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Unraveling the Interrelationship of Digitalization, Renewable Energy, and Ecological Footprints within the EKC Framework: Empirical Insights from the United States

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Abstract: The study seeks to better comprehend the ecological footprint of the United States by analyzing the effects of digital financial inclusion (FinTech) as well as renewable and non-renewable energy usage. Data from 2005 Q1 to 2020 Q4 were analyzed using the quantile autoregressive lag (QARDL) method. It also used Granger causality in quantiles to analyze the correlation between variables and draw conclusions about their relative importance. Quantile-wise, the error correction parameter is statistically significant with the predicted negative sign, as shown by the results obtained using the QARDL method. Indications are mounting that the relationship between these variables and the United States' ecological footprint is returning to its long-term equilibrium. However, in the long/short-run period, across all quantiles, economic growth and consumption of non-renewable energy have a positive impact on the ecological footprint. The environmental Kuznets curve (EKC) theory was also examined, which holds that an inverted U-shaped link exists between economic growth and environmental degradation. The QARDL study's findings corroborated the presence of an EKC in the US, lending credence to the theory that while economic growth at first promotes environmental deterioration, further progress ultimately promotes environmental improvement. The study additionally checked the results of the QARDL test for robustness using the ARDL approach. Recommendations for public policy are included in the paper for consideration by legislators and policymakers.

Keywords: ecological footprint; EKC; FinTech; renewable energy; QARDL; United States; economic growth

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1. Introduction

To agree on steps to combat climate change and keep temperatures below a 1.5 °C increase, government leaders and environmental experts convened at the 26th United Nations Climate Change Conference (COP26) in the first half of November 2021. The goals of COP26 underscore the interconnectedness of finance, sustainability, and technology. Green FinTech describes this merging of financial and environmental technologies, which will be essential in achieving sustainable development. We divide a country's ecological footprint by its population to obtain its per-capita footprint. To live within Earth's resources, the world's ecological footprint must match the biocapacity per person, which is 1.6 global hectares. A country with an ecological footprint per person of 6.4 global hectares uses four times as much material as the Earth can renew and recycle. The US has seven times India's and twice China's ecological footprint per person. The footprint helps nations to improve sustainability and quality of life, local authorities to maximize public project returns, and individuals to realize their global footprint. The US has the second-largest ecological footprint after China, which has four times the US population. The existing population of the United States is using twice as much of the renewable natural resources and services that are available in the country as can be replenished. Alaska, Montana, South Dakota, Wyoming, and Arkansas have the smallest ecological footprints per citizen. According to the data presented in Figure 1, the states of Arizona, California, Colorado, Florida, and Virginia have the largest ecological footprints for their respective populations. Texas and Michigan have the most abundant natural resources, according to biodiversity, which is a measure of how bio-productive land is. Rhode Island (RI), Delaware, and Arizona are the three states in the United States that have the lowest biocapacity. California, Florida, and Texas are the three states that have the biggest ecological gaps in the United States. South Dakota and Montana are home to some of the most important ecological preserves in the United States.

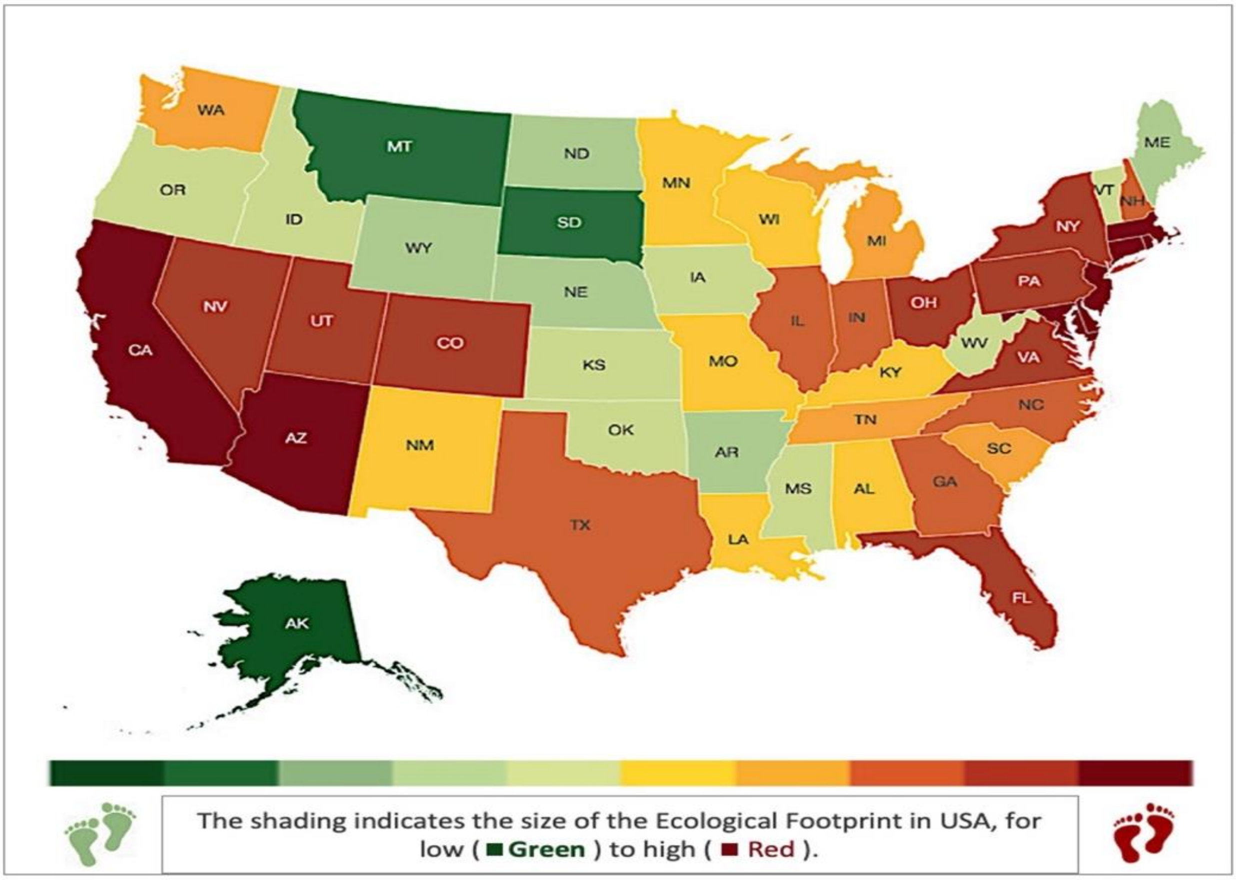

Figure 1. Ecological footprint in USA.

Following China in terms of total carbon emissions, the United States ranks in second place [1]. Recently, the economy of the United States, which was the second-largest emitter of greenhouse gases (GHG) in 2017, set a goal for a significant reduction in the amount of GHG emissions by approximately 27% in 2025 when compared to the level of emissions in 2005 [2]. In order to tackle challenges related to global warming and other dangers to the environment, a synergistic plan to manage excessive levels of CO_2 emissions is required. Spending money on research and development could end up being the most productive tactic. This is because lowering carbon emissions and encouraging the growth of eco-friendly economies necessitate the creation of new environmentally friendly products and technologies [3,4].

