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How Does the Circular Economy Asymmetrically Affect Clean Energy Adoption in EU Economies?

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Abstract

The European Union's commitment to achieving climate neutrality by 2050 requires sustainable economic models that address both environmental degradation and energy security. While renewable energy technologies are recognized solutions to climate change, the relationship between circular economy principles and clean energy transition remains underexplored empirically. This study investigates the asymmetric relationship between circular economy implementation and clean energy development across 27 EU economies from 2010–2023. Using Method of Moments Quantile Regression to capture distributional heterogeneity, we reveal pronounced asymmetric effects of circular economy shocks on clean energy adoption. Positive circular economy shocks demonstrate amplified benefits in high-performing clean energy economies, with elasticity coefficients increasing across quantiles, indicating that nations with established renewable infrastructure optimally capitalize on circular economy improvements through synergistic effects. Conversely, negative shocks manifest heterogeneous impacts: lower-performing countries experience significant clean energy contractions, while advanced economies exhibit resilience, suggesting adaptive mechanisms that enable resource reallocation toward alternative sustainability pathways. These findings provide policymakers with an analytical foundation for optimizing circular economy strategies to accelerate EU climate-neutrality objectives while accounting for heterogeneous national circumstances and transition pathways.

Keywords: circular economy; clean energy; EU members; method of moments quantile regression

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1. Introduction

Contemporary business environments are increasingly acknowledging the transformative impact of circular economy principles as a key shift in how resources are managed. This economic model redefines traditional production methods by moving away from the linear "extract-produce-discard" model toward a sustainable "reduce-reuse-recycle" model. Organizations adopting circular economy practices often experience improvements in cost efficiency, operational resilience, and a reduced environmental footprint [1]. At the same time, the corporate sector recognizes the limited supply of traditional energy resources and raw materials, prompting the broad adoption of renewable energy technologies. Historically, businesses have operated within linear production systems that prioritize resource extraction for manufacturing, while neglecting the potential economic value embedded in waste [2,3].

The circular economy framework encourages businesses to shift from ownership-based models to access-based consumption patterns, such as peer-to-peer platforms, sharing economies, and collaborative consumption networks, to reduce raw material requirements and energy consumption in producing final products [4]. Beyond material recycling and energy recovery, the circular economy encompasses comprehensive closed-loop production systems that can be integrated into strategic planning to enhance operational efficiency and preserve the environment. Businesses committed to environmental sustainability consider the circular economy approach effective when combined with the adoption of renewable energy [5]. Achieving maximum value creation within circular economy frameworks requires minimizing energy inputs, especially those derived from non-renewable sources, thereby extending material lifecycles within production systems and reducing waste generation.

Circular economy stakeholders aim to achieve better environmental performance through strategic energy management that emphasizes green and sustainable energy integration in the production process [6]. Green energy sources are broadly recognized as effective solutions for reducing greenhouse gas outputs during production while delivering substantial long-term improvements in environmental quality [7–9]. Businesses are increasingly integrating clean and low-emission transport solutions into their supply chains by replacing traditional diesel vehicles with battery-electric alternatives for freight and distribution. For instance, in 2022, Norway achieved a milestone with electric vehicles accounting for about 80% of new vehicle registrations across corporate fleets, private automobiles, and public transportation. Similarly, rapid electrification of transport has been observed in major economies, including the United States, China, India, Germany, and France [10].

Enhancing energy efficiency throughout value chains during the clean energy transition represents a concrete application of circular economy principles. To this end, businesses must conduct comprehensive energy audits and assessments to evaluate energy requirements at each value chain stage, including energy and resource losses during production processes [11–13]. After benchmarking their energy performance, businesses can reduce overall consumption by integrating renewable sources, using biodegradable inputs, and implementing systems that capture and repurpose lost process heat. Moreover, by developing strategic partnerships to exchange materials, energy flows, and by-products, businesses can lessen waste and reduce their dependence on carbon-intensive fuels [14]. To fully integrate renewables into a circular model, businesses may adopt technologies that transform residual waste into usable energy. Although conceptual frameworks propose that circular economy strategies should promote the adoption of clean energy, there is a lack of empirical analysis on this relationship. The circular economy framework, rooted in the "reduce, reuse, recycle" approach, is rapidly displacing traditional linear models of resource extraction, manufacturing, consumption, and disposal [15]. In the energy domain, the strategies include enhancing generation efficiency, optimizing end-use processes, and valorizing excess energy and residual materials [16]. By retaining material value throughout multiple life cycles, circular approaches outperform conventional economic systems in preserving resources and minimizing waste. Moreover, they offer a pathway to diminish reliance on fossil fuels: for example, converting organic residues into biomethane can satisfy a significant proportion of natural gas demand [17].

The circular economy concept was initially introduced by ref. [18] through their research on interconnections between environmental factors and economic activity. Subsequently, the circular economy literature has expanded significantly, with numerous studies devoted to conceptual development [19,20]. A substantial body of literature has confirmed the optimistic view that the circular economy can enhance environmental outcomes [21,22]. Despite growing interest in circular economy principles, their intersection with clean energy

has attracted relatively little empirical attention. In particular, no existing study has analyzed how circular economy practices asymmetrically influence clean energy outcomes in European economies. This omission represents a critical gap in the existing literature. The present study aims to bridge this gap by empirically examining the impact of implementing a circular economy on renewable energy expansion and energy security across EU member states. Given the pivotal role of energy in fostering economic growth and ecological preservation, policymakers are increasingly focusing on clean and renewable energy solutions. In this context, circular economy strategies, which focus on maximizing resource efficiency, minimizing waste, and promoting material reuse, have gained recognition as a coherent approach to enhance energy efficiency while simultaneously achieving sustainable growth. Despite theoretical arguments, there remains a notable lack of empirical studies examining how the circular economy accelerates the shift to renewable energy. This study aims to fill this gap by exploring the impact of the circular economy on the adoption of clean energy.

Building on the discussion above, this investigation presents various contributions to the scholarly discourse on circular economy and energy transition.

Primary contribution: This research represents the inaugural empirical investigation of nonlinear relationships between the development of the circular economy and the adoption of clean energy sources within European Union member states. The absence of prior empirical studies examining the asymmetric dynamics between circularity principles and clean energy represents a significant knowledge gap, which this study addresses through comprehensive quantitative analysis. By outlining a novel research trajectory, this research provides foundational insights that can guide future theoretical and empirical developments within this emerging interdisciplinary field.

Regional significance: Given the European Union's pioneering role in implementing the circular economy and its substantial investment in renewable energy infrastructure, examining the interconnections between circularity and sustainability within this context may yield critical insights for global policy formulation. The European Union's role as a global leader makes this regional analysis particularly valuable for implementing circular economy strategies and achieving climate neutrality. This investigation addresses the urgent need for evidence-based guidance on the potential of the circular economy to accelerate clean energy transition in advanced economies.

Methodological novelty: The research employs a methodologically rigorous circular economy index constructed through an entropy-weighted composite measure. The constructed index incorporates four distinct dimensions: circular innovation indicators, recyclable material trade flows, circular economy investments, and circular material flow metrics. This multidimensional measurement approach exceeds the limitations of unidimensional proxies, offering a more comprehensive representation of the complexity of the circular economy across various economic sectors and institutional contexts.

Advanced analytical tools: The study employs the Method of Moments Quantile Regression (MMQR) technique to address potential model misspecification issues while capturing heterogeneous effects across the distribution of clean energy. This non-parametric approach not only reduces the statistical bias inherent in traditional regression methods but also provides insights into the impacts across various quantiles of the renewable energy distribution. The analysis further employs an asymmetric decomposition of key regressors using partial sum techniques, isolating the effects of upward versus downward movements in the circular economy index. By considering the effects of increases and decreases in the circular economy, this study offers a more nuanced understanding, particularly relevant given the profound structural shifts in EU economies, and yields more reliable insights than standard linear models.

The empirical study confirms that the circular economy has asymmetric effects on energy transitions in European countries. Improvements in the adoption of the circular economy positively influence the adoption of renewable energy across all quantiles, with effects strengthening from lower to higher quantiles. This indicates that energy systems in countries with more advanced energy transitions benefit more from the circular economy. Conversely, a decline in circular economy frameworks impacts the energy transition differently across quantiles, indicating that the effect varies depending on each country's stage in the energy transition. These results significantly add to the existing literature by not only supporting and extending previous research but also offering new insights with important policy implications. To the best of the authors' knowledge, this is the first study to combine MMQR with an asymmetric analysis to explore how the circular economy influences energy transition, marking a new methodological contribution to the field.

The subsequent analysis unfolds through four interconnected sections: Section 2 synthesizes existing literature examining the nexus between circular economy principles and renewable energy adoption. Section 3 outlines the methodological framework, data collection procedures, and analytical techniques employed. Section 4 presents empirical findings alongside detailed policy implications for the European Union and broader international contexts. Finally, Section 5 concludes with strategic recommendations.

2. Theoretical Framework

2.1. Understanding the Circular Economy

The conceptualization of the circular economy remains complex and multifaceted. This model was initially presented as a regenerative system. The primary objective of this framework is to minimize waste of material and energy inputs while mitigating the associated environmental impacts. The circular economy concept was first articulated by David Pearce in 1990, emphasizing interconnections among four essential environmental economic functions [23]. The circular economy has evolved into an innovative economic paradigm, driven by technological progress and transformed business models, thereby offering a revolutionary approach to goods production [24]. However, the most widely accepted definition presents the circular economy as a systemic model focused on the reuse and regeneration of products, components, and materials via remanufacturing, refurbishment, repair, cascading, and upgrades. It also emphasizes the integration of clean energy sources throughout product life cycles [25]. This characterization received endorsement from ref. [26]. Widely regarded as pivotal to achieving sustainable development targets, the circular economy fosters economic growth by shifting production systems away from the traditional linear sequence of extraction, manufacture, consumption, and disposal toward circular flows of materials and energy. This shift is critical for preserving ecological integrity and reducing environmental degradation.

