold may signify a tipping point in developing RE and sustainable technologies. As GIN reaches a critical mass, it may catalyze transformative changes in the energy sector, triggering a shift from a negative to a positive correlation with ENI. This could be driven by a cascading effect where increased funding facilitates technological breakthroughs, spurs market adoption, and eventually fosters a conducive environment for innovation. Moreover, policy interventions and regulatory frameworks could influence the relationship between GIN and ENI at a specific threshold. Governments in Spain may implement strategic policies that initially face challenges in synchronizing GIN with ENI. However, as these policies mature and gain traction, they may contribute to the observed positive correlation beyond a critical threshold, signaling the success of targeted interventions in fostering a mutually reinforcing relationship.

As noted earlier, the diverse effects of GIN on the examined economies are tied to fluctuations in several economic indicators. The alterations in the slope coefficients of GIN and ENI in these countries suggest that economic disparities, particularly those associated with economic cycles such as recessions or expansions, impact ENI through economic mechanisms. During periods of economic recession, the relationship between GIN and ENI may experience shifts due to distinct economic dynamics. Recessions often lead to decreased overall investment levels as businesses and governments may tighten their budgets. In such circumstances, the positive influence of GIN on ENI may be tempered, as financial constraints and risk aversion can hinder the flow of resources towards innovative energy projects. Conversely, increased financial stability and a more favorable investment climate during economic booms may amplify the positive relationship between GIN and ENI. The economic upswing provides a conducive environment for implementing and scaling innovative energy solutions, reinforcing the positive impact of GNI.

Moreover, the role of economic conditions extends beyond mere financial resources. Recessions may trigger a heightened focus on cost-cutting measures, potentially impacting the allocation of funds to innovative yet cost-intensive energy projects. In contrast, economic booms may create a scenario where increased financial flexibility allows for greater experimentation and adoption of cutting-edge technologies in the energy sector. These economic conditions influence the prioritization and feasibility of GIN, contributing to the observed variations in the GIN-ENI relationship. Additionally, government policies and interventions during economic fluctuations can further shape the relationship between GIN and ENI. Governments may implement stimulus measures targeting GIN during recessions to spur economic recovery and job creation. These targeted policies counterbalance the negative impact of economic downturns on ENI, potentially leading to a more resilient and positive relationship. In contrast, policy frameworks may evolve during economic booms to regulate and encourage sustainable practices, reinforcing the positive link between GIN and ENI. Furthermore, each country encounters challenges that cannot be addressed solely within panel data tools. Consequently, to accomplish an exhaustive knowledge quality of the specific properties of whole economies, we have opted to use the QQ approach.

6. Conclusion and policy recommendations

Diverging from conventional methodologies seen in earlier studies, our research harnessed the innovative Quantile-on-Quantile (QQ) technique to probe the impact of GIN on ENI in the top ten European countries with the highest GIN—namely, Italy, Spain, the Netherlands, the UK, Sweden, Denmark, Germany, Finland, France, and Austria. The results, derived through the QQ technique, unveiled a significant and nuanced increase in ENI across various quantiles in these nations and developed a more intricate comprehension of the GIN-ENI interrelationship. Notably, Spain exhibited mixed outcomes, highlighting the nuanced superiority of the QQ approach in delivering insightful and convenient results compared to the conventional techniques employed in prior research.

The research consistently reveals a positive GIN-ENI interconnection in the top ten European nations with the highest GIN. To strengthen this connection, policymakers should prioritize sustained investment in RE and sustainable technologies. This includes enhancing financial incentives like tax credits and subsidies to attract private and public GIN. A supportive regulatory framework for the long-term growth of green industries can provide stability, fostering ongoing innovation in the energy sector. Collaboration between government, private enterprises, and research institutions is vital, and public-private partnerships for research and development can speed up innovation and technology adoption. Policymakers should also consider targeted programs for skills and expertise in the green technology sector through investments in education and training. Aligning policies with these findings can solidify European countries' leadership in green investment, promoting sustainable and innovative energy.

The observed distinct and significant positive relationship between GIN and ENI in countries like Germany, Spain, Denmark, and Finland, especially at higher quantiles of GIN, underscores the need for targeted policy interventions to enhance this connection further. Policymakers should consider implementing measures to facilitate the scaling up of GIN in these countries, acknowledging the incremental positive impact on ENI. This could involve streamlining regulatory processes, offering additional financial incentives for large-scale green projects, and fostering public-private partnerships to mobilize resources for sustainable technology research and development. Emphasizing policies that support the growth of RE industries, coupled with strategic investments in education and workforce development, will contribute to sustaining and strengthening the positive correlation between GIN and ENI in these nations, positioning them as trailblazers in the transition towards innovative and sustainable energy systems.

The identified distinct and significant positive relationship between GIN and ENI in countries like France, Italy, the UK, the Netherlands, Austria, and Finland, particularly at higher quantiles of ENI, signals a positive feedback loop that policymakers should leverage. To strengthen this correlation, governments can implement targeted policies that incentivize and accelerate innovation in the energy sector. This could involve increasing funding for research and development initiatives, creating regulatory frameworks that encourage the adoption of cutting-edge technologies, and fostering collaborations between public and private entities. Moreover, enhancing support for startups and small enterprises involved in ENI can contribute to a more robust ecosystem. These countries can foster sustainable technological advancements by aligning policies with the observed positive relationship between GIN and ENI at higher quantiles, ensuring continued leadership in the global transition towards innovative and eco-friendly energy solutions.

The unique scenario in Spain, where the negative relationship between GIN and ENI shifts to a positive correlation beyond a specific threshold, calls for targeted policy measures to capitalize on this transition. Policymakers should focus on identifying and understanding the critical threshold that triggers the positive correlation and adjusting policies accordingly. Strategies may include creating incentives to surpass this threshold, such as offering additional support for green projects once the tipping point is reached. Furthermore, implementing flexible regulatory frameworks that adapt to changing conditions and encourage sustainable innovation can enhance the positive correlation. The transition point could be leveraged to bolster Spain's position as a hub for sustainable technology, with policies tailored to foster continued growth in GIN and ENI beyond the identified threshold.

This study acknowledges certain limitations with promising implications for future research. Primarily, our analysis focused exclusively on ENI, neglecting other environmental factors like CH_4, SO_2, and N_2O. Future research incorporating these additional indicators could provide valuable insights into result alterations utilizing diverse environmental proxies. Exploring the interaction between GIN and ENI between several economic blocs, namely the MENA, G20, G7, European Union, and others, can significantly uplift our apprehension of this relationship. Detailed analyses in these assorted circumstances can offer vital foresight into fluctuations in the association between GIN and ENI across different regions. That is crucial to note that the QQ tool has boundaries when considering added variables influencing the GIN-ENI interrelation. To address this, upcoming research could probe multivariate approaches like Quantile ARDL modeling for a more holistic understanding. Addressing these constraints in upcoming investigations will significantly enhance our grasp of the complex dynamics of the GIN-ENI nexus.

Human and animal rights

No human or animals were harmed to do this research.

Availability of data

The datasets used during the current study are available from the corresponding author on reasonable request.

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Consent for publication

N/A.

CRediT authorship contribution statement

Jingli Jiu: Formal analysis, Supervision, Writing – original draft. **Sajid Ali:** Conceptualization, Data curation, Writing – original draft. **Raima Nazar:** Writing – review & editing, Writing – original draft. **Ahmad Imran Khan:** Writing – original draft, Software.

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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