The 27th Conference of the Parties, often known as COP27, brought together nations from all around the world in an effort to raise the bar for achieving already established goals as well as to enhance commitments. Programs and initiatives hosted by the United States concentrate on the ways in which the leadership of the United States is delivering solutions to the climate crisis and the approaches by which the United States is engaging with allies from across the world. In order to bolster climate ambition and ensure substantial results at the 27th Conference of the Parties (COP27), the United States exhibits a steadfast dedication to collaborating with international allies. With the overarching objective of advancing the global trajectory towards attaining a state of net-zero emissions by the year 2050, the United States assumes a pivotal role in combating the looming climate catastrophe, consistently upholding this responsibility both presently and in the future.

The use of FinTech has the potential to make significant contributions toward achieving environmental sustainability in the United States. By financing the installation of solar panels, advancing renewable energy sources, and monitoring environmental impact, it can aid in the reduction of ecological footprints. Loans for firms and individuals trying to mitigate their environmental effect are possible due to FinTech, which also facilitates the flow of capital into environmentally conscious businesses. The switch to renewable energy, however, calls for heavy spending on infrastructure, R&D, and mass acceptance of clean energy technology. This is where the importance of the connection between financial inclusion and FinTech really emerges. By making it simpler to secure funding for renewable energy projects, FinTech platforms can encourage more people and businesses to adopt this clean energy technology. Renewable energy initiatives can now gain access to capital from a wider spectrum of investors by utilizing digital platforms, crowdfunding, and peer-to-peer financing.

Reducing a state's or nation's ecological footprint can be accomplished in a number of effective ways, but one of the most powerful is to make the switch to renewable energy. Earlier this year, California made history by becoming the first state to produce more than 5% of its electricity from utility-scale solar. However, there are currently six states that are further ahead of California in terms of overall dependency on renewable energy. Hydropower, on the other hand, accounts for the vast bulk of these states' renewable energy resources; nevertheless, this resource is already being heavily utilized and is very location-dependent. Despite this, it is evident that the United States is planning for a future in which FinTech and renewable energy play a considerably larger role, and the majority of states still have a significant chance to tap into renewable energy in order to lower the carbon intensity of their economies. Although the United States cannot function without energy, the majority of its principal sources cannot be maintained indefinitely. The existing fuel mix is linked to a wide variety of negative effects on the surrounding environment, and countries such as the United States that produce a sizable portion of the world's output and are mostly responsible for global warming. However, the United States also has one of the highest concentrations of financial technology worldwide.

The United Nations' declaration of climate change as a "code red" emergency has highlighted the urgency of climate-related concerns. Financial services organizations have been found to annually dispatch 5.2 billion paper documents to customers, resulting in a loss of 2.4 million trees. FinTech is making the sector greener by eliminating paper, cutting energy waste, and tracking environmental impact in real time. FinTech can expedite the transition to a greener economy by equipping financial institutions and consumers with sustainable practices. Carbon emissions will not disappear overnight, but adopting new technology could help meet current and future environmental concerns. The first crucial point to make is that renewable energy consumption has a negative impact on the ecological footprint, in contrast to the positive impact that using non-renewable energy sources has. However, the United States has not joined the Kyoto Protocol or made any other global commitment to reduce its ecological footprint, despite its outsized influence on the worldwide energy market, international concerns, and its share of global production and emissions. This is a fascinating subject because Figure 2a shows that in both 1990 and 2020, around 87% and 83% of world energy consumption originated from fossil fuels in the USA, respectively. It can be seen in Figure 2b that renewable energy contributed only 4% of final energy consumption in 1990, but that amount is projected to surge to 10% by 2020. However, we believe the United States government should be open to trying to employ renewable energy and do what it can for the environment.

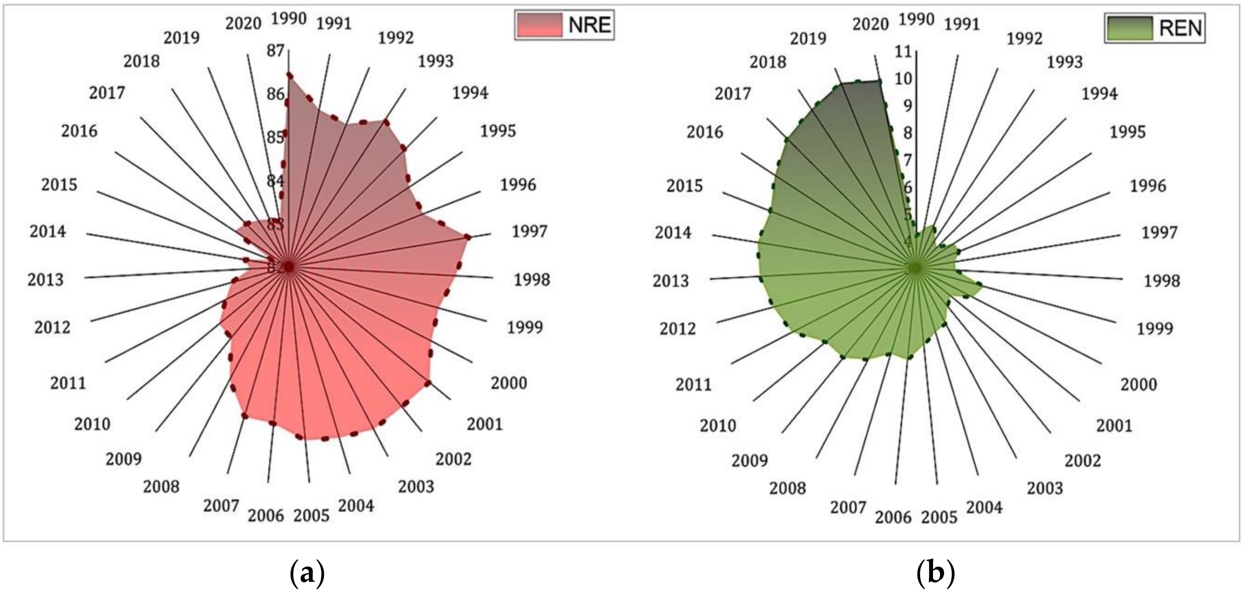

Figure 2. (**a**) Fossil fuel energy consumption (% of total). (**b**) Renewable energy consumption (% of total final energy consumption).

This research examines the interplay between FinTech, economic growth, renewable energy, non-renewable energy, and ecological footprint, making a contribution to global discourse on environmental sustainability. Additionally, in order to confirm the environmental Kuznets curve (EKC) hypothesis, a more recent estimation technique, the QARDL approach, is utilized in order to gain new insights into the analysis of the United States. The QARDL model uncovers non-linear patterns and explores implications within the context of the EKC hypothesis. These unique aspects contribute to the novelty of our research and differentiate it from existing studies in the field. In conclusion, the Quantile Granger Causality Strategy, which is currently the method that has proven to be the most reliable, is used to investigate the causality test. Due to the fact that the development of financial technology in a nation has a negative effect on its ecological footprint, our research has shown that this type of growth is beneficial to the process of shifting towards a low-carbon economy. Our findings, which are both enlightening and applicable, contribute significantly to the resolution of a contentious issue about the ambiguous role that FinTech development and renewable energy play in the improvement or destruction of the environment. These findings also provide regulators and policymakers with knowledge, which enables them to promote the agenda of FinTech development with more assurance and determination.