2.2. Circular Economy and Renewable Energy Adoption: Transmission Channels

Ref. [27] identifies three fundamental pillars of the circular economy: preserving and enhancing natural capital, maximizing resource yields, and improving system efficiency. Based on these foundations, [28] outline a hierarchical sequence of value-creation activities: sourcing renewable inputs, enabling reuse and sharing schemes, instituting repair and remanufacturing processes, and implementing robust recycling systems. Renewable resource development, particularly renewable energy, is at the top of this hierarchy because it supports all three principles and is essential to circular economy models [29]. According to ecological modernization theory, environmental protection and economic growth are compatible goals that can be achieved together through technological innovation, institutional reform, and effective environmental governance [30,31]. The theory also suggests that

developed nations can take a leading role in shifting toward sustainable development by integrating environmental issues into the core of their economic and industrial systems [32]. To this end, it is essential to deploy sustainable technologies and adopt circular economy models, among others. The implementation of waste management systems, carbon pricing policies, green innovation, and clean energy sources provides a tangible application of ecological modernization theory, which may explain the development of the circular economy and the deployment of energy transition.

On the other hand, socio-technical transition theory underscores the importance of the circular economy and the adoption of renewable energy in achieving sustainable development. Grin et al. [33] define socio-technical transitions as long-term, multidimensional processes through which established systems of production and consumption evolve toward more sustainable configurations. Within this framework, the circular economy aligns closely with socio-technical transition theory, as it requires a fundamental shift in how resources are used and waste is managed [34]. Furthermore, the transition towards clean energy sources aligns with socio-technical transition theory, as it represents an increased reliance on sustainable energy sources. Therefore, the socio-technical transition theory highlights the move from a linear to a circular economic model, challenging the traditional "*take-make-dispose*" paradigm by advocating for closed-loop systems, resource efficiency, and regenerative design [35].

The circular economy can promote energy transition through multiple pathways, including increasing the supply of critical raw materials (CRMs) for the renewable sector, reducing the risks of supply chain disruptions, and reducing the costs of renewable energy technologies. First, since the circular economy promotes the recycling, reuse, and refurbishment of materials, it can increase the supply of CRMs from recycling and reduce the dependence of renewable energy producers on the extraction/imports of these primary raw materials [36]. Indeed, renewable energy technologies, including wind turbines, solar panels, electric vehicle batteries, and power storage batteries, depend on various CRMs like lithium, cobalt, and copper. However, CRM reserves are concentrated in a small number of countries.

Second, the circular economy allows for the recovery of CRMs from end-of-life products, thereby creating a more stable and diversified supply chain. Indeed, monitoring and mitigating the risk of CRM supply disruptions is essential for a stable supply of clean energy technologies. According to the World Economic Forum, transitioning to a circular economy could save over USD 4.5 trillion globally by 2030. This is achieved by creating more efficient value chains that are less susceptible to fluctuations in primary resource prices. The circular economy may provide producers of renewable energy technologies with the required materials, thereby reducing their reliance on imports of new materials in resource-importing countries. This is particularly important in an increasingly volatile international landscape, shaped by increasing uncertainty and heightened geopolitical tensions. This situation has been illustrated by two recent major events: the COVID-19 pandemic and the Russia–Ukraine conflict, both of which have exposed vulnerabilities in global CRM production and the renewable energy market. Some mineral-producing countries may experience internal conflicts and economic difficulties that could impact the production of CRMs. This is the case of some developing and emerging countries, particularly African and South American nations, where political instability and armed conflicts often disrupt mining activities and supply chains, thereby exacerbating global supply risks for renewable energy producers.

Third, the circular economy may reduce the vulnerability of some countries importing CRMs to international price volatility, which represents a barrier to the development of the energy transition. As an illustration, the spike in the price of some critical materials

due to the COVID-19 pandemic and the Russia-Ukraine war led to a supply shortage in the European electric vehicle market. The importance of this channel lies in the fact that material costs represent the main component of the total cost of renewable technologies [37]. By extending product lifespans and recovering waste, the circular economy can decrease the need for new material extraction and processing, which are energy- and cost-intensive. Consequently, the circular economy may provide more cost-efficient material inputs, leading to a decrease in the overall costs of renewable technologies. This makes clean energy solutions more competitive, accelerating their adoption and contributing to more economically viable renewable energy technologies. Saadaoui et al. [38] analyzed the impact of geopolitical risks on the prices of selected critical minerals and found that, although the effects vary over time, geopolitical threats and acts significantly influence these prices. Finally, Aydin et al. [39] confirmed the importance of costs by emphasizing that lowering material costs during the production of green energy technologies enhances their competitiveness. Consequently, the circular economy may reduce the cost of materials required for the production of renewable energy technologies. This, in turn, increases demand for renewable energy products, consistent with the law of demand, and promotes the energy transition.

The circular economy has also been shown to be connected to broader sustainability initiatives, particularly Environmental, Social, and Governance (ESG) performance [40]. To provide evidence of the significant linkage between the circular economy and ESG, Khan [41] proposed a circular-ESG framework that integrates circular economy principles with ESG components. Provensi et al. [42] suggested that combining ESG and circular economy principles in Brazilian firms provides a more comprehensive view of sustainability, moving beyond treating them as separate strategies. Ref. [43] highlighted that adopting circular economy practices enhances environmental performance, thereby contributing to the environmental dimension of ESG. Although the literature increasingly links the circular economy to ESG, recent studies, including Garefalakis and Dimitras [44], have criticized the ESG framework as a broad measure of sustainability and proposed alternative methods to quantify sustainability outcomes.

Empirical studies underscore the relationship between circularity and energy transitions. Ref. [45] demonstrated that integrating circular principles can significantly enhance renewable energy output by leveraging synergies among waste reduction, material reuse, and sustainable power generation. Moreover, circular interventions—such as component reuse, remanufacturing, and material recovery—have been shown to lower capital costs for renewables infrastructure (e.g., solar panels, wind turbines, battery systems). Consequently, embedding circular economy tenets within renewable energy value chains not only reduces waste and enhances resource utilization but also drives down costs and expedites the deployment of clean energy technologies.

3. Methodology

3.1. Econometric Model

The present investigation employs the conceptual foundations established by ref. [46,47] as a point of departure, synthesizing empirical evidence from the extant literature to examine the key drivers influencing renewable energy adoption. The study proposes that sustainable energy transition is contingent upon multiple explanatory factors encompassing socioeconomic characteristics, macroeconomic indicators, and innovation. The analytical framework specifies the following functional relationship:

$$clean_{i,t} = f\left(CEI_{i,t}, GDP_{i,t}, FDI_{i,t}, TO_{i,t}, EMP_{i,t}, POP_{i,t}\right) \quad (1)$$

where subscripts i and t denote countries and temporal dimensions, respectively. RE represents renewable energy deployment, CEI indicates the circular economy index, GDP captures economic growth, FDI reflects foreign direct investment inflows, TO measures international trade, EMP represents total employment, and POP denotes demographic scale. To mitigate heteroskedasticity concerns, all variables undergo a logarithmic transformation, yielding the specification

$$clean_{i,t} = \beta_0 + \alpha_1 CEI_{i,t} + \alpha_2 GDP_{i,t} + \alpha_3 FDI_{i,t} + \alpha_4 TO_{i,t} + \alpha_5 EMP_{i,t} + \alpha_6 POP_{i,t} + \mu_{i,t} \quad (2)$$

where the parameters α_1 through α_6 represent the percentage change in the share of renewable energy resulting from a 1% increase in the circular economy index, gross domestic product, foreign direct investments, trade openness flows, employment, and population, respectively. This study particularly focuses on α_1, which captures the impact of the circular economy on clean energy transition. The intercept β_0 represents the autonomous component, while ε denotes the stochastic disturbance term.

The baseline specification in Equation (2) assumes symmetric responses to circular economy index variations. However, recent theoretical developments suggest that potential asymmetric dynamics may exist, wherein positive and negative variations may exert different impacts. To investigate this assumption, the circular economy index is decomposed into directional components:

$$\begin{cases} CEI^{+}_{i,t} = \ max(0, \ \Delta CEI_{i,t}) \\ \\ CEI^{-}_{i,t} = min(0, \ \Delta CEI_{i,t}) \end{cases}$$

where $CEI^{+}_{i,t}$ captures positive changes in the circular economy index, while $CEI^{-}_{i,t}$ captures negative changes. This inclusion of positive and negative changes in the circular economy index gives the following augmented specifications:

$$clean_{i,t} = \beta_0 + \alpha_{1,1} CEI^{+}_{i,t} + \alpha_2 GDP_{i,t} + \alpha_3 FDI_{i,t} + \alpha_4 TO_{i,t} + \alpha_5 EMP_{i,t} + \alpha_6 POP_{i,t} + \mu_{i,t} \quad (3)$$

$$clean_{i,t} = \beta_0 + \alpha_{1,2} CEI^{-}_{i,t} + \alpha_2 GDP_{i,t} + \alpha_3 FDI_{i,t} + \alpha_4 TO_{i,t} + \alpha_5 EMP_{i,t} + \alpha_6 POP_{i,t} + \mu_{i,t} \quad (4)$$

where $\alpha_{1,1}$ and $\alpha_{1,2}$ capture the effects of increases and decreases in the circular economy index on the clean energy transition.

