

Article

The Criticality of the Digital Economy in Environmental Sustainability: Fresh Insights from a Wavelet-Based Quantile-on-Quantile Approach

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Abstract: Achieving environmental sustainability has become an urgent priority in the era of rapid digital economic expansion, which presents both opportunities and challenges for environmental sustainable development. This study investigates the impact of digital economy (DIE) on environmental sustainability (ENS) through the dual dimensions of digital industrialization (DII) and industrial digitalization (IND), employing the wavelet-based quantile-on-quantile regression method to capture both quantile dependencies and temporal variations. The results reveal that DIE positively impacts ENS in the long term, while its short-term effects are mixed, with positive effects at lower and higher quantiles but negative impacts at mid-range quantiles of [0.35–0.45] and [0.65–0.7]. Specifically, DII exerts a predominantly negative short-term effect on ENS due to the environmental costs of digital infrastructure expansion, but turns positive in the long term as digital industrialization matures, especially in [0.85–0.95]. IND, conversely, exerts a consistently positive impact on ENS in both short- and long-term scenarios, highlighting its role in enhancing industrial efficiency and reducing emissions. These results emphasize the need for targeted policies, including prioritizing industrial digitalization, developing green infrastructure, and adopting phased digital development strategies to maximize environmental benefits.

Keywords: digital economy; environmental sustainability; industrial digitalization; digital industrialization; wavelet-based quantile on quantile method



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1. Introduction

Amid escalating resource depletion and intensifying climate crises, environmental sustainability has become a critical concern on the global agenda [1–4]. The deterioration of the economic, environmental, and social pillars of sustainability threatens the stability of natural ecosystems, global economies, and societal well-being, highlighting the urgency of advancing sustainable development goals (SDGs) [5,6]. In this context, international policy frameworks and management strategies have increasingly centered on mitigating the long-term environmental and societal impacts of human activities through coordinated global efforts [7,8]. Concurrently, the rapid progression of the digital revolution has prompted a paradigm shift in sustainability discourse, positioning digitalization as a transformative

force capable of addressing complex sustainability challenges. Researchers and policy-makers have recognized the strategic role of digital technologies in fostering sustainable development through enhanced data-driven decision-making, process optimization, and resource efficiency [9,10]. Digital technologies, characterized by their high penetration across sectors, capacity for value creation, and potential to drive long-term sustainability transitions, are increasingly perceived as indispensable enablers of a sustainable future [11]. Therefore, comprehensively understanding digitalization's impact on sustainable development is crucial in designing innovative solutions that promote environmental sustainability (ENS) in the digital era.

As digital technologies become deeply integrated into economic and social development processes, the digital economy (DIE) has emerged as a key global driver of sustainable growth, reshaping industries and transforming societal functions [12,13]. The unique attributes of the digital economy, such as enhanced connectivity, real-time data processing, and automation, enable enterprises and industries to address sustainability challenges with greater precision and efficiency [14,15]. By facilitating streamlined operations, reducing resource consumption, and optimizing supply chain management, digital technologies play a pivotal role in enhancing environmental performance and promoting economic resilience [16,17]. In addition, the digital economy fosters innovation by enabling businesses to adapt rapidly to evolving market dynamics, encouraging the development of sustainable business models, products, and services [18]. This dynamic environment supports eco-friendly innovations such as smart grids, energy-efficient manufacturing, and digital agriculture, which contribute to reducing environmental footprints while ensuring economic productivity. For example, digital technologies enable the large-scale deployment and intelligent management of renewable energy systems, improving energy efficiency and reducing carbon emissions [19,20]. Moreover, the digital economy generates new employment opportunities by creating jobs in emerging digital sectors while supporting entrepreneurship through digital platforms and e-commerce ecosystems. This dual effect promotes inclusive economic growth, empowering countries to progress toward achieving the SDGs [21]. In this context, exploring digital solutions is crucial in analyzing global sustainability challenges and informing evidence-based policy decisions [22].

This study conducted an in-depth analysis of China to investigate the intricate relationship between the digital economy and environmental sustainability. As the world's second-largest economy and a major contributor to global carbon emissions, China occupies a critical position in global sustainability discourse. Its unique development trajectory, characterized by rapid industrialization, technological advancement, and pressing environmental challenges, provides a valuable context for examining how digital transformation can drive sustainable development. Furthermore, the findings offer broader implications for economies navigating similar sustainability transitions through digital innovation. Currently, the digital economy, powered by interconnected, digital, and intelligent technological tools, holds the potential to transform pollution-intensive sectors by enabling structural upgrades, enhancing resource efficiency, and reducing environmental footprints. In China, the digital economy has rapidly evolved into a critical driver of economic growth and sustainability efforts. By 2021, its market size had reached RMB 45.5 trillion, accounting for 39.8% of the country's GDP, underscoring its growing significance in national economic development (the data are sourced from the *China Digital Economy Development Report* (2022)). Despite these advancements, China continues to grapple with deep-rooted structural challenges that impede its transition toward sustainable development. As the world's largest emitter of carbon dioxide, China faces mounting pressure to decouple economic growth from environmental degradation. In 2021, only 64.3% of its cities met air quality standards, reflecting persistent environmental concerns. Moreover, China's economic trajec-

tory is constrained by a shrinking demographic dividend, tightening resource availability, and complex global economic dynamics, which complicate its sustainable development goals [23]. Therefore, exploring the influence of the digital economy on environmental sustainability can contribute to achieving sustainable development in China. In addition, the findings also provide a systematic framework for understanding the role of the digital economy in achieving sustainable development, which can be extended to other countries facing similar development trajectories.