The remaining portions of the paper are organized as follows: In the following section, a literature assessment is presented that focuses on the connection between FinTech and renewable energy, with the goal of finding a solution to the problem of climate change. After that, the third section illuminates the intricacies of the models and methodological framework used to conduct empirical research. Moving on, the outcomes of our study are detailed in Section 4, along with a discussion of how these results compare to prior research in the same field. Finally, Section 5 of this study presents our conclusion, with key findings for scholars as well as policymakers.

2. Review Literature

The ecological footprint, which is associated with FinTech, renewable energy, economic growth, and non-renewable energy sources, can be a representation of environmental deterioration. The associated environmental Kuznets curve (EKC) suggests that there is an inverted U-shaped relationship between economic growth and environmental degradation. The EKC theory states that high income levels bring about a reversal of environmental deterioration and pollution that occurred during the early stages of economic development. As a result, when more people are able to participate in the economy, the environment benefits. That is to say, environmental pollution indicators have an inverse U-shaped relationship with economic growth [5–7]. Since the introduction of the EKC idea, numerous further investigations have been conducted within the EKC framework [8–12] and are included in this group of studies. Even for the same countries and regions, during the early phases of economic development, the EKC hypothesis anticipates that environmental quality might deteriorate; however, this deterioration will be followed by an improvement as income levels raised. For instance, whereas Ref. [13] found evidence to support the EKC hypothesis for the United States, Ref. [14] found no evidence to support the notion that the EKC hypothesis is accurate for the same nation.

The literature on environmental topics during the past two decades has given extensive attention to the effects of technological progress, alternative energy sources, economic development, and ecological footprint. Researchers are split into two camps, with the first believing that technological advances have helped the environment as a whole by reducing ecological footprints and increasing energy efficiency [15–19], and according to the second set of studies, technology has a negative impact on the environment because of the massive ecological footprint it leaves behind when used and consumed [20,21]. The interesting view is that technology is a double-edged sword, positively affecting the environment through the creation of more effective infrastructure systems, smarter cities, and energy-saving industries, and negatively through the manufacture, use, and eventual disposal of technological devices. However, new technologies are promoted as the best way to curb rising pollution. Based on the current discussion, it is obvious that the environmental impact of global economic development and technological advancement is multifaceted and understudied, and that conventional linear approaches and one-dimensional proxies are unable to capture this complexity [22].

As a direct consequence of the so-called "fourth industrial revolution", a significant amount of progress has been made in the field of technology. In this light, it is anticipated that the financial sector will be one of the key beneficiaries of the growth of established businesses as well as the introduction of novel technology [23]. Additionally, the financial technology sector has witnessed great expansion, which has been accompanied by enormous increases in both the quantity invested and the rates of return [24]. The widespread adoption of these financial technologies can be attributed to a number of variables, including but not limited to demography; social system; financial climate; knowledge; income level; accessibility; velocity; cost of maintenance; and so forth [25–28].

Previous study has proven a link between financial innovations and their influence on banking systems and economic growth within countries [29–31]. According to [32], which proposes the technology compared to an innovative-growth approach, developments in financial technology and innovations can have positive and detrimental impacts on the growth of the economy [29,33,34], contend that financial innovations facilitate risk sharing, cultivate industry integration, and enhance resource allocation efficiency. However, it is essential to observe that the excessive credit provision that may result from financial innovations may contribute to financial crises [35]. Currently, FinTech has altered the financial environment and had far-reaching impacts on economies around the world [36]. On top of that, it has made banks and the overall financial system more effective [37]. That is to say, the rise of e-banking and other examples of FinTech has increased efficiency and competitiveness among banks [38]. FinTech is the primary factor propelling the growth of stock markets [39]. Even though the relationship between FinTech and economic, financial, and banking development has been well studied, there is an absence of research that examines how FinTech is linked with the environment [40]. This is despite the fact that rapid financial innovations and development have positive externalities, such as increasing financial inclusion and decentralizing financial services.

However, digitalization's results are energy-saving because of increased energy efficiency and industry shifts. A country can increase its economy's energy efficiency through the use of ICT (information and communication technology). It is still unknown how exactly digitalization affects the tertiarization of the economy; however, there is evidence to suggest it has an energy-reducing effect. If we are going to talk about how cutting-edge technology is changing the banking industry, we have to talk about how it is changing the economy as a whole, too. As a result, there has been a rise in the worldwide production and consumption of ICT goods and services, which has led to higher demands for power and other environmental costs [41]. The importance of ICT in raising both productivity and efficiency has been well recognized. However, there is still no agreement on how it will affect the ecosystem in the long run. There is strong empirical evidence linking the use of ICT to the reduction of GHG emissions, as shown by a number of different studies. On the other hand, some people argue that the widespread use of ICT products and services increases worldwide CO2 emissions because of the increased need for power [42]. Additionally, Ref. [43] examines the influence of ICT on power consumption in developing countries using panel data analysis techniques such as the dynamic generalized method of moments (GMM), pooled ordinary least squares (OLS), fixed effects, and random effects. Different methods provide different findings; for example, dynamic-GMM and pooled OLS analyses show a negative and statistically insignificant association between ICT and power use.

However, the fact is that all these studies look at how cryptocurrency might damage the ecosystem. Nevertheless, there is noticeably less research on the subject of how the growth and development of FinTech have altered an economy's ecosystem. As such, a recent literature review has been provided by [44], focusing on the intersection of technology and ecology. The authors have stated that innovation and sustainability are the two key drivers of financial business today. This subject has been studied, but only in a limited capacity. FinTech, however, is now being viewed as potentially instrumental in addressing climate change and its effects. Therefore, it is crucial to comprehend the complexities that go beyond blockchain and cryptocurrencies, as well as how the growth of the FinTech ecosystem is connected to the economic ecosystem as a whole. To address this gap, this study provides an empirical evaluation of the connection between FinTech advancement and environmental quality, arguing that the more advanced a country's financial ecosystem, the higher the quality of its environment would be. The impact of FinTech on ecological footprint in the presence of renewable and non-renewable energy, GDP, and its square relied on the work of [45–47].

This study primarily contributes to FinTech, an innovative financial strategy that uses information technology and includes all necessary financial services activities. While there is a growing body of research looking at how blockchain and cryptocurrencies might affect environmental impacts, we are not aware of any that evaluates the relationship between FinTech development and ecological well-being. Moreover, we hypothesize that less environmental harm will occur in countries with more advanced FinTech ecosystems. The connection is explained through a number of pathways, including new developments in systems and processes, increased efficiency, green finance, etc. We have also argued that technological progress is enabled by strategic corporate investment and well-timed government regulation. Therefore, governments play a crucial role in fostering an atmosphere conducive to eco-friendly inventions.