3.2. Method of Moments Quantile Regression (MMQR)

Energy sector datasets often exhibit extreme values and asymmetric distributions, posing substantial challenges for conventional econometric approaches. The reliance on panel data frameworks using ordinary least squares estimation focuses exclusively on central tendency, thereby ignoring the heterogeneous impacts of the explanatory variable on the distribution of the dependent variable. This methodological limitation can lead to potential estimation bias and compromise analytical robustness, especially in the presence of nonnormally distributed time series. To address this drawback, the present investigation implements panel quantile regression techniques for parameter estimation. The quantile regression enables a comprehensive examination of covariate influences on renewable energy deployment across all segments of the conditional distribution within European Union member states. The existing literature has proposed various panel quantile methodologies. Rios-Avila and Maroto [48] introduced a two-step estimator for fixed effects quantile regression models, while Powell [49] developed a panel quantile regression approach that accounts for endogenous regressors. However, these methodologies have significant limitations when compared to MMQR. According to [33], the conventional panel quantile

regressions suffer from several drawbacks, including the incidental parameters problem, high computational complexity, a reliance on restrictive assumptions, and difficulties when confronting weakly correlated predictors and latent cross-sectional heterogeneity. The MMQR framework, developed by ref. [48], successfully addresses these methodological challenges through innovative estimation procedures. Indeed, MMQR methodology distinguishes itself from simple location-shift models by simultaneously incorporating both location and scale effects within the conditional distribution of sustainable energy. This technique demonstrates superior performance among non-parametric approaches due to its capacity to accommodate non-symmetrical relationships, simultaneity bias, and cross-unit heterogeneity, as emphasized by ref. [49,50]. These methodological advantages establish MMQR as an appropriate analytical framework for the current investigation.

The fundamental quantile regression specification follows:

$$Q_{y_{i,t}}(\tau|X_{i,t}) = \beta_\tau + X'_{i,t}\alpha_\tau \tag{5}$$

Here, $0 < \tau < 1$ and $Q_{y_{i,t}}(\tau|x_{i,t})$ denotes the τ-th conditional quantile of the dependent variable Y given the covariate vector X. The parameter vector α_τ captures the marginal impact of the regressors at that quantile, while β_τ represents fixed effects or other unobserved heterogeneity. Formally, the quantile-specific coefficients are obtained by solving:

$$\hat{\alpha}_\tau = argmin \sum_{i=1}^{n} \rho_\tau \left(y_i - \beta_\tau - X'_{i,t}\alpha_\tau\right) \tag{6}$$

The check function is defined as $\rho_\tau = \mu(\tau - I(\mu < 0))$

where $I(.)$ is an indicator function. Ensuring that the estimated ατ corresponds to the τ-th conditional quantile. This loss function ensures that the solution ατ corresponds to the τ-th conditional quantile of the dependent variable. When applied to the nonlinear specification in Equation (3), the quantile-regression models can be written as

$$Q_{clean_{i,t}}\left(\tau\middle|\beta_i, X_{i,t}\right) = \beta_i + \alpha_{1,1}CEI^{+}_{i,t} + \alpha_2 GDP_{i,t} + \alpha_3 FDI_{i,t} + \alpha_4 TO_{i,t} + \alpha_5 EMP_{i,t} + \alpha_6 POP_{i,t} + \mu_{i,t} \tag{7}$$

$$Q_{clean_{i,t}}\left(\tau\middle|\beta_i, X_{i,t}\right) = \beta_i + \alpha_{1,2}CEI^{-}_{i,t} + \alpha_2 GDP_{i,t} + \alpha_3 FDI_{i,t} + \alpha_4 TO_{i,t} + \alpha_5 EMP_{i,t} + \alpha_6 POP_{i,t} + \mu_{i,t} \tag{8}$$

We estimate these models at nine quantiles: τ = 0.10, 0.20,. . ., 0.90, to capture the full distributional response of clean energy adoption to each explanatory variable:

- Lower quantiles (0.10–0.30): Countries with limited clean energy adoption
- Middle quantiles (0.40–0.60): Countries with moderate clean energy adoption
- Higher quantiles (0.70–0.90): Countries with advanced clean energy adoption.

3.3. MMQR Implementation and Computational Procedures

The empirical estimation of MMQR models was conducted using Stata statistical software (version 19.5), employing the mmqreg command, which was developed specifically for method of moments quantile regression analysis. This command operationalizes the Machado and Silva [48] framework through an efficient computational algorithm that addresses the theoretical specifications outlined above. The mmqreg estimation procedure was implemented with the following technical specifications:

- Quantile specifications: Estimations were performed across nine quantiles (τ = 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90) to capture comprehensive distributional effects across the entire conditional distribution of renewable energy adoption.
- Bootstrap procedures: Standard errors were computed using bootstrap resampling methods with 500 replications to ensure robust inference and account for potential heteroskedasticity in the panel structure.

- Convergence criteria: The optimization algorithm achieved convergence for all quantile specifications, with convergence tolerance set at 1×10^{-6} and maximum iterations capped at 1000. All models converged successfully within the specified computational parameters.
- Fixed effect treatment: The mmqreg command automatically accommodates location-scale transformations, effectively addressing individual fixed effects without requiring explicit dummy variable inclusion. This approach circumvents the incidental parameters problem inherent in traditional fixed effects quantile regression.

The computational efficiency of the mmqreg command, combined with its theoretical rigor in handling panel data complexities, ensures that the estimation results provide reliable and interpretable coefficients across the entire distribution of renewable energy outcomes. The successful convergence across all quantiles and robust standard error estimation validates the appropriateness of this approach for the current empirical investigation.

3.4. Data

3.4.1. Sample Selection and Data Sources

Our empirical analysis covers 27 European Union member states over the 2010–2023 period. We begin in 2010, the earliest year for which comprehensive, harmonized circular-economy indicators are available, and extend through 2023 to capture recent trends. All variables, including the Circular Economy Index (CEI) and clean energy adoption, were retrieved from international repositories (Eurostat and the World Bank), ensuring a consistent and high-quality panel dataset.

3.4.2. Dependent Variable

The dependent variable, clean energy adoption, is operationalized through the share of renewable energy in gross final energy consumption, sourced from Eurostat's renewable energy statistics [51]. It is worth acknowledging that the share of renewable energy in final energy consumption does not capture all aspects of clean energy deployment, such as energy efficiency improvements, and carbon capture and storage. However, our study specifically focuses on the clean energy transition, emphasizing the structural shift from fossil fuels to renewable energy sources. The used metric measures the proportion of energy derived from renewable sources, including solar, wind, hydroelectric, biomass, and geothermal, relative to total final energy consumption. According to the Renewable Energy Directive framework, gross final energy consumption includes energy used by end-users (final energy consumption), transmission and distribution losses, and auxiliary consumption by power plants. This comprehensive measure provides a robust proxy for clean energy deployment, reflecting both the scale and penetration of sustainable energy technologies within national energy systems.

3.4.3. Explanatory Variable

This study employs a Circular Economy Index (CEI) as its central independent variable to examine how closed-loop economic systems affect clean energy adoption. Given that the circular economy involves complex mechanisms, scholars, including [50], have identified critical shortcomings in single-metric approaches for representing the full spectrum of resource circularity. Addressing this methodological gap requires constructing an aggregate measure that integrates different foundational pillars of closed-loop economic achievement.

The CEI architecture encompasses four principal pillars that together capture the vital aspects of implementing closed-loop systems:

Pillar 1: Material system efficiency: This pillar assesses how effectively nations incorporate reclaimed materials into their manufacturing workflows, tracking the shift away from take-make-dispose models toward regenerative resource pathways.

Pillar 2: Technological innovation capacity: This component assesses scientific progress and knowledge creation within resource regeneration sectors, measured through intellectual property registrations related to material reclamation and the utilization of reprocessed inputs.

Pillar 3: International circular trade integration: This pillar gauges participation in international regenerative supply networks by quantifying transnational exchanges of recoverable feedstocks, indicating both national regenerative capabilities and worldwide market involvement.

Pillar 4: Economic system commitment: This dimension assesses financial dedication toward closed-loop transformation by combining market capital deployment and economic value generation stemming from regenerative activities.

The CEI employs an information-entropy weighting methodology to guarantee unbiased determination of each component's relative significance. This empirical strategy reduces potential bias by allowing the intrinsic informational characteristics of each pillar to dictate its overall contribution. Information-entropy techniques compute weights based on variability patterns within each indicator, allocating greater emphasis to pillars that demonstrate stronger differentiation among nations. This methodological structure corresponds with recognized composite measurement protocols outlined in prior literature. [52], while integrating modifications tailored to the governance and market characteristics of European Union nations. Such an approach balances methodological precision with situational appropriateness.

The construction of CEI proceeds through a structured sequential process:

(a) Normalization phase: All metrics undergo standardization procedures to enable comparison across disparate measurement scales and units.
(b) Information-entropy computation: Unbiased weights emerge from calculations based on informational entropy properties of each pillar.
(c) Composite synthesis: Combined scores are derived by applying calculated weights for each nation and temporal observation.

The multifaceted CEI structure delivers numerous analytical benefits. By consolidating multiple circularity pillars, it authentically captures the holistic nature of closed-loop economic systems. Information-entropy-derived weights ensure an empirical and unbiased allocation of component significance, thereby removing researcher subjectivity. The application of uniform standardization protocols across European Union members enables valid inter-nation assessments. The metric's architecture permits temporal tracking, facilitating longitudinal observation of national closed-loop economic evolution. Additionally, by disaggregating achievement into separate yet interconnected pillars, the CEI generates practical intelligence suitable for informing specifically calibrated policy interventions.

Figure 1 illustrates the comprehensive theoretical architecture of the CEI, depicting the layered organization and interconnections between pillars that constitute this holistic measurement strategy.

This rigorous, data-anchored metric construction facilitates sophisticated examination of connections between closed-loop economic achievement and ecological sustainability results, establishing a strong basis for subsequent statistical modeling and regulatory evaluation.