This paper contributes to the existing research in the following ways. First, existing studies in the field of the digital economy currently tend to be confined to a single perspective, either focusing on the macro-level development of the digital economy as a whole or solely on the micro-level applications of digital technology [24]. Few studies have delved deeper into the level of deep integration between technology and industry to comprehensively assess its far-reaching impact on environmental sustainability [25,26]. This gap hinders a holistic understanding of how digital transformation affects environmental outcomes. To address this, we aimed to broaden the research framework to encompass the dual dimensions of digital industrialization (DII) and industrial digitalization (IND). This distinction allowed a deeper examination of how technological infrastructure development and digital technology adoption in industrial processes influence environmental sustainability. Unlike prior studies that rely on aggregate digital economy metrics, this approach enabled a more precise evaluation of digital economy-environment dynamics. Through comparative analysis, it evaluated the different pathways and effects of these two dimensions in empowering environmental sustainability, aiming to offer new theoretical perspectives and practical guidance for promoting the harmonious coexistence of the digital economy and environmental protection [27].

Second, previous literature on the response of sustainable development to the digital economy has primarily been limited to examining its direct reaction to the original sequence of DIE, overlooking the possibility of differentiated impacts across different time scales [28,29]. This temporal limitation restricts the understanding of long-term versus short-term dynamics. To overcome this, we innovatively introduced the multiscale wavelet decomposition technique to capture high-frequency and low-frequency components of series, providing a detailed analysis of the dynamic correlation between DIE and ENS in short- and long-term trends [30]. The findings provide policymakers with a more comprehensive and detailed basis for decision-making, enabling them to formulate more forward-looking and targeted policies based on economic cycles and long-term environmental protection goals.

Third, current literature overlooks the diverse effects that varying levels of digitalization can have on environmental sustainability, assuming a uniform impact regardless of economic conditions. This simplification masks potential asymmetries, which highlights a notable void in the research landscape that demands attention. In response, this study employed an advanced quantile-on-quantile regression (QQR) method to deeply explore the asymmetry in the structured dependency between the digital economy and environmental sustainability under different economic and environmental conditions [31]. This method cleverly combined the flexibility of non-parametric estimation with the robustness of standard quantile regression, allowing for precise examination of the impact of the independent variable on the conditional mean of the dependent variable at specific quantiles [32]. Therefore, by addressing these critical research gaps, the findings can provide a solid scientific basis for the targeted policy formulation in environmental protection and economic development, contributing to the achievement of environmental sustainability goals in the context of the digital era.

This paper proceeds as follows. Section 2 outlines the literature review. The methodology is presented in Section 3. Section 4 shows the corresponding data and discusses the empirical results. Section 5 presents concluding remarks.

2. Literature Review

The relationship between the digital economy and sustainable development has garnered extensive scholarly attention, yet key debates and gaps persist [7,24]. Several studies emphasize the transformative role of digital technologies in enhancing cost efficiency, enabling data-driven decision-making, and optimizing resource allocation, which collectively advance sustainability goals [13,28,33]. Specifically, digital tools reduce transaction costs, improve market efficiency, and streamline supply chains, thereby minimizing environmental footprints [34]. For instance, digital platforms facilitate energy-saving practices in manufacturing and logistics, reducing emissions and waste [35]. Treating data as a core production factor reduces reliance on resource-intensive processes, contributing to sustainability [11]. For example, the use of digital technologies to optimize energy consumption in manufacturing and logistics can result in significant reductions in greenhouse gas emissions and overall energy usage [35]. Additionally, by integrating fragmented data across various sectors, such as demand and supply chains, market trends, and resource usage, the digital economy reduces information asymmetry and lowers the search costs associated with finding relevant data. This streamlined flow of information enhances decision-making processes, enabling businesses to better manage resources and environmental impacts. Through the adoption of data-driven models, companies can identify inefficiencies, reduce waste, and make more informed, sustainable choices [9]. This optimization leads to more efficient resource allocation and supports environmental sustainability [15,36]. Recent studies extend this perspective by examining sector-specific impacts of digitalization, including agriculture and urban systems. For example, He et al. (2025) investigate the role of digitalization in reducing carbon emissions within animal husbandry, demonstrating that digitalization technologies provide new solutions for sustainable development [37]. Guo et al. (2024) decompose urban green productivity growth in China, highlighting digitalization's capacity to enhance resource efficiency and promote low-carbon urbanization [38].

On the other hand, existing studies emphasize the digital economy's significant contribution to sustainable development via its innovation effects [18,39]. Digital technologies' high permeability accelerates knowledge innovation and spillover, stimulating green innovation and sustainable technology development [29]. Sorescu and Schreier (2021) argue that digitalization fosters technological innovation and industrial structure upgrading, driving sustainable growth [40]. Furthermore, digital technologies enable intelligent environmental monitoring and protection, such as using bio-sensors, infrared sensors, and satellite remote sensing for timely and efficient pollutant management, enhancing ecological protection and sustainability [2,41].

However, some studies argue that digitalization does not always yield positive outcomes for environmental sustainability [41,42]. The widespread adoption of digital technologies has the potential to exacerbate carbon emissions, as the expansion of digital infrastructure is often accompanied by increased energy consumption, thereby posing challenges to energy sustainability [43]. Specifically, the proliferation of digital technologies and the associated infrastructure—such as the installation of servers, data centers, and communication networks—demands substantial energy inputs, which may undermine efforts to achieve sustainable energy systems [44,45]. Moreover, the production, deployment, and dissemination of digital infrastructure frequently involve the use of hazardous materials, which not only contribute to the emission of harmful pollutants but also lead to a deterioration in environmental quality [46]. For instance, Shabani and Shahnazi (2019)

estimate that the manufacturing of digital devices alone accounts for approximately 2% to 3% of global greenhouse gas emissions [25]. In addition, the continuous operation and maintenance of digital infrastructure, including data processing and storage facilities, result in persistent emissions that may lead to long-term environmental degradation [7,47]. These findings highlight the paradoxical relationship between digitalization and environmental sustainability, underscoring the need for further investigation into the complex impacts of digital technologies on supporting sustainable development.