3. Data and Modelling Strategy

3.1. Data

This study examined 2005 Q1–2020 Q4 time-series data. After completing the annual data collection and quarterly data transformation using the match-sum approach as conducted by [48], according to the changes proposed by [49], the Quantile Autoregressive

Distributed Lag Model (QARDL) requires long data series, and the quadratic match sum method solved this problem. This method lowers data variance and modifies periodic irregularity, transforming frequency information from low to high. In light of this rationale, the analysis compares the impact on ecological footprints with the growth of per capita energy consumption, renewable energy, and financial inclusion indicators such as ATM density per 100,000 adults, bank branch density per 100,000 adults, commercial bank deposit accounts per 1000 adults, and commercial bank borrowers per 1000 adults. Financial technology accounts for mobile phones' significance in helping Americans access financial services. Table 1 defines and sources variables.

Table 1. Data variables and sources.

Parameters	Symbol	Metrics	Resources
Ecological footprint	EFP	Global hectares per person	GFN
Economic Growth	GDP	GDP per capita	WDI
Financial Technology	FTEC	Financial Inclusion, Digital Payments, and Resilience	World Bank—Global Findex
Renewable energy	REN	Geothermal, biomass, and wind energy in the total energy used.	WDI
Non-renewable energy	NRE	Energy consumption per capita (kWh)	WDI

3.2. Modelling Strategy

This study studied a time series that extends from 2005 to 2020. Quarterly data were derived from the annual data using the match-sum approach, as in [48]. Using a quadratic match sum approach proved useful for dealing with the large data series necessary for QARDL's application, as suggested by [49]. This method is useful for transforming low-frequency data into high-frequency data because it permits the adjustment of periodic abnormalities through the diminution of informational discrepancies. Using advanced econometric techniques, the sequential testing framework consists of five distinct steps to investigate the relationships between variables. Quantile Unit Root Test, Quantile Autoregressive Distributed Lag Model (QARDL) Test, Wald Test, Quantile Granger Causality Test, and Autoregressive Distributed Lag (ARDL) Test are included. The framework offers a rigorous method for analyzing complex economic phenomena, thereby providing valuable insights for policy formulation and the decision-making processes. This study's modeling strategy is depicted in Figure 3 below.

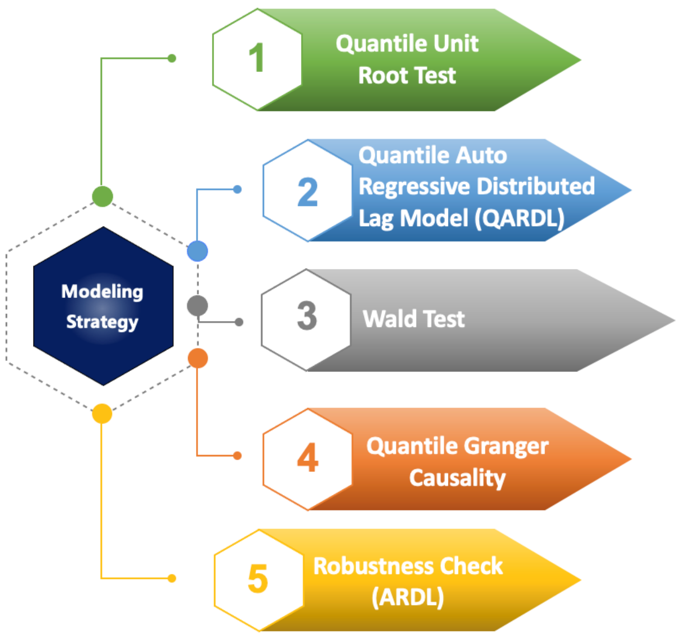

Figure 3. Modeling Strategy.

3.2.1. Unit-Root Test

We study the matter of whether or not the time series is stationary by employing a technique that was developed by [50] called the Quantile Auto-Regressive (QAR) unit root test. It is helpful to validate the stationarity of time series data using the QAR approach of the unit root test at the conditional variance and at each quantile of the conditional probability distribution. In addition to this, [51] extended the QAR model by including variables as well as a linear trend. We make use of a mechanism called X_i, which is a time series method that has been demonstrated to be strictly steady through the use of prior evidence. The formula that we have been using to construct $M_i^X := (X_{i-1}, \ldots, X_{i-o})' \in \mathbb{R}^o$. We utilize the function $F_X(. \mid M_i^X)$ in order to calculate the conditional distribution of X_i given M_i^X. This allows us to determine how likely it is that any given value of X_i will cur.

In order to calculate the conditional distribution of X_i given M_i^X, we make use of the function $F_X(. \mid M_i^X)$. Using the Equation (1) below, we can conduct the quantile unit root test, which is adapted to the chosen quantile linear regression model.

$$Q_\pi^X\left(X_i \mid M_i^X\right) = \gamma_1(\pi) + \gamma_2(\pi)i + \beta(\pi)X_{i-1} + \sum_{k=1}^{n} \beta_k(\pi)\Delta X_{i-k} + F_v^{-1}(\pi), \quad (1)$$

where $Q_\pi^X(. \mid M_i^X)$ is the π-quantile of $F_X(. \mid M_i^X)$, $\gamma_1(\pi)$ denotes drift, i is a linear trend, $\beta(\pi)$ is the constraint which tests the persistence, and or each quantile, $\pi \in \partial \subset [0,1]$, the error terms are conditionally scattered, denoted by the inverse function F_v^{-1}. Therefore, a special persistence parameter (β) is used for conditional dispersion of X_i quantiles. In this instance, we use the t-statistics provided by [50,51] to test the $H_o : \beta(\pi) = 1$, which is obtained by the deployment of the t-statistics over the available quantiles $\pi \in$.

3.2.2. Quantile Autoregressive Distributed Lag Model (QARDL)

Ecological footprints (EFP), gross domestic product (GDP) and its square, FinTech development (FTEC), renewable energy (REN), and non-renewable energy (NRE) were used in the QARDL model proposed by [49] to demonstrate the long- and short-term nexus between these variables. As a result, we have used the QARDL framework within the EKC framework to examine the short-term and long-term relationships between the variables of interest. Additionally, the Wald test has been used to investigate both temporary and permanent equilibriums by analyzing the quantiles of reliability metrics. The basic idea of QARDL was developed from the classic ARDL model, as seen in Equations (2) and (3):

$$\begin{gathered} Y_t = \alpha + \sum_{i=1}^{o} \beta_1 Y_{t-ji} + \sum_{i=1}^{p} \beta_2 X1_{t-ji} + \sum_{i=1}^{q} \beta_3 X2_{t-ji} + \sum_{i=1}^{r} \beta_4 X3_{t-ji} + \\ \sum_{i=1}^{m} \beta_5 X4_{t-ji} + \sum_{i=1}^{n} \beta_6 X5_{t-ji} + \epsilon_t, \end{gathered} \quad (2)$$

or

$$\begin{gathered} EFP_t = \alpha + \sum_{i=1}^{o} \beta_1 EFP_{t-ji} + \sum_{i=1}^{p} \beta_2 GDP_{t-ji} + \sum_{i=1}^{q} \beta_3 GDP_{t-ji}^2 \\ + \sum_{i=1}^{r} \beta_4 FTEC_{t-ji} + \sum_{i=1}^{m} \beta_5 REN_{t-ji} + \sum_{i=1}^{n} \beta_6 NRE_{t-ji} + \epsilon_t. \end{gathered} \quad (3)$$