Index	Index Dimension	Component Indicators	Weight
Circular Economy Index (CEI)	Material Efficiency	Material circulation efficiency	12%
	Technological Innovation	Innovation in resource recovery	30%
	Trade Integration	Recyclable Trade Flows	26%
	Economic Commitment	Economic commitment to circularity	32%

Figure 1. Theoretical architecture for the national-level CEI.

3.4.4. Other Variables

To ensure that other factors do not confound the estimated relationship between the CEI and clean energy adoption, we include a suite of control variables drawn from recent empirical studies. Consistent with [53], our model incorporates key socioeconomic determinants, each of which has been shown to exert significant and potentially distinct effects on clean energy adoption (see Table 1).

Table 1. Key variables, operational definitions, and data sources.

Variable	Code	Operational Definition	Data Source
Renewable energy share	CLEAN	Proportion of total energy output derived from renewable sources	Eurostat
Circular Economy Index	CEI	Entropy-weighted index comprising material reuse rates, innovation metrics, trade in secondary materials, and CE investments	Compiled from Eurostat data
GDP per capita	GDP	Gross domestic product divided by population (measured in current USD)	World Bank
FDI inflows	FDI	Net foreign direct investment inflows as a percentage of GDP	World Bank
Employment	EMP	Percentage of individuals aged 15+ who are employed	World Bank
Trade openness	TO	Sum of exports and imports expressed as a percentage of GDP	World Bank
Total population	POP	Mid-year national resident count	World Bank

GDP per capita: Higher income levels are generally associated with increased overall energy consumption and heightened demand for energy services, which may favor conventional energy sources. However, wealthier nations often possess greater financial capacity to invest in renewable energy infrastructure, clean technology R&D, and energy transition policies, potentially accelerating clean energy adoption [54–57].

FDI: Foreign direct investment can boost clean energy development by introducing advanced renewable energy technologies, providing capital for green infrastructure projects, and transferring technical expertise. Conversely, it may hinder clean energy progress if

investments predominantly flow toward fossil fuel industries or carbon-intensive manufacturing sectors [58–60].

Trade openness: Greater trade openness can promote clean energy adoption by facilitating access to renewable energy technologies, enabling technology transfer, and creating competitive pressures for energy efficiency. However, it may also reduce clean energy incentives if it increases energy-intensive export production or promotes reliance on cheap fossil fuel imports [61].

Employment: Higher employment rates may drive increased energy consumption through expanded economic activity, potentially favoring conventional energy sources for immediate energy security. Alternatively, robust employment in green sectors and renewable energy industries can accelerate clean energy transitions through skilled workforce development and innovation [62].

Population size: Larger populations typically generate greater energy demand, which may initially favor established fossil fuel infrastructure due to scalability concerns. However, population density can also create economies of scale for renewable energy deployment and smart grid technologies, potentially supporting clean energy adoption [63].

4. Empirical Results and Discussion

4.1. Validation of Distributional Characteristics

Standard econometric models operate under the fundamental assumption that variables exhibit Gaussian distributional properties. The present investigation employed dual diagnostic approaches to examine the applicability of this assumption to the examined dataset:

Visual diagnostics: A quantile-quantile graphical representation was generated for renewable energy variables. Normal distribution conditions would manifest as data points exhibiting strong linear alignment with the theoretical reference trajectory. Figure 2 demonstrates substantial deviations from linearity, indicating significant departures from normality.

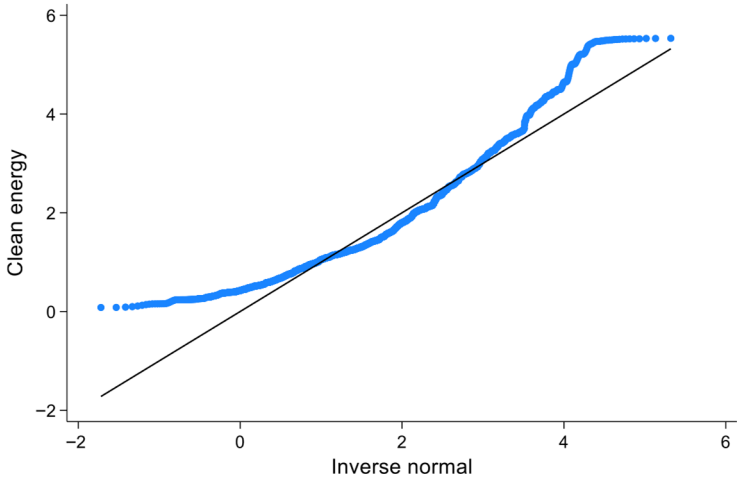


Figure 2. QQ plot for clean energy.

Formal testing procedures: We applied the Shapiro–Wilk test to evaluate whether each variable follows a Gaussian distribution. As shown in Table 2, all series reject the null hypothesis of normality at the 5% significance level, indicating pronounced departures from normal distribution.

Table 2. Data characteristics.

Variable	Mean	Std. Dev.	Min.	Max.	Skewness	Kurtosis	Shapiro–Wilk	Prob.	VIF
Clean	0.970	0.341	0.229	1.793	0.137	2.592	6.882	0.000	-
CEI	5.859	1.535	3.067	9.203	0.213	2.073	10.956	0.000	1.20
GDP	23.486	1.478	20.575	26.440	0.123	2.214	10.562	0.000	2.06
FDI	0.358	0.752	−2.023	3.245	1.424	8.159	16.867	0.000	1.10
EMP	1.703	0.088	1.455	1.888	−0.464	3.074	10.198	0.000	2.92
TO	2.397	0.395	1.712	3.490	0.392	2.838	11.094	0.000	4.23
POP	13.332	1.342	10.497	15.751	−0.108	2.511	11.368	0.000	4.29

These findings demonstrate that key assumptions of standard linear regression (i.e., normally distributed errors) are violated, which can bias coefficient estimates and inflate inference errors. To overcome these limitations and capture variation across the outcome's distribution, we employ panel quantile regression. This method requires no distributional assumptions and allows the effects of explanatory variables on clean energy adoption to differ at distinct points of its conditional distribution.

Multicollinearity diagnostics. We computed variance inflation factors (VIFs) to assess the extent of multicollinearity among regressors; the VIFs are reported in Table 2. All VIF values lie well below common concern thresholds (VIF = 5). The largest VIFs appear for POP (4.29) and TO (4.23), indicating these two covariates share some linear association with the remaining regressors but do not display severe multicollinearity. Overall, the VIF diagnostics indicate that collinearity is unlikely to materially bias coefficient estimates or invalidate inference in our baseline specifications.

4.2. Analysis of Cross-Sectional Dependence and Parameter Heterogeneity

Panel data econometrics has recently evolved to place a central emphasis on explicitly modeling the interdependence between cross-sectional units, particularly in studies involving geographically or economically interconnected units such as European Union member states. CSD arises when observations exhibit correlation due to unobservable common shocks or interlinked transmission mechanisms—such as regional policy diffusion, environmental spillovers, or trade integration—thereby violating the independence assumptions fundamental to conventional first-generation estimators. Neglecting these dependencies may lead to biased or inconsistent parameter estimates. To detect such interconnections, we apply two widely adopted diagnostics: the Breusch–Pagan Lagrange Multiplier (LM) procedure and Pesaran's Cross-Sectional Dependence (CD) test. As shown in Panel A of Table 3, both tests yield highly significant statistics for every variable (p-values below 0.001), confirming that cross-sectional dependence is present. These findings suggest that national-level clean energy trends are shaped, at least in part, by broader supranational dynamics or shared external shocks—necessitating the use of robust estimators that allow for such dependencies. In parallel, the investigation also examines slope heterogeneity—i.e., whether the estimated coefficients differ significantly across countries—using the Blomquist-Westerlund test for parameter heterogeneity. Panel B of Table 3 presents the results of both the conventional delta (Δ) test and its bias-corrected version. In each case, the null hypothesis of homogeneous slopes is rejected at the 1% significance level, indicating considerable heterogeneity in the factors driving clean energy uptake across EU member states.

Taken together, these diagnostic tests recommend using second-generation econometric techniques, particularly quantile regression methods that are robust to both cross-sectional dependence and heterogeneous slope coefficients. This approach ensures a more accurate estimation of the asymmetric and distribution-sensitive effects of the circular economy on renewable energy adoption.

Table 3. Cross-sectional dependence outcomes.

Panel (A). Cross-Sectional Dependence Test				
Tests	**LM Test**	***p*-Values**	**Pesaran Test**	***p*-Values**
Clean	5951.810 ***	0.000	62.693 ***	0.000
CEI	20,083.530 ***	0.000	40.102 ***	0.000
GDP	216,515.590 ***	0.000	12.467 ***	0.000
FDI	973,180.730 ***	0.000	21.867 ***	0.000
EMP	70,884.010 ***	0.000	20.327 ***	0.000
TO	2348.510 ***	0.000	63.412 ***	0.000
POP	140,372.750 ***	0.000	25.551 ***	0.000
Panel (B). Homogeneity test				
	Test value		Prob.	
Tilde (Delta)	191.180 ***		0.0000	
Adjusted tilde (Delta)	195.902 ***		0.0000	

Notes: *** indicates rejection of the unit root null hypothesis at the 1% significance level.

4.3. Panel Unit Root Testing

After establishing the presence of cross-sectional dependence, the next step involves evaluating the stationarity properties of the dataset using second-generation panel unit root tests that account for cross-sectional correlations, i.e., the Cross-Sectionally Augmented Dickey–Fuller (CADF) test. As reported in Table 4, each series is stationary in levels, confirming that all variables are integrated of order zero, I(0). These findings guided the econometric strategy in the subsequent stages of analysis. Since all variables are I(0), the data do not require differencing or cointegration testing, as cointegration analysis is applicable only when variables are integrated of order one, I(1), or of mixed integration orders. The stationarity of all series at levels ensures that standard regression techniques can be applied without the risk of spurious regression, allowing for the direct estimation of relationships between the circular economy and clean energy development variables.