While prior research demonstrates the multifaceted impacts of digitalization on sustainability, several limitations persist. First, most studies focus on aggregate impacts of digitalization, overlooking sub-components such as digital industrialization and industrial digitalization, which have divergent effects on environmental outcomes. For instance, DII's infrastructure expansion initially increases energy use, whereas IND might improve efficiency and reduces emissions. This differentiation is underexplored in the existing literature, which is crucial for developing effective and precise digital solutions for sustainable development. To address the gap, this study developed a dual-dimensional framework that distinguishes the effects of DII and IND, offering a more precise understanding of how each dimension uniquely contributes to environmental sustainability. Second, temporal dimensions are often neglected, as existing studies typically assume static relationships between digitalization and sustainability. In contrast, our study employed a multiscale wavelet decomposition approach to disentangle short- and long-term effects, addressing the need for time-sensitive policy insights. Third, most prior work adopts linear models, assuming uniform effects of digitalization across economic and environmental conditions, which overlooks nonlinear dependencies and heterogeneous impacts across different conditions. Building on this insight, our research employed the QQR method, which captures asymmetries and nonlinearities, providing a more granular analysis of dependencies between digital economy and environmental sustainability.

3. Wavelet-Based Quantile on Quantile Regression Method

This study employed a wavelet-based QQR approach to capture nonlinear, asymmetric, and time-varying relationships between the digital economy and environmental sustainability. On the one hand, by integrating wavelet transformations, we decomposed the data into multiple frequency domains, enabling the detection of short- and long-term effects. This temporal analysis is crucial in identifying dynamic transitions in environmental responses to digitalization, which are often overlooked by traditional regression techniques. On the other hand, based on the QQR method, we examined nonlinear dependencies across quantile distributions, capturing heterogeneous effects that depend on both the levels of digitalization and environmental sustainability.

3.1. Wavelet Decomposition Method

First, to filter the inherent analytical insights and derive precise conclusions, this study integrated the QQR approach with the multiscale wavelet decomposition technique. This involves subjecting the time-series data of a given variable to wavelet analysis, which operates across both temporal and spectral domains. This approach enabled us to address the non-stationary nature of time series by identifying data associated with temporal intervals and positions [30]. Similarly, the nonparametric characterization of each time series can be accomplished by decomposing the data into orthogonal temporal segments. Consequently, the wavelet is split into two components and subsequently transformed through the application of functions φ and ψ :

$$\int^{\varphi}(t)dt = 1 \quad (1)$$

$$\int^{\psi}(t)dt = 0 \quad (2)$$

where φ denotes the father wavelet, recording the low-frequency (smooth) components, while ψ denotes the mother wavelet, providing the high-frequency (detailed) components of series. Consequently, the resultant wavelet can be represented based on the formulations:

$$\varphi_{j,k}(t) = 2^{j/2}\varphi(2^j t - k) \quad (3)$$

$$\psi_{jk}(t) = 2^{j/2}\psi(2^j t - k) \quad (4)$$

where j , which ranges from 1 to J , corresponds to the scale level, while $k = 1, \dots, 2^j$ denotes the subsequent translation step. Notably, the upper limit of scale levels is constrained by the number of observations ($T \geq 2^j$).

3.2. Quantile-on-Quantile Regression

Following Sim and Zhou (2015) [31], the QQR methodology integrates the conventional quantile regression approach with non-parametric techniques, thereby enhancing the conventional quantile regression model. Unlike the conventional ordinary least squares method, QQR offers a robust means to encapsulate the inherent asymmetry of response variables within various distributions. The QQR framework is based on the following non-parametric quantile regression equation:

$$ENS_t = \beta^{\varphi} DIE_t + \xi_t^{\varphi} \quad (5)$$

where ENS_t represents environmental sustainability, and DIE_t denotes digital economy. Furthermore, φ is marked as the conditional φ th quantile distribution of ENS_t . ξ_t^{φ} denotes the quantile error term with the φ th conditional quantile being 0. An unidentified function $\beta^{\varphi}(\cdot)$ arises due to the lack of a priori information linking DIE_t and ENS_t . Consequently, a first-order Taylor expansion centered at DIE^{τ} is employed to linearize $\beta^{\varphi}(\cdot)$, thereby facilitating the resolution of the given equation:

$$\beta^{\varphi}(DIE_t) \approx \beta^{\varphi}(DIE^{\tau}) + \beta^{\varphi'}(DIE^{\tau})(DIE_t - DIE^{\tau}) \quad (6)$$

where $\beta^{\varphi'}$ signifies the partial derivative with respect to $\beta^{\varphi}(DIE)$. This term analogously conveys the meaning of the slope coefficient within the context of linear regression analysis. Moreover, both φ and τ are double-indexed, with the respective parameters expressed as $\beta^{\varphi}(DIE)$ and $\beta^{\varphi'}(DIE^{\tau})$. These parameters are the function of φ and τ , which are also denoted as $\beta(\varphi, \tau)$ and $\beta_1(\varphi, \tau)$. Consequently, the representation of $\beta^{\varphi}(DIE)$ is formulated as follows:

$$\beta^{\varphi}(DIE_t) \approx \beta_0(\varphi, \tau) + \beta_1(\varphi, \tau)(DIE_t - DIE^{\tau}) \quad (7)$$

Utilizing Equation (7) to replace $\beta^{\varphi}(DIE_t)$ within Equation (5) yields the following expression:

$$ENS_t = \underbrace{\beta_0(\varphi, \tau) + \beta_1(\varphi, \tau)(DIE_t - DIE^{\tau})}_{(*)} + \xi_t^{\varphi} \quad (8)$$