In the aforementioned formula, ϵ_t stands for the white-noise error term defined by $\{EFP_t, GDP_t, GDP_{t,}^2\ FTEC_t, REN_t, NRE_t\}$ and $\{o, p, q, r, m, n\}$ indicates the orders of lag depicted using Schwarz Information Criterion (SIC). Moreover, $EFP_t, GDP_t, GDP_{t,}^2\ FTEC_t, REN_t, NRE_t$ indicate the natural logarithm series of ecological footprints, gross domestic product and its square, FinTech development, renewable energy, and non-renewable energy. Using the foregoing steps as a guideline, we propose the following configuration for the QARDL method by modifying the previously stated Equation (4):

$$\begin{gathered} Q_{EFP_t} = \alpha(\tau) + \sum_{i=1}^{o} \beta_1(\tau) EFP_{t-ji} + \sum_{i=1}^{p} \beta_2(\tau) GDP_{t-ji} + \sum_{i=1}^{q} \beta_3(\tau) GDP_{t-ji}^2 + \sum_{i=1}^{r} \beta_4(\tau) FTEC_{t-ji} + \\ \sum_{i=1}^{m} \beta_5(\tau) REN_{t-ji} + \sum_{i=1}^{n} \beta_6(\tau) NRE_{t-ji} + \epsilon_t(\tau). \end{gathered} \quad (4)$$

Consider the above equation, $\epsilon_t(\tau) = TE_t - Q_{TE_t}\left(\frac{\tau}{\epsilon_{t-1}}\right)$; $0 < \tau < 1$ is quantile. The study employs the following range of quantiles to analyze the data [0.05, 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, 0.90, and 0.95]. In addition, Equation (4), which was discussed before, can be altered in such a way as to offer the error correction model remeasurement of the QARDL framework as follows [49]:

$$\begin{gathered}Q_{\Delta \mathrm{EFP_t}} = \alpha(\tau) + \rho(\tau)(\mathrm{EFP}_{\mathrm{t}-ji} - \omega_1(\tau)\mathrm{GDP}_{\mathrm{t}-ji} - \omega_2(\tau)\mathrm{GDP}^2_{\mathrm{t}-ji} - \\ \omega_3(\tau)\mathrm{FTEC}_{\mathrm{t}-ji} - \omega_4(\tau)\mathrm{REC}_{\mathrm{t}-ji}. - \omega_5(\tau)NEC_{t-ji}) + \textstyle\sum_{\mathrm{i=1}}^{\mathrm{o}-1} \beta_1(\tau)\Delta\mathrm{EFP}_{\mathrm{t}-ji} + \\ \textstyle\sum_{\mathrm{i=1}}^{\mathrm{p}-1} \beta_2(\tau)\Delta\mathrm{GDP}_{\mathrm{t}-ji} + \textstyle\sum_{\mathrm{i=1}}^{\mathrm{q}-1} \beta_3(\tau)\Delta\mathrm{GDP}^2_{t-ji} + \textstyle\sum_{\mathrm{i=1}}^{\mathrm{r}-1} \beta_4(\tau)\Delta\mathrm{FTEC}_{\mathrm{t}-ji} + \\ \textstyle\sum_{\mathrm{i=1}}^{\mathrm{m}-1} \beta_5(\tau)\Delta\mathrm{REN}_{\mathrm{t}-ji} + \textstyle\sum_{\mathrm{i=1}}^{\mathrm{n}-1} \beta_6(\tau)\Delta\mathrm{NRE}_{\mathrm{t}-ji} + \varepsilon_{\mathrm{t}}(\tau).\end{gathered} \tag{5}$$

In addition, short-term influence of the current level of ecological footprint can be determined by using (Δ); furthermore, short-term influence of ecological footprint is calculated by $\beta_{*i} = \sum_{i=1}^{0-1} \beta_{i1}$, although the collective short-term impact of simultaneous and foregoing non-renewable energy on the current stage of ecological footprints has been quantified as $\beta_{*i} = \sum_{i=1}^{r-1} \beta_{i6}$. Using the same technique, one may calculate the remaining cumulative short-term use at the current level of ecological footprint. It is expected that in Equation (5), the coefficient of conditional volatility ρ will be significantly negative and statistically significant.

3.2.3. Long-Run Asymmetries

The Wald test is carried out in order to evaluate the particular H_0 and H_A in order to obtain the short-term and long-term parameters needed to measure the asymmetrical influence of GDP, FTEC, REN, and NRE on EFP. As a result, various previously unseen factors in the underlying equations became apparent. It is clear from this phenomenon that the short- and long-term coefficients in the QARDL framework can be different on each quantile, indicating that they can have a different effect on each interval. Additionally, the quantile bounds for both the short- and long-term coefficients could be examined using the Wald test [49]. These H_0 and H_A for the short- and long-term parameters φ_*, w_*, β_*, and ρ_* can be tested with the Wald test [52], which asymptotically follows a Chi-squared distribution.

$$H_0^{\varphi} : F\varphi_*(\tau) = F \text{ versus } H_1^{\varphi} : F\varphi_*(\tau) \neq F$$

$$H_0^{\varphi} : S\omega_*(\tau) = S \text{ versus } H_1^{\varphi} : S\omega_*(\tau) \neq S$$

$$H_0^{\varphi} : S\beta_{i^*}(\tau) = S \text{ versus } H_1^{\varphi} : S\beta_{i^*}(\tau) \neq S$$

$$H_0^{\varphi} : S\rho_*(\tau) = S \text{ versus } H_1^{\varphi} : S\rho_*(\tau) \neq S$$

Finally, the long-run asymmetric effect will be supported if the Wald test [52] rejects the H_0 based on the Equation below (6):

$$\frac{\varphi_1}{-\varphi_0} = \frac{\varphi_2}{-\varphi_0}. \tag{6}$$

3.2.4. Quantile Granger Causality Test

A given variable Y_i cannot Granger cause a different variable X_i, as stated by [53] if earlier Y_i does is not able to estimate X_i, giving the prior X_i, so let us pretend that there is a vector for identifying labels $\left(M_i = M_i^X, M_i^y\right)' \in \mathbb{R}^e, e = o + q$, where M_i^y is the former evidence set of $Y_i M_i^y := (Y_{i-1}, \ldots, Y_{i-q})' \in \mathbb{R}^q$. In Equation (7), we see why it is reasonable to reject the H_A, i.e., that Granger non-causality runs from Y_i to X_i.