Table 4. Panel unit root test results.

Variable	**Level**	**First Difference**
Clean	−5.641 ***	−6.190 ***
CEI	−5.999 ***	−6.157 ***
GDP	−5.136 ***	−6.190 ***
FDI	−5.450 ***	−6.096 ***
EMP	−5.273 ***	−6.129 ***
TO	−4.767 ***	−6.031 ***
POP	−4.510 ***	−6.190 ***

Notes: *** indicates rejection of the unit root null hypothesis at the 1% significance level.

4.4. Asymmetric MMQR Estimation Results

Building on the diagnostics for unit root testing, slope heterogeneity, and cross-sectional dependence, our empirical strategy advances to the estimation of the quantile regression. MMQR is particularly well-suited for this context, as it uncovers how asymmetric shifts in the CEI exert varying influences across the entire distribution of clean energy adoption. Tables 5 and 6 present the estimated coefficients for both positive and negative CEI shocks across conditional quantiles, offering a disaggregated view of their impact on renewable energy outcomes. These findings are further visualized in Figures 3 and 4, which highlight the varying intensity and direction of CEI influences across the clean energy distribution spectrum. Moreover, the model accounts for other socioeconomic

and structural factors that may affect clean energy development, thereby enhancing the robustness and interpretability of the estimated relationships.

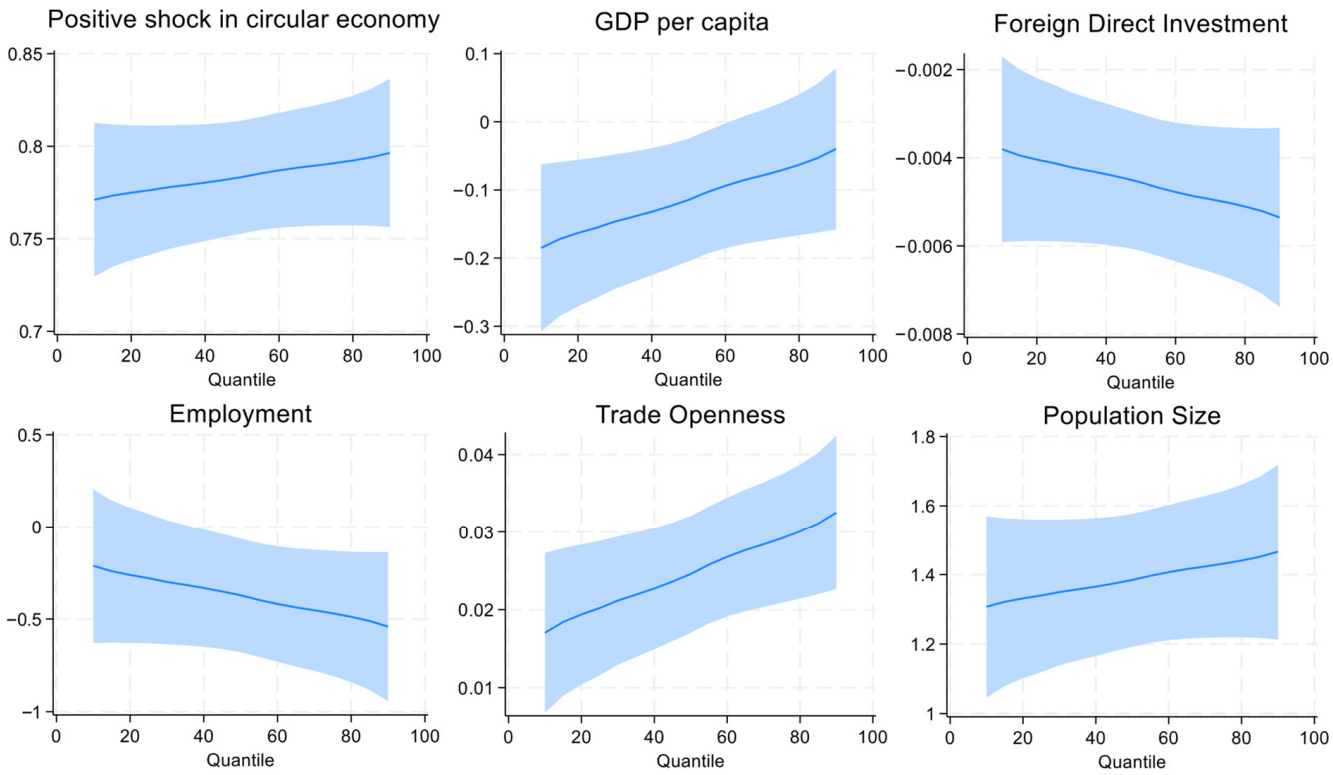


Figure 3. MMQR-based estimates for Model I.

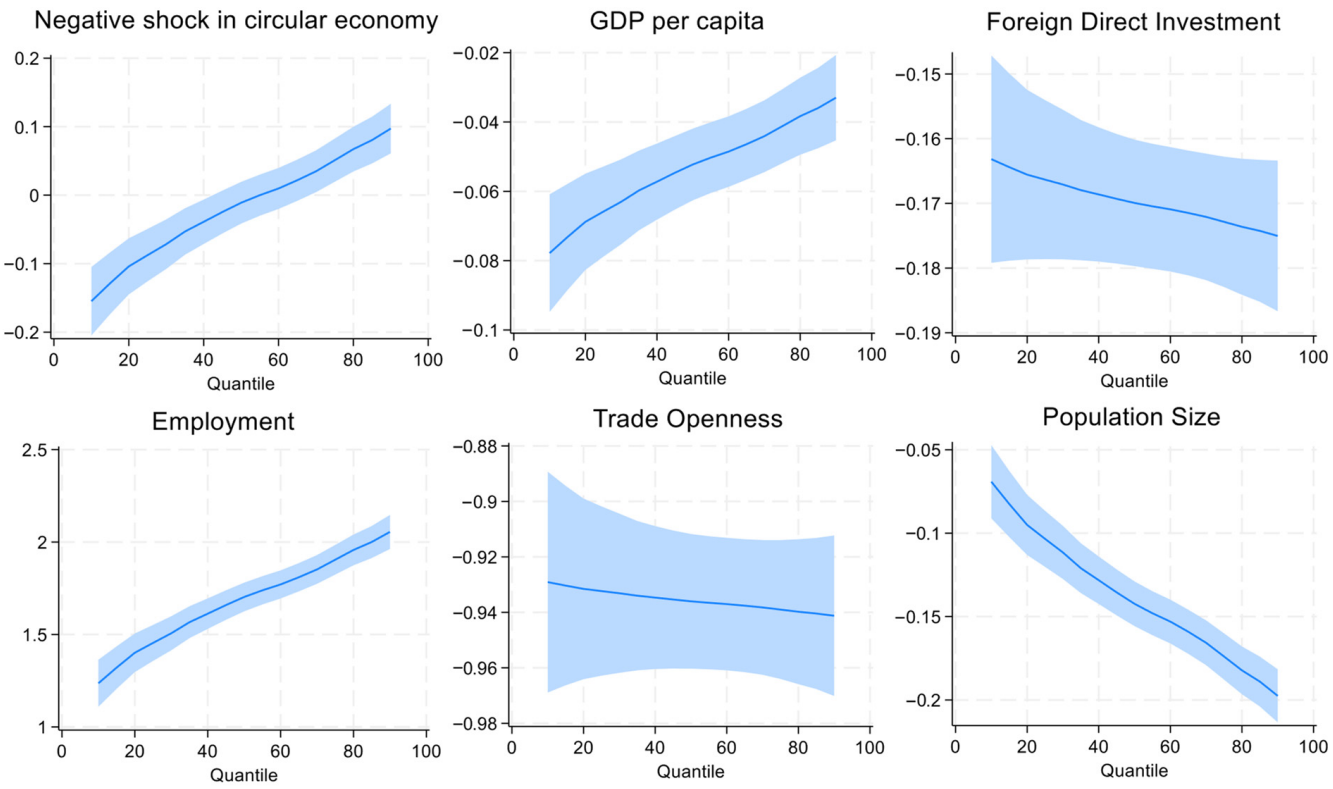


Figure 4. MMQR-based estimates for Model II.

Table 5. Impact of positive CEI shocks on clean energy adoption: MMQR results.

	Lower Quantile Limited Clean Energy Adoption			**Middle Quantile Moderate Clean Energy Adoption**			**Upper Quantile Advanced Clean Energy Adoption**		
	10th	**20th**	**30th**	**40th**	**50th**	**60th**	**70th**	**80th**	**90th**
					Model I				
CEI^{+}	0.771 ***	0.775 ***	0.778 ***	0.780 ***	0.783 ***	0.787 ***	0.790 ***	0.792 ***	0.796 ***
	(0.021)	(0.019)	(0.017)	(0.016)	(0.016)	(0.016)	(0.017)	(0.018)	(0.020)
GDP	−0.185 ***	−0.163 ***	−0.146 ***	−0.132 ***	−0.115 **	−0.094 **	−0.079	−0.063	−0.04
	(0.062)	(0.055)	(0.050)	(0.048)	(0.046)	(0.047)	(0.049)	(0.053)	(0.060)
FDI	−0.004 ***	−0.004 ***	−0.004 ***	−0.004 ***	−0.005 ***	−0.005 ***	−0.005 ***	−0.005 ***	−0.005 ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EMP	−0.212	−0.262	−0.300 *	−0.332 **	−0.372 **	−0.418 ***	−0.453 ***	−0.488 ***	−0.541 ***
	(0.213)	(0.187)	(0.171)	(0.162)	(0.157)	(0.159)	(0.167)	(0.180)	(0.206)
TO	0.017 ***	0.019 ***	0.021 ***	0.023 ***	0.025 ***	0.027 ***	0.028 ***	0.030 ***	0.033 ***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
POP	1.307 ***	1.331 ***	1.350 ***	1.365 ***	1.384 ***	1.407 ***	1.423 ***	1.440 ***	1.466 ***
	(0.134)	(0.117)	(0.108)	(0.102)	(0.098)	(0.100)	(0.105)	(0.113)	(0.129)

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. Impact of negative CEI shocks on clean energy adoption: MMQR results.