For each quantile, the relationship between DIE and ENS can be delineated, since the parameters β_0 and β_1 vary with φ and τ . Moreover, Equation (8) necessitates the substitution of the estimated counterparts $\hat{DIE}_t$ and $\hat{DIE}^{\tau}$ for DIE_t and DIE^{τ} , respectively, to facilitate approximation. Consequently, the following minimization problem can be

employed to derive the estimates for the coefficients d_0 and d_1 , corresponding to the estimates of β_0 and β_1 :

$$\min_{d_0, d_1} \sum_{i=1}^n \rho_{\varphi} \left[ENS_t - d_0 - d_1 \left(\hat{DIE}_t - \hat{DIE}^{\tau} \right) \right] \times K \left(\frac{F_n \left(\hat{DIE}^{\tau} \right) - \tau}{h} \right) \quad (9)$$

where $\rho_{\varphi}(\xi) = \xi (\varphi - P(\xi < 0))$. $\rho_{\varphi}(\xi)$ and P are respectively characterized as the quantile loss function and the standard indicator function. In addition, $K(\cdot)$ represents the Gaussian kernel, with h denoting the bandwidth parameter of kernel. In the context of non-parametric estimation, the choice of bandwidth is pivotal for accurate identification. A larger bandwidth may lead to increased estimation bias but reduced variance, and conversely, a smaller bandwidth may result in the opposite. The optimal bandwidth strikes a balance between these two opposing effects, ensuring accurate and stable estimation. As indicated by Sim and Zhou (2015), the ideal bandwidth parameter is set as $h = 0.05$ [31]. This selection is based on its widespread use in empirical studies involving non-parametric quantile regression and its proven ability to provide robust and consistent estimation results [2]. Additionally, it is demonstrated that this bandwidth can effectively balance precision and stability in analyzing dynamic relationships [43]. To sum up, by integrating the QQR methodology with wavelet analysis, we elucidated the intuitive and specific effects among series at each quantile across various temporal scales.

4. Data and Empirical Results

4.1. Data Source and Description

This paper identified the asymmetrical structure of the dependency between the digital economy and environmental sustainability across various time domains and quantile levels. First, the development of the digital economy in China was gauged through the digital economy index, with data from the Wind database. In the existing literature, the degree of digitalization is customarily denoted by the proportion of individuals using the internet and mobile cellular users. This approach tends to adopt a unidimensional viewpoint, potentially falling short in delivering a holistic and uniform evaluation of the digital landscape [15,48]. In contrast, the digital economy index transcends the limitations of prior measures by integrating a multifaceted perspective that encapsulates the intricate interplay between digital infrastructure, industry application, and technological innovation, thereby offering a more robust and insightful assessment of the digital economy's progress. Second, to gain a more precise understanding of how the digital economy contributes to achieving environmental sustainability goals in various ways, this paper delved deeper by segmenting digital economy into the digital industrialization index and the industrial digitalization index, sourced from the Wind database. The indices are intended to examine the distinct roles played by the development of digital industries and the application scenarios of technology integration in fostering environmental sustainability. Specifically, the digital economy index is composed of digital industrialization, industrial digitalization, digital economy spillover, and digital infrastructure. The digital industrialization index encompasses sectors including the big data industry, the internet industry, and the artificial intelligence industry [49]. Conversely, the industrial digitalization index embraces areas including the industrial internet, smart supply chains, the sharing economy, and financial technology. Third, the metric employed for assessing environmental sustainability is based on the inverse of the mean monthly PM2.5 concentrations across 338 Chinese cities, which comes from the Wind database. The indicator is grounded in its capacity to encapsulate improvements in environmental quality, providing a direct and gauge of the effectiveness

of environmental governance and the status of environmental sustainability [50]. In this context, PM2.5 levels are closely linked to industrial emissions and pollution control efforts, making them a timely and sensitive proxy for evaluating the immediate impacts of digital transformation on environmental outcomes. Furthermore, the indicator boasts high sensitivity and is well-suited to detecting changes in the short term, thereby facilitating the identification of variations in environmental sustainability [51]. In light of data availability and comparability, the selected timeframe spanned from January 2016 to September 2024. This period encapsulates significant fluctuations within the realms of digitalization and sustainable development, encompassing milestones such as the exponential rise of artificial intelligence, the pursuit of carbon neutrality, economic downturns, and upheavals in global politics. As a result, the research sample was able to reveal the dynamic and quantile-specific interplay between DIE and ENS.

Based on a wavelet transform framework, this study delved deeper into the specific impacts across multiple time scales by decomposing DIE, DII, and IND series into distinct frequency bands of 1–2 months and 6–12 months (DIE_1 , DIE_2 , DII_1 , DII_2 , IND_1 , IND_2), representing the short- and long-term perspectives. Figure 1 illustrates the outcomes of the decomposed DIE, DII, IND series and ENS series. While coherence and specificity cannot be inferred solely from variations in different frequencies, this decomposition technique significantly reduces signal noise and smooths out trends from the short to long terms. Consequently, it enhances the ability to capture features across various time scales and mitigates inaccuracies stemming from anomalous events, thereby offering greater flexibility in assessing the linkages between DIE, DII, IND, and ENS [32].