$$H_o^{Y \nrightarrow X} : F_X\left(x \mid M_i^X, M_i^y\right) = F_X\left(x \mid M_i^X\right), \text{ for all } x \in \mathbb{R}, \tag{7}$$

where $F_X\left(x \mid M_i^X, M_i^y\right)$ is the given function of X_i, provided (M_i^X, M_i^y). Utilizing H_0 from Equation (7), and following [54], the current study can replicate the D_T test by recognizing the QAR framework $m(\cdot)$ for the entire $\pi \in \Gamma \subset [0,1]$ on the causal relationship of non-Granger H_0 as follows in Equation (8):

$$QAR(1) : m^1\left(M_i^X, \partial(\pi)\right) = \lambda_1(\pi) + \lambda_2(\pi)X_{i-1} + \mu_t \Omega_Y^{-1}(\pi), \tag{8}$$

where the values $\partial(\pi) = \lambda_1(\pi), \lambda_2(\pi)$ and μ_t are measured by supremum of the probability in an identical space of grid of quantiles, while $\Omega_Y^{-1}(.)$ is the opposite of an old-style distributing method. Calculating the quantile autoregressive using a model described in Equation (9) that includes a factor that is laggard to the other factors enables one to remedy an incorrect suggestion of causality between FT and RE. In light of Equation (8), the previously presented equation of the QAR model can be described as follows in Equation (9):

$$Q_\pi^X\left(X_i \mid M_i^X, M_i^Y\right) = \lambda_1(\pi) + \lambda_2(\pi)X_{i-1} + \eta(\pi)Y_{i-1} + \mu_t \Omega_Y^{-1}(\pi). \tag{9}$$

4. Estimation and Results

4.1. Preliminary Test Results

The average value, the least significant value, and the most significant value are all examples of measures of central tendency. Positive numbers may be seen in the minimum value, mean value, and maximum value of the variables that were selected to be analyzed in Table 2, which displays a summary of all the variables that were used in the research.

Table 2. Preliminary test.

Variables	Mean	Max.	Min.	Std. Dev	Skewness	Kurtosis	Jarque-Bera	Prob.	Correlation
EFP	4.7912	7.5813	3.3312	2.0518	0.1812	1.4311	16.1217	0.0001	-
GDP	3.9480	4.5819	2.7312	0.5131	−0.0996	1.8236	9.7331	0.0104	0.9661 *
GDP^2	7.8960	8.4638	5.4624	1.0262	−0.0996	1.8236	9.7331	0.0104	0.09973 *
FTEC	8.3240	11.6315	5.1716	1.5732	0.7152	3.0182	9.1221	0.0111	0.9673 *
RNE	4.1340	5.4210	2.1336	0.9238	0.0721	1.6617	18.9812	0.0002	0.9469 *
NRE	5.8213	8.6613	3.6131	3.6610	0.1092	2.0001	5.1810	0.0015	0.9991 *

Note: * demonstrates a substantial degree of non-linear dependence at the 5% level. Source: Authors' Estimation.

EFP (Mean = 4.7912, Max= 7.5813, Min = 3.3312), GDP (Mean = 4.0819, Max= 3.9480, Min = 2.7312), GDP^2 (Mean = 8.1638, Max= 7.8960, Min = 5.4624), FTEC (Mean = 8.3240, Max= 11.6315, Min = 5.1716), RNE (Mean = 4.1340, Max= 5.4210, Min = 2.1336), and NRE (Mean = 5.8213, Max= 8.6613, Min = 3.6131). The Jarque–Bera test was utilized in this research work in order to verify that the data followed a normal distribution. In other words, the Jarque–Bera test contradicts the assumption that each variable follows a normal distribution at a 1% level of significance. Thus, quantile methods are appropriate and warranted in this investigation [54,55].

A box plot analysis of the variables that were looked at can be seen in Figure 4. These factors include ecological footprints (EFP), economic growth (GDP) and its square, financial technology (FTEC), renewable energy (REN), and non-renewable energy (NRE).

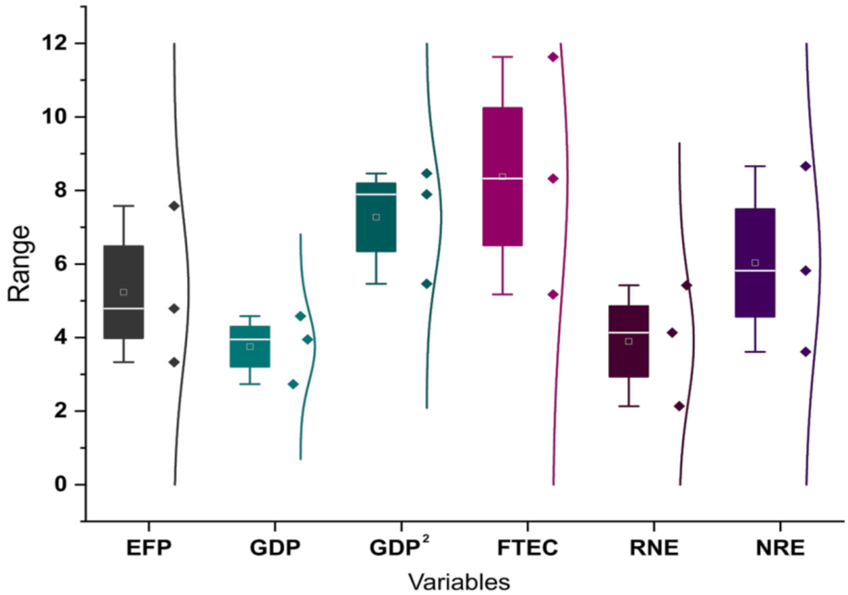

Figure 4. Analysis of the variables using a box plot.

4.2. Quantile Unit Root Test Results

The examination and discussion of the empirical data that were collected was the major purpose of this particular investigation. The evaluation of the stationarity qualities of the variables is a necessary step that must come before applying the QARDL model. As a result of the fact that the data do not follow a normal distribution, it is essential to make use of non-standard unit root tests. These tests include quantile-based alternatives to the conventional augmented Dickey Fuller and Phillips and Perron tests. Inferences that are more accurate and effective in mitigating potential biases can be drawn by applying quantile unit root methodologies [50]. Table 3 displays the quantile unit root test outcomes for the study variables across multiple quantiles. It is interesting to note that all of the coefficient values are higher than the threshold. In light of this, the null hypothesis (H_0) of $\alpha(\tau) = 1$ cannot be statistically rejected at a 5% significance level, regardless of the chosen quantile. According to the results of the quantile unit root tests, this suggests that there is not adequate evidence that the variables demonstrate stationarity.

Table 3. Unit-root test results.