	Lower Quantile Limited Clean Energy Adoption			**Middle Quantile Moderate Clean Energy Integration**			**Upper Quantile Advanced Clean Energy Transition**		
	10th	**20th**	**30th**	**40th**	**50th**	**60th**	**70th**	**80th**	**90th**
					Model II				
CEI^{-}	−0.155 ***	−0.104 ***	−0.072 ***	−0.039 **	−0.011	0.01	0.035 **	0.067 ***	0.097 ***
	(0.026)	(0.021)	(0.018)	(0.017)	(0.016)	(0.015)	(0.016)	(0.017)	(0.018)
GDP	−0.078 ***	−0.069 ***	−0.063 ***	−0.057 ***	−0.052 ***	−0.049 ***	−0.044 ***	−0.038 ***	−0.033 ***
	(0.009)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
FDI	−0.163 ***	−0.166 ***	−0.167 ***	−0.169 ***	−0.170 ***	−0.171 ***	−0.172 ***	−0.174 ***	−0.175 ***
	(0.008)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
EMP	1.236 ***	1.401 ***	1.507 ***	1.613 ***	1.703 ***	1.771 ***	1.852 ***	1.957 ***	2.055 ***
	(0.065)	(0.053)	(0.047)	(0.042)	(0.040)	(0.039)	(0.040)	(0.042)	(0.047)
TO	−0.929 ***	−0.932 ***	−0.933 ***	−0.935 ***	−0.936 ***	−0.937 ***	−0.938 ***	−0.940 ***	−0.941 ***
	(0.020)	(0.017)	(0.015)	(0.013)	(0.012)	(0.012)	(0.012)	(0.013)	(0.015)
POP	−0.069 ***	−0.095 ***	−0.112 ***	−0.128 ***	−0.142 ***	−0.153 ***	−0.166 ***	−0.182 ***	−0.198 ***
	(0.011)	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)

Notes: Standard errors in parentheses. ** $p < 0.05$ and *** $p < 0.01$.

4.4.1. Impact of Positive Shocks in CEI on Clean Energy Adoption

Model I in Table 5 presents the impacts of positive shocks in the Circular Economy Index (CEI^{+}) on renewable energy adoption. The CEI^{+} coefficients are uniformly positive and statistically significant at the 1% level across all examined quantiles, affirming the hypothesis that the development of the circular economy consistently fosters the uptake of clean energy technologies throughout the EU nations. A notable increasing marginal effect across the conditional distribution of clean energy is observed when moving from lower to higher quantiles. Specifically, a 1% increase in CEI^{+} corresponds to an approximate 0.771% rise in clean energy adoption at the 10th quantile, whereas the effect increases to 0.796% at the 90th quantile. This pattern suggests that the relative responsiveness to circular economy improvements is more pronounced in member states with initially higher shares of renewable energy adoption. Therefore, nations at advanced stages of the energy

transition derive proportionally greater benefits from circular economy advancements compared to those with low levels of clean energy deployment. These empirical findings corroborate recent research emphasizing the enabling role of circular economy practices in facilitating energy system decarbonization across Europe [64]. Several interpretations can account for the observed variation in CEI^{+} impacts across the clean energy distribution:

First, the consistent statistical significance of CEI^{+} across all quantiles confirms that circular economy reforms are broadly effective, regardless of a country's clean energy baseline. This reinforces the strategic relevance of the European Commission's Circular Economy Action Plan (CEAP), which is explicitly positioned as a key mechanism to align resource efficiency with climate neutrality goals. As noted by Johansson [65], the CEAP is integral to the EU's 2050 net-zero target. The current results support this assertion, indicating that core circular economy interventions, such as eco-design, recycling, and reuse, operate as systemic catalysts for the use of clean energy across diverse member states.

Second, the highest elasticities are identified at higher quantile points, indicating a late-stage advantage: EU nations that rely more on renewable energy sources gain more from an equivalent percentage enhancement in CE. This could be attributed to the fact that developed clean energy markets are better equipped to leverage benefits from positive investments or regulations related to the circular economy. In contrast, nations with a low share of renewable energy in their energy mix might encounter fundamental challenges, yet still experience positive effects. From a policy perspective, developed renewable markets could experience particularly significant returns from additional investments in circular economy practices, including material efficiency and innovations linked to renewable resources.

Third, the results imply that circular economy investments serve as a compelling catalyst for conducting the renewable transition process. For EU countries with advanced clean energy sectors, CEI enhancements appear to translate into stronger proportional growth in renewables. This suggests a staged approach to sustainability policy: while all countries benefit from advances in the circular economy, countries with more developed renewable energy may have accelerated gains. Policymakers might leverage this by tailoring CE policies (e.g., eco-design standards, waste-to-energy projects) to support countries lagging in renewables, helping to accelerate the EU's overall clean energy transition.

By uncovering quantile-specific heterogeneity, the MMQR analysis goes beyond the traditional mean-based analysis. Earlier mean regression analyses reported only average effects of CEI on renewables in Europe, whereas our approach shows that the marginal impact of CEI^{+} varies with a country's renewable baseline. Circular economy improvements significantly boost clean energy, with the most considerable proportional impacts in countries that have higher initial levels of renewable energy adoption. These results are in line with Kandpal et al. [66], who concluded that the circular economy practices enhance resource efficiency, minimize waste, and stimulate innovation, thereby contributing to energy transition. The results further support the predictions of socio-technical transition theory, indicating that the circular economy acts as an accelerator of the energy transition. In this context, socio-technical transitions are understood as complex, long-term, and multidimensional processes through which existing production and consumption systems evolve toward more sustainable structures. The findings also corroborate the ecological modernization theory, which advocates integrating environmental issues into the core of economic and industrial systems by deploying sustainable technologies and adopting circular economy practices.

4.4.2. Impact of Negative Shocks in CEI on Clean Energy Adoption

Model 2 estimates reveal a complex, asymmetric pattern for negative CEI shocks. In the lower tail of the clean energy distribution, negative CEI disturbances (CEI^{-}) are associated with declines in renewable energy. In contrast, in the upper tail, they paradoxically coincide with modest gains. For example, at the 10th quantile, a 1% drop in CEI corresponds to a 0.155% reduction in renewables (i.e., a relatively large negative effect), whereas at the 90th quantile, the coefficient is +0.097 (i.e., a relatively small positive effect). This shift from negative to positive effects across quantiles is statistically significant in the lower (10th–30th) and upper (70th–90th) ranges, with a transitional neutral zone around the median. These asymmetric results highlight that CEI downturns harm the clean energy shares of some countries far more than others. Key observations from the negative shock results include:

Lower quantiles (10th–30th): In countries with low initial renewable penetration (10th–30th quantiles), CEI decreases damage to clean energy outcomes. A 1% CEI drop yields approximately a 0.155% decline in renewables at the 10th quantile, and remains at −0.072% at the 30th quantile. This suggests that nascent clean energy systems are vulnerable to backsliding when efforts to establish a circular economy weaken. In practice, emerging renewable markets may depend on continued resource efficiency and material flow innovations. Any decline in circular activities can set these countries back proportionally more.

Middle quantiles (40th–60th): Between roughly the 40th and 60th quantiles, the negative CEI coefficients shrink toward zero and lose statistical significance (e.g., −0.011 at the median). In this range, countries with moderate renewable energy integration exhibit a "transition zone" where adverse CEI shocks neither harm nor benefit clean energy. This could reflect a balancing point, as nations with average renewable energy use have enough infrastructure to partially absorb shocks, but not so much reliance that a slight change in the CEI dominates their trajectory.

Higher quantiles (70th–90th): Surprisingly, in the highest renewable quantiles (70th–90th), adverse CEI shocks are associated with slight increases in clean energy. At the 90th quantile, the CEI^{-} coefficient is +0.097, suggesting that a decline in CEI induces a marginal rise in renewables. One speculative interpretation is resource reallocation: highly advanced clean energy economies might offset a circular economy downturn by reorienting investments directly into renewable sectors, or by accelerating alternative sustainability initiatives. This result may also indicate that countries with advanced clean energy adoption have flexible systems that maintain (or even boost) renewables despite minor disruptions in circular economy practices.

Overall, the asymmetric effects of CEI^{-} reveal different responses depending on a country's clean energy stage. Countries with low renewable energy shares experience adverse impacts from declines in the CEI, reinforcing the idea that reduced circular activity can impede clean energy growth. In contrast, countries with high renewable penetration appear resilient due to more diversified and mature sustainability strategies. These findings suggest non-uniform impacts of the circular economy. Ref. [52] found that CE initiatives could dampen specific environmental quality indicators (like biodiversity) at the regional level. Our results likewise underscore that CEI shocks do not translate into uniform environmental outcomes. Practically, these results suggest that the EU nations should ensure the continued advancement of circular economy efforts in countries with emerging renewable sectors, given their heightened exposure to adverse shocks on the circular economy.

Figure 5 presents a summary of the estimated MMQR coefficients for positive (CEI^{+}, in light blue) and negative (CEI^{-}, in orange) circular economy shocks across nine quantiles

of the dependent variable. The findings demonstrate a consistently positive impact of positive circular economy shocks (CEI^+) on energy transition throughout all quantiles, with coefficients increasing from 0.771 at the lowest quantile to 0.796 at the highest quantile. This result indicates that enhancements in the circular economy promote energy transition, irrespective of the stage of the transition process. The impact of negative shocks (CEI^-) exhibits variation in magnitude throughout the distribution. The most adverse effects are observed in the lower quantiles (10th to 30th), suggesting that nations with less developed energy transition processes face detrimental consequences from declines in circular economy progress. In the upper quantiles, the effect turns positive. Overall, the asymmetry between CEI^+ and CEI^- highlights the varying impact of circular economy dynamics on the energy transition in European countries.