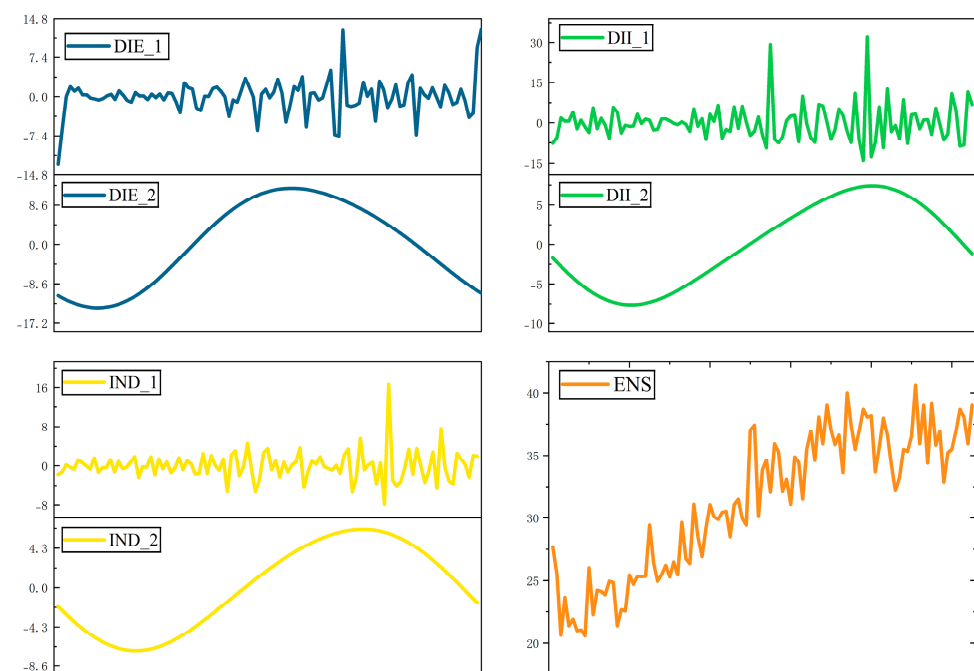


Figure 1. Time series of DIE, DII, and IND with wavelet decomposition and ENS.

Table 1 outlines the descriptive statistics for DIE, DII, IND, and ENS series. As illustrated in Table 1, the medians of DIE_1 , DIE_2 , DII_1 , DII_2 , IND_1 , IND_2 , and ENS are 0.127, 0.657, -0.538 , 0.089, -0.210 , 0.235, and 32.054, respectively. As for the standard deviation, the DIE_2 series shows the largest value, suggesting that digital economy development exhibits greater volatility. Variations in ENS highlight fluctuations in environmental sustainability, potentially driven by policy interventions and localized industrial emissions. The negative skewness of DIE_2 , DII_2 , IND_2 , and ENS indicates the characteristics of left-

skewed distribution, while the positive skewness of DIE_1 , DII_1 , and IND_1 series indicates the right-skewed distribution. Finally, according to the kurtosis parameters, DIE_2 , DII_2 , IND_2 , and ENS follow a platykurtic distribution, characterized by flatter tails and more dispersed values. DIE_1 , DII_1 , and IND_1 are leptokurtic distributed, indicating a higher concentration of values near the mean. By analyzing distributional characteristics, this study lays a solid empirical foundation for exploring asymmetric dependencies between the digital economy and environmental sustainability across different quantiles and time scales.

Table 1. Descriptive statistics for DIE, DII, IND, and ENS series.

	DIE_1	DIE_2	DII_1	DII_2	IND_1	IND_2	ENS
Median	0.127	0.657	−0.538	0.089	−0.210	0.235	32.054
Maximum	12.723	12.290	32.053	7.412	16.659	6.352	40.601
Minimum	−12.696	−13.816	−14.052	−7.637	−7.816	−6.893	20.585
Std. dev.	3.331	9.214	6.815	5.241	2.916	4.690	5.614
Skewness	0.268	−0.130	1.687	−0.038	1.644	−0.089	−0.289
Kurtosis	7.971	1.527	9.113	1.543	12.262	1.515	1.822
Jarque-Bera	109.353 ***	9.787 ***	213.336 ***	9.310 ***	422.604 ***	9.790 ***	7.534 **

Note: *** and ** represent significance at the 1% and 5% levels.

4.2. Quantile-on-Quantile Results

Empirical results of linkages between digital economy and environmental sustainability across various quantiles are first presented via the QQR method, as depicted in Figure 2. The magnitude of the color gradient in the bars corresponds to the influence coefficients of DIE on ENS, signifying the influence degrees at different quantile levels. Shades of dark blue correspond to the minimum coefficient values, while dark red denotes the maximum values. Specifically, Figure 2a,b correspond to the effects of digital economy on environmental sustainability in the short and long runs, respectively.

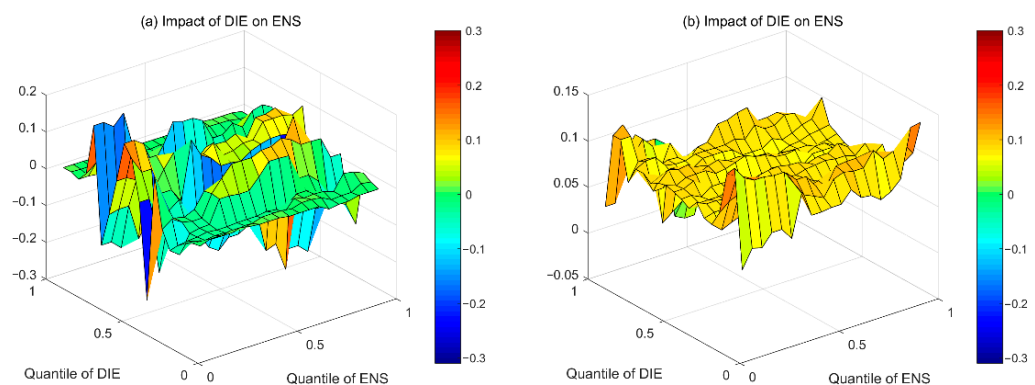


Figure 2. The influence coefficients of DIE on ENS.

With regard to the short-term scenario, Figure 2a reveals that the relationship between the digital economy and environmental sustainability is mixed, with varying effects depending on the quantile levels. Specifically, DIE exhibits a negative influence on ENS across the mid-range quantiles, particularly within the quantiles of [0.35–0.45] and [0.65–0.7]. This finding implies that increasing digital economic activities appear to coincide with a reduction in environmental sustainability in the short term. The negative correlation may be associated with the environmental costs tied to digital expansion, such as heightened energy consumption, emissions, and electronic waste generation. On one hand, the integration of digital technologies into traditional industries may not yet achieve the efficiency thresholds necessary to offset environmental costs, such as higher energy consumption or

the generation of electronic waste [7]. On the other hand, while digitalization holds the promise of efficiency improvements, the mid-range quantile effects could indicate scenarios where the heightened demand for resources and infrastructure to support digitalization temporarily outweighs its environmental benefits. These findings align with the usage effect in theoretical analysis, which suggests that the digital economy (DIE) could contribute to greater environmental degradation due to the resource-intensive nature of digital infrastructure required in the digitalization process [25].