Quantiles	EFP			GDP			GDP^2			FTEC			RNE			NRE		
	$\alpha(\tau)$	t-Stats	C.V	$\alpha(\tau)$	t-Stats	C.V	$\alpha(\tau)$	t-Stats	C.V	$\alpha(\tau)$	t-Stats	C.V	$\alpha(\tau)$	t-Stats	C.V	$\alpha(\tau)$	t-Stats	C.V
0.05	0.854	−2.342	−3.015	0.966	−0.771	−2.455	0.987	−0.733	−2.428	0.846	−2.111	−2.343	0.868	−2.123	−2.355	0.825	−1.850	−2.683
0.10	0.867	−1.836	−2.827	0.932	−0.982	−2.767	0.921	−0.971	−2.737	0.722	−1.121	−2.362	0.725	−1.133	−2.374	0.813	−2.504	−2.742
0.20	0.877	−2.013	−2.937	0.923	−1.277	−2.963	0.913	−1.263	−2.922	0.854	−0.454	−2.367	0.867	−0.453	−2.366	0.837	−2.613	−2.929
0.30	0.882	−2.482	−3.015	0.910	−1.244	−3.047	0.916	−1.215	−3.015	0.897	−0.022	−2.359	0.902	−0.022	−2.374	0.862	−2.336	−3.029
0.40	0.891	−2.129	−2.827	0.856	−1.713	−3.079	0.847	−1.689	−3.048	0.977	1.392	−2.353	0.994	1.385	−2.360	0.889	−1.657	−3.126
0.50	0.898	−2.032	−2.937	0.816	−2.014	−3.123	0.808	−1.986	−3.083	0.983	1.287	−2.615	1.099	1.395	−2.507	1.060	−1.219	−3.028
0.60	0.930	−1.642	−3.015	0.826	−1.771	−2.950	0.827	−1.747	−2.914	1.036	2.746	−2.635	1.178	2.873	−2.508	0.985	−0.178	−3.102
0.70	0.941	−1.600	−2.827	0.804	−1.887	−2.853	0.805	−1.866	−2.822	0.991	1.905	−2.514	1.008	1.908	−2.511	0.877	−1.349	−2.965
0.80	0.901	−1.891	−2.937	0.774	−2.644	−2.818	0.784	−2.627	−2.787	1.078	1.990	−2.450	1.111	2.001	−2.439	0.953	0.645	−2.732
0.90	0.943	−1.449	−3.015	0.741	−2.087	−2.514	0.748	−2.069	−2.486	1.074	2.924	−2.358	1.095	2.926	−2.356	1.089	0.455	−2.435
0.95	0.955	−1.211	−2.827	0.770	−2.256	−2.363	0.771	−2.221	−2.337	1.114	5.539	−2.363	1.134	5.545	−2.346	0.959	1.016	−2.610

Note: Estimates at a 5% level of significance. Source: Authors Estimation.

4.3. Quantile Autoregressive Distributed Lag Model (QARDL) Test Results

Application of the Quantile Autoregressive Distributed Lag (QARDL) model yielded the estimation results shown in Table 4. Moreover, the results show that across all quantiles, the anticipated coefficient for the rate of adaption (ρ*) is significantly negative. This points to a significant slowing down of the adjusting process. Thus, more proof is offered that economic indicators such as the United States' ecological footprint, financial technology, renewable energy, non-renewable energy, gross domestic product, and GDP2 converge to a long-term equilibrium over time. To elaborate, the final quantile features the highest adjustment rate (−3.633). There is a positive long-term link between EFP and GDP across all quantiles, as indicated by the positive GDP cointegration coefficient. In contrast, GDP2's cointegration value is consistently negative across all quantiles. This result lends credence to the EKC hypothesis in the USA, demonstrating a long-term correlation with an inverted U-shaped pattern between GDP, GDP2, and EFP. Ecological sustainability, however, becomes problematic at advanced stages of economic development, and the importance of GDP2 declines with increasing quantiles. Additionally, between the 0.05 and 0.80 quantiles, the turning points of the EKCs start to grow, suggesting that the energy and environmental policies in the United States are insufficient to prevent environmental degradation.

Table 4. Results of Quantile Autoregressive Distributed Lag Model (QARDL).

Quantiles (τ)	Constant	ECM	Long-Run						Short-Run				
	α (τ)	ρ *	β_{GDP} (τ)	β_{GDP^2} (τ)	β_{FTEC} (τ)	β_{RNE} (τ)	β_{NRE} (τ)	$\varphi_{1\ (EFP)}$	$\omega_{0\ (GDP)}$	$\lambda_{0\ (GDP^2)}$	$\delta_{0\ (FTEC)}$	$\psi_{0\ (RNE)}$	$\theta_{0\ (NRE)}$
0.05	0.324 * (3.395)	−0.262 * (−4.281)	0.438 * (6.483)	−0.225 * (−3.742)	−0.008 *** (−1.319)	−0.007 *** (−1.340)	0.505 * (7.363)	0.377 * (3.373)	0.304 * (3.597)	−0.011 (−0.364)	−0.281 (−0.423)	−0.026 (−0.475)	0.026 (0.608)
0.10	0.323 * (3.390)	−0.273 * (−4.472)	0.427 * (6.182)	−0.219 * (−3.522)	−0.073 *** (−1.382)	−0.057 *** (−1.392)	0.448 * (6.791)	0.312 * (3.469)	0.226 * (3.241)	−0.067 (−0.340)	−0.300 (−0.631)	−0.011 (−0.500)	0.036 (0.546)
0.20	0.329 * (3.367)	−0.275 * (−4.577)	0.426 * (6.113)	−0.197 * (−2.968)	−0.121 *** (−1.632)	−0.239 ** (−2.432)	0.433 * (6.860)	0.304 * (3.488)	0.026 (0.492)	−0.023 (−0.287)	−0.262 (−0.690)	−0.020 (−0.575)	0.024 (0.503)
0.30	0.341 * (3.409)	−0.273 * (−4.667)	0.517 * (5.902)	−0.330 * (−2.868)	−0.052 *** (−1.778)	−0.172 ** (−2.198)	0.495 * (6.499)	0.356 * (3.467)	0.071 (0.408)	−0.011 (−0.299)	−0.152 (−2.187)	−0.105 (−0.638)	0.074 (0.473)
0.40	0.355 * (3.522)	−0.265 * (−4.408)	0.420 * (5.873)	−0.168 * (−2.763)	−0.206 ** (−2.222)	−0.226 ** (−2.259)	0.447 * (6.681)	0.304 * (3.690)	0.023 (0.588)	−0.001 (−0.363)	−0.007 (−1.479)	−0.015 (−0.734)	0.022 (0.371)
0.50	0.360 * (3.418)	−0.276 * (−4.143)	0.399 * (5.712)	−0.228 * (−2.627)	−0.243 * (−2.733)	−0.251 * (−2.743)	0.462 * (6.668)	0.320 * (3.623)	0.036 (0.479)	−0.010 (−0.344)	−0.011 (−1.152)	−0.003 (−0.753)	0.036 (0.406)
0.60	0.388 * (3.219)	−0.254 * (−4.037)	0.413 * (5.165)	−0.125 ** (−2.133)	−0.243 * (−2.833)	−0.287 * (−2.891)	0.448 * (6.891)	0.311 * (3.780)	0.001 (−0.893)	−0.008 (−0.470)	−0.005 (−1.080)	−0.013 (−0.829)	0.022 (0.476)
0.70	0.409 * (3.173)	−0.242 * (−3.893)	0.429 * (4.972)	−0.084 ** (−2.038)	−0.231 * (−3.293)	−0.298 * (−3.303)	0.460 * (7.024)	0.316 * (3.731)	−0.001 (−0.805)	−0.007 (−0.427)	−0.006 (−0.827)	−0.014 (−0.786)	0.015 (0.569)
0.80	0.431 * (3.104)	−0.227 * (−3.844)	0.442 * (4.631)	−0.083 *** (−1.782)	−0.283 * (−3.783)	−0.308 * (−3.878)	0.525 * (7.113)	0.385 * (3.878)	0.073 (0.479)	0.042 (−0.543)	0.052 (−0.831)	−0.009 (−0.867)	0.024 (0.555)
0.90	0.452 * (3.079)	−0.310 * (−3.735)	0.353 * (3.998)	−0.175 *** (−1.803)	−0.383 * (−4.163)	−0.382 * (−4.180)	0.474 * (7.190)	0.331 * (3.471)	0.044 (0.338)	−0.002 (−0.592)	−0.010 (−0.809)	−0.007 (−0.891)	0.026 (0.600)
0.95	0.478 * (3.055)	−0.206 * (−3.633)	0.470 * (3.848)	−0.073 *** (−1.782)	−0.271 * (−4.062)	−0.337 * (−4.040)	0.527 * (6.996)	0.385 * (3.369)	0.104 (0.518)	−0.007 (−0.589)	−0.005 (−0.740)	−0.001 (−0.892)	0.017 (0.675)