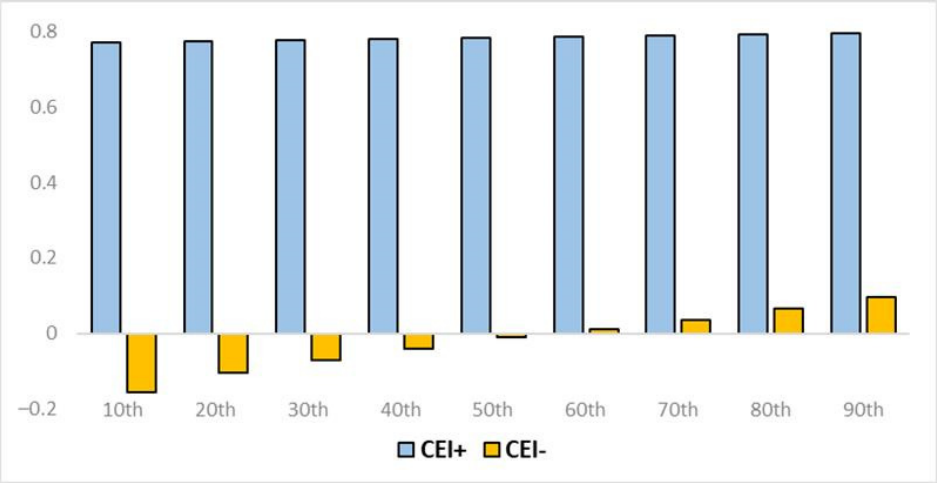


Figure 5. Asymmetric effects of CEI^+ and CEI^- on energy transition across quantiles.

4.4.3. Effect of Control Variables on Clean Energy Adoption

Finally, we examine how control variables behave across the clean energy distribution to ensure omitted factors do not drive findings. Each control has a significant quantile-specific pattern:

GDP: We find a negative association between GDP per capita and the share of renewable energy across all quantiles. This suggests that faster GDP puts pressure on sustainability, perhaps because expanding economies tend to consume more energy before cleaner technologies can catch up. Interestingly, the influence of GDP weakens at upper quantiles of the clean energy distribution, suggesting that more developed economies tend to implement institutional frameworks and adopt green technologies that facilitate the decoupling of economic growth from environmental harm.

FDI: FDI shows a consistently small adverse effect on renewables. This pattern may be attributed to the fact that incoming investment is often channeled into energy-intensive sectors, which slightly increases energy demand. The negative impact is relatively uniform across quantiles, although it intensifies marginally at higher renewable levels, indicating that even green governance can be challenged by large capital inflows.

Employment: Employment has a positive influence on renewable energy in Model II, with its impact increasing as the quantiles rise. This pattern suggests that labor markets that foster green jobs support the adoption of clean energy. In countries with advanced renewable energy systems, each percentage point of employment appears to yield larger gains in renewables, perhaps because they capitalize on a skilled workforce in renewable energy sectors and innovation. This finding is consistent with the EU experience, which shows that an expanding renewable energy industry creates more jobs. For example, the

European Commission notes that increasing the renewable share "will also benefit citizens by creating new job opportunities" across various sectors.

Trade Openness: In Model I, trade openness positively correlates with clean energy, with effects tapering at higher quantiles. This aligns with the role of trade in spreading green technologies: open trade networks allow countries to import advanced renewable technologies and export sustainable products. In fact, studies have noted that trade integration can facilitate the transfer of cleaner technologies and practices, which can improve resource management and support renewable adoption. Hence, more open economies tend to have higher renewable shares, although the incremental benefit diminishes for the most renewable-rich countries.

Population: Population size shows a positive effect on renewables in Model I. This might seem counterintuitive at first, but it suggests that larger populations may drive greater absolute investment and innovation in renewables, especially when other conditions (like income or policy) are favorable. The rising influence observed at higher quantiles suggests that nations characterized by large populations and proactive environmental policies effectively harness human capital and innovation to enhance sustainable development outcomes.

4.5. Robustness Check

To validate the robustness of our findings and address potential methodological concerns, we complement the MMQR estimation with four alternative econometric approaches: Dynamic Ordinary Least Squares (DOLS), Fully Modified Ordinary Least Squares (FMOLS), Instrumental Variable Two-Stage Least Squares (IV-2SLS), and High-Dimensional Fixed Effects (HD-FE) regressions. These techniques serve distinct purposes in verifying our core results while explicitly addressing endogeneity and unobserved heterogeneity concerns. The DOLS and FMOLS approaches assess long-run associations between circular economy shocks and renewable energy development, while the IV-2SLS and HD-FE models specifically address potential endogeneity and unobserved heterogeneity. The HD-FE estimator, in particular, controls for a comprehensive set of fixed effects that absorb time-invariant country-specific characteristics, thus mitigating concerns about unobserved heterogeneity. The results are summarized in Table 7.

The consistency of results across these diverse methodologies reinforces the credibility of our empirical findings. Specifically, positive shocks to the circular economy index (CEI^{+}) exhibit a robust and statistically significant positive influence on renewable energy adoption across all estimation methods, with coefficients remaining stable between 0.213 and 0.221 in the cointegration models and 0.039 in the HD-FE specification. The attenuation in magnitude within the HD-FE model suggests that some portion of the observed relationship may be attributed to time-invariant country characteristics. Nevertheless, the effect remains economically and statistically significant. For negative CEI shocks (CEI^{-}), the results demonstrate greater variability across specifications, with coefficients ranging from -0.238 in DOLS to -0.054 in HD-FE. This pattern aligns with the heterogeneous effects identified in the MMQR analysis. It suggests that the impact of negative circular economy shocks is more context-dependent and potentially mediated by unobserved country-specific factors. The HD-FE results are particularly informative for addressing unobserved heterogeneity concerns, as this estimator controls for all time-invariant country characteristics. The fact that both positive and negative CEI shocks remain statistically significant in this stringent specification provides compelling evidence that the circular-economy–clean-energy relationship is not merely an artifact of omitted variable bias. Furthermore, the IV-2SLS results, which instrument for potential reverse causality, confirm the robustness of our findings to endogeneity concerns. The consistency between IV-2SLS and other estimators

suggests that reverse causality, while a theoretical concern, does not substantially alter our core conclusions about the circular-economy–clean-energy relationship.

Table 7. Alternative estimation techniques results.

	DOLS		FMOLS		IV-2SLS		HD-FE		COVID-19		Russia-Ukraine Conflict	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
CEI^{+}	0.213 ***		0.221 ***		0.218 ***		0.039 ***		0.117 ***		0.144 ***	
	[0.080]		[0.076]		[0.009]		[0.007]		[0.018]		[0.032]	
CEI^{-}		−0.238 *		−0.338 **		−0.056 ***		−0.054 ***		−0.248 ***		−0.072 **
		[0.124]		[0.133]		[0.010]		[0.010]		[0.023]		[0.035]
GDP	−0.044	−0.05	−0.070 *	−0.06	−0.043 ***	−0.200 ***	−0.194 ***	−0.199 ***	−0.456 ***	−0.465 ***	0.014	0.073
	[0.044]	[0.043]	[0.042]	[0.046]	[0.005]	[0.013]	[0.013]	[0.013]	[0.040]	[0.038]	[0.058]	[0.057]
FDI	−0.182 ***	−0.183 ***	−0.349 ***	−0.313 ***	−0.175 ***	−0.019 ***	−0.021 ***	−0.019 ***	−0.006 ***	−0.004 **	−0.015 ***	−0.016 ***
	[0.036]	[0.035]	[0.034]	[0.037]	[0.004]	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]	[0.003]	[0.003]
EMP	1.758 ***	1.844 ***	2.271 ***	2.207 ***	1.748 ***	0.621 ***	0.574 ***	0.614 ***	0.507 ***	0.381 ***	0.791 ***	0.626 ***
	[0.352]	[0.341]	[0.337]	[0.367]	[0.042]	[0.032]	[0.033]	[0.032]	[0.081]	[0.077]	[0.133]	[0.136]
TO	−0.932 ***	−0.890 ***	−1.017 ***	−0.918 ***	−0.929 ***	0.198 ***	0.207 ***	0.203 ***	0.148 ***	0.198 ***	−0.106 ***	−0.124 ***
	[0.098]	[0.095]	[0.094]	[0.102]	[0.012]	[0.012]	[0.012]	[0.012]	[0.024]	[0.023]	[0.022]	[0.023]
POP	−0.142 **	−0.123 **	−0.166 ***	−0.138 **	−0.141 ***	1.130 ***	1.128 ***	1.119 ***	2.455 ***	2.368 ***	0.513 ***	0.647 ***
	[0.057]	[0.055]	[0.054]	[0.059]	[0.007]	[0.024]	[0.023]	[0.024]	[0.143]	[0.136]	[0.113]	[0.109]
Obs.	4533	4533	4535	4535	4509	4509	4536	4536	972	972	648	648

Notes. Standard errors in brackets. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To control for major global shocks, we exclude the COVID-19 pandemic (2019–2021) and the Russia–Ukraine conflict (2022–2023) in all model specifications. The results remain qualitatively consistent after excluding these years, confirming the robustness of our main findings. These robustness checks collectively enhance confidence in our empirical strategy while acknowledging the complex nature of the relationships under study. The persistent significance of circular economy across methodologies addressing various econometric concerns strengthens the case for a substantial relationship between circular economy practices and clean energy adoption in the EU context.