Conversely, positive effects are observed in both low and high quantiles, indicating a dual nature of digital economic development on ENS in the short term. In the lower quantiles, limited digital infrastructure might yield minimal environmental impacts, as the scale of digital integration remains manageable. In this regard, the environmental burden from DIE appears insignificant, likely due to the constrained application scope and digital penetration at these quantiles. Additionally, in the higher quantiles, DIE's positive effect suggests that advanced levels of digital economic development can support environmental sustainability improvements. This could result from enhanced efficiency and improved environmental management through the resource optimization and innovation effects [11]. For example, the use of big data and artificial intelligence in environmental monitoring and management can help to identify and address environmental issues more effectively. Digital innovations also promote green supply chain management by enabling real-time monitoring and sustainable logistics planning. As a result, the transition to a digitally enabled economy can foster sustainability by driving improvements in environmental performance, reducing carbon footprints, and enhancing eco-efficiency across sectors. The findings are consistent with Seele and Lock (2017) and Hosan et al. (2022), confirming that technology and digital innovation generally support environmental benefits [15,28]. However, the results of this study reveal a more complex relationship in the short term, where digitalization does not unilaterally promote ENS but rather varies across different stages of digital economic development. The observed mixed effects underscore that the potential of DIE to foster ENS may depend on the phase of digital integration within the Chinese economic landscape.

Regarding the long-term scenario, the long-term relationship between DIE and ENS presents a contrasting picture, where a predominantly positive effect emerges across most quantiles, as shown in Figure 2b. This suggests that, over time, the digital economy's capacity to promote sustainability becomes more pronounced and stable. The long-term benefits of DIE on ENS can likely be attributed to the resource optimization and innovation effects of digital advancements, which gradually improve operational efficiencies and promote sustainable practices [18]. Over extended periods, digitalization facilitates deeper integration of environmentally friendly practices, such as smart energy management and predictive analytics for resource optimization. For example, technologies such as artificial intelligence (AI), machine learning, and the IoT enable smart energy management by optimizing electricity consumption and reducing energy waste through real-time monitoring and automated adjustments. Predictive analytics support resource optimization by enabling accurate forecasting of production needs, minimizing material waste, and improving supply chain logistics. These advancements contribute to reducing greenhouse gas emissions and mitigating environmental degradation. Additionally, as the DIE matures, regulatory support and policy measures aimed at reducing emissions and enhancing sustainability practices may further amplify these benefits. The long-term positive effect also aligns with the development trajectory of China's digital economy, which is increasingly directed towards green growth and low-carbon innovations. National initiatives such as the digital China strategy and the green development agenda have fostered an environment where digital innovations are expected to play a crucial role in achieving sustainability

targets [2]. These insights emphasize the importance of strategically managing the pace and scale of digital economic expansion to optimize environmental benefits at each stage of development.

Furthermore, this study refines digital economy into the dual dimensions of digital industrialization and industrial digitalization to identify deeper heterogeneous effects on ENS. Figure 3a,b correspond to the effects of digital industrialization on environmental sustainability in the short and long runs, respectively. A predominantly negative influence coefficient is observed across most quantiles, except for the quantile range of [0.45–0.6]. This result suggests that, in the short term, the expansion of digital industries might lead to increased environmental pressure, possibly due to heightened energy consumption and emissions related to digital infrastructure development and maintenance of energy-intensive data centers. However, in the high quantiles of ENS, the negative influence of DII diminishes, suggesting that areas with stronger environmental performance are somewhat resilient to the adverse effects of digital industrialization. This resilience could be attributed to more advanced regulatory frameworks or higher levels of resource efficiency in regions or sectors that are already more environmentally sustainable.

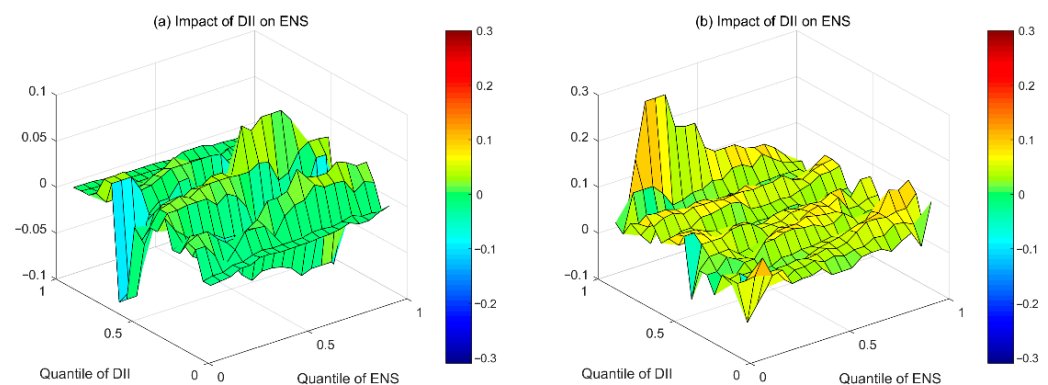


Figure 3. The influence coefficients of DII on ENS.

In the long term, the influence of DII on ENS shifts to a positive effect, with its impact becoming more pronounced in the high quantile range of [0.85–0.95]. This trend indicates that the benefits of digital industrialization accumulate over time, contributing positively to environmental sustainability. In the Chinese context, the long-term improvement could result from the increased efficiency of digital infrastructure as it matures, along with advancements in energy-saving technologies within data centers and manufacturing processes. Furthermore, China's ongoing policy emphasis on sustainable digital development, as seen in initiatives like the Green Data Center Pilot Program, supports the positive environmental impact of DII over time. This trend suggests that, as the digital industrial base reaches higher sophistication, its operations become more aligned with environmental objectives, thereby reducing resource waste and emissions.

As to industrial digitalization, the results shown in Figure 4a indicate a predominantly positive effect on ENS in the short term, with the exception of the mid-range quantile of [0.55–0.65]. The positive impact of IND aligns with the expectation that the integration of digital technologies into traditional industries enhances environmental sustainability by increasing efficiency and reducing resource consumption. For instance, digital tools such as predictive maintenance, smart manufacturing, and supply chain optimization reduce waste and energy consumption within industrial processes. However, the observed negative influence in the mid-range quantile likely reflects transitional inefficiencies that industries experience when adopting digital solutions, potentially due to the initial learning curve or the temporary rise in energy demand during the deployment phase.

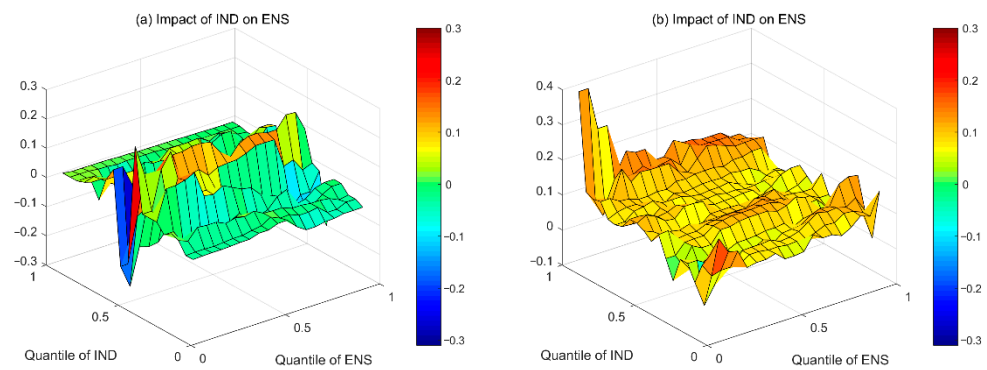


Figure 4. The influence coefficients of IND on ENS.

In the long-term scenario, IND consistently demonstrates a positive influence on ENS, with the impact intensifying in the high-quantile range of IND. This pattern underscores that, as industrial digitalization deepens, it significantly contributes to sustainability goals by promoting cleaner and more efficient production processes.

The goals for “smart manufacturing” and its support for green digital transformation within industries in China further reinforce the positive trajectory of IND’s impact on ENS. The high impact in the upper quantile range suggests that regions or industries with more advanced levels of industrial digitalization achieve greater environmental benefits, likely due to the full integration of smart technologies that reduce emissions and optimize resource use.

Finally, compared with DII, the influence of IND with direct focus on transforming industrial processes offers a greater and more immediate impact on environmental sustainability. IND, which involves the integration of digital technologies into traditional industrial processes, directly addresses efficiency improvements and resource optimization across various sectors. By enabling smarter manufacturing, supply chain enhancements, and predictive maintenance, IND reduces energy consumption, minimizes waste, and lowers emissions. These efficiency gains make IND a powerful driver of environmental sustainability, particularly as industries adopt advanced technologies like artificial intelligence, the internet of things (IoT), and big data analytics. In the context of China, where industrial processes contribute significantly to the national carbon footprint, the role of IND is especially pronounced. For example, digitalized manufacturing processes can significantly reduce emissions in key industries such as steel and cement, where China holds major global production shares. In addition, smart grid technologies and digital energy management systems can help factories monitor and reduce their energy consumption in real time, leading to improvements in carbon emissions. In contrast, DII’s foundational role in providing infrastructure has indirect benefits for ENS, as it serves as the underlying support system for broader digital transformation efforts. These findings suggest that prioritizing industrial digitalization within digital economy strategies may yield faster progress toward the sustainability goals of China. At the same time, a balanced approach that also supports green advancements in digital infrastructure is essential for ensuring sustained environmental benefits across all sectors in the long term.

4.3. Robust Test

To assess the robustness and accuracy of the empirical results, we contrasted the results obtained through the QQR method with those derived from the QR method [32]. The QQR method exhibited heterogeneity across various quantiles, enabling it to retrieve estimates from the conventional QR. Consequently, the parameters of QR φ , could be assessed by

calculating the average of the QQR parameters along τ . Specifically, the slope coefficient $\zeta_1\varphi$ measures the effect of DIE on ENS:

$$\zeta_1\varphi \equiv \overline{\hat{\beta}_1(\varphi)} \frac{1}{y} = \frac{1}{y} \sum_{\tau} \hat{\beta}_1(\varphi, \tau) \quad (10)$$

where y represents the quantile number. Figure 5 compares the impact of DIE on ENS employing both QQR and QR methodologies. Overall, it can be concluded that the two techniques revealed concordant patterns in the comparative findings, affirming the robustness of empirical results [32].