4.6. Heterogeneous Panel Causality Analysis

The results of the heterogeneous panel Granger non-causality test, as implemented following the methodology of [67,68] and reported in Table 8, reveal complex causal linkages between renewable energy adoption and key macroeconomic variables within the European Union. The results underscore both reciprocal and directional causality pathways that significantly shape the region's transition toward sustainable energy systems.

Bidirectional causality: Evidence of bidirectional causality is observed between renewable energy and variables such as gross domestic product (GDP), foreign direct investment (FDI), employment (EMP), and population (POP). This mutual influence indicates dynamic feedback loops wherein economic development promotes clean energy expansion—likely through targeted investments in low-carbon infrastructure and innovation—while increased renewable energy deployment contributes to long-term economic growth. The highly significant *p*-values ($p = 0.0000$ for both directions) support the existence of a reinforcing cycle consistent with the Environmental Kuznets Curve (EKC) hypothesis, which posits that environmental conditions improve in advanced economic stages due to strengthened institutions and technological advancement.

Unidirectional causality: The test results also identify several one-way causal relationships. Specifically, positive shocks in the Circular Economy Index (CEI^+) significantly influence renewable energy deployment ($p = 0.0000$), affirming the proactive role of circular economy practices—such as recycling, eco-innovation, and material reuse—in accelerating clean energy transitions. Conversely, a unidirectional causal link is detected from renewable energy to negative CEI shocks (CEI^-), with statistical significance at $p = 0.0004$. This suggests that strong performance in renewable energy may act as a buffer against regression in circular economy activities, possibly through institutional reinforcement or behavioral shifts favoring sustainability.

Table 8. Panel Granger Causality Outcomes.

H_0	Wald Test	Prob	Conclusion
CEI^+ does not Granger-cause CLEAN	104.0123	0.0000	One-way causality
CLEAN does not Granger-cause CEI^+	2.0960	0.1477	
CEI^- does not Granger-cause CLEAN	2.4816	0.1152	One-way causality
CLEAN does not Granger-cause CEI^-	12.3576	0.0004	
GDP does not Granger-cause CLEAN	181.3812	0.0000	Two-way causality
CLEAN does not Granger-cause GDP	192.1882	0.0000	
FDI does not Granger-cause CLEAN	9.5842	0.0020	Two-way causality
CLEAN does not Granger-cause FDI	8.8671	0.0029	
EMP does not Granger-cause CLEAN	52.1987	0.0000	Two-way causality
CLEAN does not Granger-cause EMP	171.6536	0.0000	
TO does not Granger-cause CLEAN	28.2672	0.0000	Two-way causality
CLEAN does not Granger-cause TO	3.0114	0.0827	
POP does not Granger-cause CLEAN	5.6344	0.0176	Two-way causality
CLEAN does not Granger-cause POP	12.4801	0.0004	

5. Concluding Remarks

5.1. Conclusions

The European Union's strategic objective of attaining climate neutrality by 2050 has increased the need for sustainable economic models that address both environmental degradation and energy security concerns. Although renewable energy technologies are widely acknowledged as central to mitigating climate change, the contribution of circular economy principles to advancing clean energy transitions remains empirically underexplored. This study addresses this gap by examining the asymmetric impacts of the circular economy on clean energy development across 27 EU nations during the 2010–2023 period. As a first contribution to the existing literature, this study develops a Circular Economy Index based on the entropy-weighted composite method, which allows avoiding critical shortcomings in single-metric approaches. Furthermore, the study employs the MMQR approach to check for potential distributional heterogeneity in how circular economy dynamics affect renewable energy expansion. The study further contributes to the literature by being the first to investigate the asymmetric impact of the circular economy on clean energy adoption, an area overlooked in prior research.

The findings indicate significant asymmetry in the influence of CEI shocks. Positive CEI shocks are associated with progressively larger coefficients in higher quantiles of the clean energy distribution, rising from 0.771 at the 10th quantile to 0.796 at the 90th. This pattern is consistent with the presence of a "sustainability amplification effect," wherein countries already advanced in renewable energy adoption may be better positioned—potentially due to institutional maturity and technological infrastructure—to realize additional gains

from circular economy enhancements. However, the causal mechanisms warrant further investigation. Negative CEI shocks demonstrate complex, heterogeneous impacts across the clean energy distribution. Lower-quantile countries (10th-30th) experience statistically significant negative associations with clean energy outcomes, while higher-quantile countries (70th-90th) show positive coefficients. This pattern, although counterintuitive, may indicate that advanced clean energy economies have adaptive mechanisms or alternative resource pathways that help mitigate circular economy setbacks. Control variables demonstrate nuanced roles in the CEI–clean-energy relationship. GDP effects vary across quantiles, with negative impacts diminishing at higher clean energy levels, which may reflect structural differences in how advanced economies integrate economic growth with environmental objectives. FDI shows increasingly negative associations at higher quantiles, potentially indicating challenges in maintaining clean energy standards during periods of foreign investment inflows.

This study contributes to the growing body of literature on the relationships between the circular economy and clean energy by providing a comprehensive analysis of asymmetries within the EU context. The findings demonstrate that the relationship between circular economy practices and clean energy adoption exhibits considerable complexity and heterogeneity across the conditional distribution. As the EU continues its efforts in circular economy implementation and clean energy transition, understanding these distributional relationships becomes increasingly relevant for evidence-based policy development.

5.2. Policy Implications

The findings offer several considerations for the governance of the environment and clean energy policy within the European Union. The asymmetric effects and quantile-specific patterns suggest that strategies considering the existing clean energy capacities of individual countries may be more effective than a uniform approach. Consequently, policy implementation should take into account the specific institutional contexts and capacities of each country.

The heterogeneous effects across quantiles suggest that policy effectiveness may vary depending on countries' existing clean energy capacity. European countries with more advanced clean energy systems may respond differently to circular economy interventions than those with emerging renewable energy sectors. Policy design might consider these differential initial conditions, with higher-performing nations benefiting from policies that build on existing infrastructure and institutions. In countries at earlier stages of the clean energy transition, foundational capacity-building, including institutional development, technological infrastructure, and policy coherence, may be necessary before the benefits of circular economy initiatives on energy transition can be fully realized. These insights are particularly applicable to European countries with low renewable energy reliance, as well as to many other countries worldwide that share similar developmental, infrastructural, and policy challenges. Adapting circular economy strategies to these contexts can effectively support their progression toward sustainable energy systems.

Policy frameworks might also incorporate adaptive policies that help countries manage disruptions to circular economy investments, particularly as the EU works toward European Green Deal targets and climate neutrality by 2050. The specific mechanisms for building such resilience may vary across member states based on their institutional capacities and governance structures. The complex relationships between clean energy outcomes and economic factors observed in this study underscore the potential value of policy approaches that consider interdependencies between circular economy practices, clean energy adoption, and economic development. Instead of handling these domains separately, policymakers should consider integrated frameworks that address cross-domain spillovers and feedback

effects. Such integration should be pursued cautiously, recognizing that the strength and direction of these relationships may vary across different national contexts and over time.

The counterintuitive findings regarding negative CEI shocks in some contexts suggest that the circular-economy–clean-energy relationship may operate through multiple, potentially compensating pathways. This complexity implies that rigid policy frameworks may be less effective than adaptive approaches that allow for country-specific implementation strategies. Policymakers should pay attention to how circular economy and clean energy policies interact within their specific institutional environments and be prepared to adjust interventions based on observed outcomes and changing circumstances. These policy considerations require translation into context-specific interventions rather than uniform prescriptions applicable across all EU member states. The heterogeneous institutional capacities, regulatory traditions, and economic structures across the EU necessitate careful adaptation of these principles to local conditions. Future policy development would benefit from complementary qualitative research, stakeholder engagement, and pilot programs to assess the applicability of these insights across diverse national contexts.

While the study concentrates on the European Union, the findings hold relevance for other regions. For developed nations outside the European Union, policy efforts should focus on optimizing existing clean energy infrastructures through Circular Economy innovations. For developing nations, policymakers should prioritize institutional reinforcement, technology transfer, and capacity development to ensure that Circular Economy Initiatives effectively promote a clean energy transition.

5.3. Limitations and Future Research Directions

Although this study provides empirical insights into the relationships between the circular economy and clean energy, several limitations should be acknowledged. First, this study is constrained to EU countries from 2010 to 2023 due to data availability. The temporal coverage, while capturing recent trends, may not fully reflect longer-term dynamics or structural breaks that could influence the circular-economy–clean-energy relationship. The geographic focus on the EU, though appropriate for addressing regional policy questions, limits generalizability to other economic and institutional contexts. Future research incorporating extended historical datasets and broader geographical coverage, including other regional blocs and developing economies, would provide valuable comparative insights. Second, although the MMQR method accounts for heterogeneity across the conditional distribution, certain forms of unobserved heterogeneity may persist. Country-specific cultural factors, political events, and institutional quality are difficult to capture in quantitative models. While our modeling approach partially accounts for time-invariant country characteristics, unobserved time-varying factors remain a limitation of the analysis. Mixed methods research combining quantitative analysis with case studies could provide deeper insights into these contextual factors. Third, the construction of the CEI composite index, while useful for capturing multidimensional concepts, may introduce measurement uncertainty and potential aggregation bias. Cross-country data comparability issues, differences in national statistical methodologies, and the challenge of capturing informal circular economy activities represent inherent limitations in comparative studies. Finally, while this investigation examines the effects of key economic and demographic variables (GDP, population, trade openness, FDI, and employment) on clean energy transition, other potentially relevant factors remain unexplored. Institutional quality indicators, technological innovation, environmental regulations, political stability, and educational attainment could provide additional explanatory power. Subsequent studies incorporating these dimensions could offer a more comprehensive understanding of the mechanisms linking circular economy practices to clean energy adoption.

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