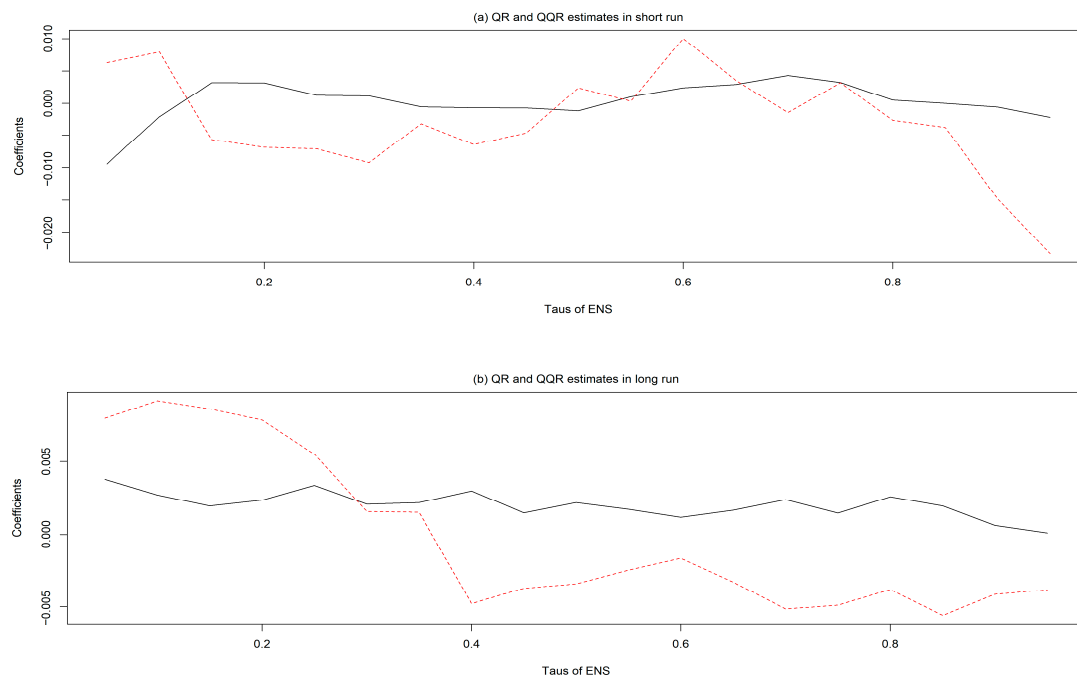


Figure 5. Quantile regression (the solid black line) and QQR estimates (the dashed red line).

5. Conclusions and Policy Implications

This study investigated the criticality of the digital economy in environmental sustainability across different time scales, utilizing the wavelet-based quantile-on-quantile regression method. The following conclusions were obtained. First, the digital economy has contributed positively to ENS over the long term, while it shows mixed effects on ENS in the short term. Lower and higher quantiles of DIE generally bolstered the ENS, whereas the mid-range quantiles of [0.35–0.45] and [0.65–0.7] displayed a tendency towards adverse impacts. Second, digital industrialization is particularly associated with short-term environmental challenges due to high energy consumption and electronic waste generation. However, as the digital infrastructure has matured, DIE has contributed positively to ENS in the long term, with benefits increasingly evident in high-digit quantiles of DIE, especially in [0.85–0.95]. Third, industrial digitalization has consistently demonstrated a positive impact on ENS in both the short and long terms, highlighting its role as a critical factor in achieving sustainability goals. The ability of IND to improve resource efficiency and reduce emissions within existing industrial processes makes it an immediate driver of environmental benefits, and its impact has intensified as digitalization deepens. The consistent benefits of IND underscore its potential as a policy focus for environmental gains, reinforcing industrial optimization and resource efficiency. Finally, compared with digital industrialization, industrial digitalization generated a stronger positive influence on ENS, due to its direct role in optimizing industrial processes and reducing resource waste.

Based on the empirical findings, the following policy implications are proposed. First, given the consistently positive impact of IND on ENS, policies should focus on accelerating the integration of digital technologies in traditional industries. Active incentives for adopting energy-efficient technologies, predictive maintenance, and smart manufacturing processes can help industrial sectors reduce their environmental footprints. Furthermore, supporting digital transformation in high-emission industries such as steel, cement, and chemicals will be crucial in making substantial progress toward the carbon neutrality goals of China. Second, while the short-term environmental costs of DII are notable, its long-term benefits can be realized by promoting energy-efficient digital infrastructure. Policies should encourage the adoption of low-energy technologies in data centers, renewable energy integration, and sustainable electronic waste management. Initiatives such as the Green Data Center program could be scaled up to ensure that digital infrastructure growth aligns with environmental targets. Targeted subsidies or incentives for energy-efficient technologies and renewable energy use in digital infrastructure would help mitigate the negative short-term impact of DII on ENS. Third, the mixed short-term impact of DIE on ENS highlights the need for a phased approach to digital economy policies. In regions or sectors where digital infrastructure is in the early stages, environmental impacts may be higher; thus, policies should prioritize sustainable practices from the outset. For advanced digital economies or regions with high DIE levels, policy efforts should focus on scaling digital technologies that have direct positive impacts on sustainability, such as smart grid solutions and IoT-enabled energy management systems. Forth, emerging economies such as India, Brazil, and South Africa can draw important lessons from the dual impact of DII and IND. These countries, often experiencing rapid industrial growth coupled with environmental pressures, can prioritize IND initiatives such as smart manufacturing and green supply chains to achieve immediate environmental benefits while gradually enhancing DII to ensure long-term sustainability. Meanwhile, developed economies, with well-established digital infrastructures, may benefit from the study's insights into the long-term environmental gains of mature DII systems. By investing in next-generation digital technologies such as AI-driven environmental monitoring, smart grids, and renewable energy management, they can further enhance their environmental sustainability agendas. Finally, promoting research and development in green digital technologies, such as low-energy processing and sustainable electronic materials, can provide long-term solutions to the environmental challenges posed by digitalization. Furthermore, policies that mandate green practices in the digital economy can help balance the environmental costs associated with rapid digital growth. Regulation of electronic waste disposal, energy usage standards for data centers, and emissions reporting requirements for digital industries will ensure that the environmental benefits of DIE are maximized.

Despite the contributions, the study has several limitations, which can be addressed in future research. First, the analysis primarily focuses on China with unique digital development and environmental sustainability characteristics. While this focus provides valuable insights, the findings may not fully capture the diverse contexts of other countries with different socioeconomic, regulatory, and environmental conditions. Second, while the study uses comprehensive and reliable national datasets, the rapid pace of digital transformation means that micro-level data might reveal detailed trends. Third, the study's methodological approach, while robust, relied on wavelet-based quantile-on-quantile regression, which assumes linear relationships within quantiles.

Future research can be further deepened from the following aspects. First, future research could conduct comparative cross-country analyses to validate and extend the findings. Second, disaggregated data at the industry or firm level could provide deeper insights into specific sectors' contributions to sustainability outcomes. Third, considering

the multidimensional nature of environmental sustainability, future research may expand the framework to include additional indicators to provide a more holistic evaluation. Finally, future studies could adopt more advanced nonlinear models or machine learning techniques to capture complex interactions more precisely.

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