Note: Significance levels are denoted by *, **, and ***, representing 1%, 5%, and 10% significance, respectively, with t-statistics presented in parentheses. Source: Authors Estimation.

This study uncovers previously unacknowledged aspects of the environmental Kuznets curve (EKC) theory in the United States by conducting an analysis of the disaggregation of EKC patterns across multiple quantiles. As a result, the current understanding is expanded beyond the scope of the existing body of literature [56–59]. Although their long-term link with EFP does not become significant until after the second quantile is passed, empirical studies show that FTEC and REN have a detrimental effect on EFP after that point. This discovery indicates that the widespread use of FinTech and renewable energy is lowering environmental impact over time. Because of this, the case for integrating FinTech and renewable energy as a powerful strategy to reduce the negative effects of climate change and environmental degradation in the United States is strengthened. The empirical results, on the other hand, show that the usage of non-renewable energy sources increases the ecological footprint at all quantiles. Furthermore, the study shows that compared to using non-renewable energy sources, utilizing FinTech and renewable energy leads to a smaller ecological footprint. This confirms the findings of prior research [60–62].

In addition, significant insights are provided by the levels of relevance and the size of the impact resulting from the use of FinTech and renewable energy. In particular, between the 0.05 and 0.20 quantiles, FinTech's influence is not significant, and between the 0.05 and 0.10 quantiles, renewable energy consumption's impact is not significant. However, between the quantiles of 0.20 and 0.40, the impact's importance is minimal. Both FTEC and REN show an increase in significance beyond the 0.40 quantile, with commensurate increases in impact size. This finding suggests that the environmental impact of using less FinTech and renewable energy sources may be small or non-existent. However, the effect becomes more noticeable at deeper penetration levels. Given that no other research has focused on this specific feature, this conclusion, which highlights the diminished influence of FTEC and REN on the ecological footprint in the United States, can be seen as an important addition to the current literature.

The results of short-term dynamics indicate that the ecological footprint at each quantile is considerably influenced by the ecological footprint at earlier phases. Notably, only in the lowest GDP quantiles do recent developments have a positive impact on the present ecological footprint. However, neither historical nor contemporaneous changes in GDP2 have an effect on the present ecological footprint. In addition, the findings indicate that the use of FTEC, REN, and NRE in the lower quantiles has a substantial and unfavorable effect on the current changes in EFP. In contrast, the historical fluctuations in FTEC, REN, and NRE have little effect on the current increases in EFP. There is a considerable negative correlation between EFP and GDP across all quantiles, as evidenced by the Table 4 primary conclusions. FTEC and REN have a detrimental influence on EFP after the second quantile is surpassed. NRE has a positive influence on EFP across all quantiles. The impact of FTEC and REN on EFP increases as their penetration grows, but NRE has a positive effect on EFP across all quantiles.

4.4. Wald Test Results

Table 5 displays the Wald test's findings regarding the stability of selected parameters across quantiles. In order to determine whether or not the parameters vary over quantiles, this statistic is employed. The results show that there is a lot of long-term parameter variation between quantiles; thus, we can rule out the null hypothesis of constant parameters. This shows that the impacts of the investigated factors on the EFP vary across quantiles. Similarly, quantiles exhibit similar variation in the effects of the regressors over the short term. These findings highlight the importance of analyzing the long-term effects of the selected determinants on EFP using the Quantile Autoregressive Distributed Lag (QARDL) approach, which takes into account non-linearity and structural breakdowns. Changes in the United States' macroeconomic variables during the research period could provide insight into these findings. The short-term cumulative effect of earlier levels of EFP does not appear to be uniform across all quantiles, as shown by the Wald test's null hypothesis. The test also rejects the hypothesis of persistent variable linearity across quantiles, suggesting that factors other than GDP, FTEC, REN, and NRE do not have a linear effect on ecological footprints. However, generally, the US ecological footprint was significantly proportional to each of GDP, FTEC, REN, and NRE. As the ecological footprint grew, so did this linear effect.

Table 5. Wald test results.

Variables	F-Statistics	Prob.
ρ	8.052 *	0.000
β_{GDP}	6.667 *	0.000
$\beta_{GDP}{}^2$	3.926 **	0.000
β_{FTEC}	5.754 *	0.000
β_{REN}	4.553 *	0.000
β_{NRE}	3.945 *	0.000
$\varphi_{1\ (EFP)}$	3.210 **	0.016
$\omega_{0\ (GDP)}$	3.001 *	0.008
$\lambda_{0\ (GDP^2)}$	2.221	0.059
$\delta_{0\ (FTEC)}$	5.952 *	0.000
$\psi_{0\ (RNE)}$	4.884 *	0.000
$\theta_{0\ (NRE)}$	3.863 *	0.000

*, and ** indicate significance at 1%, and 5% levels, respectively. Source: Authors Estimations.

Furthermore, at the 1% significance level across all quantiles, the results show that the aggregate short-run influence of GDP, FTEC, REN, and NRE on EFP is non-linear. The study of the data, which investigates the connection between these factors and the ecological footprint, leads to this result. A thorough examination of the data revealed that there is a non-linear link between these factors and the ecological footprint. The major takeaways from the Wald test results are that the QARDL model's long-term parameters are not stable across quantiles, and that the QARDL model's short-run parameters are likewise not stable across quantiles. Compared to a standard linear regression model, the QARDL model is superior for studying the correlation between EFP and the explanatory factors.

4.5. Granger Causality in Quantile Test Results

Table 6 displays the p-values obtained from the Quantile Granger causality tests. When we expanded the quantile range to include [0.05–0.95], we found that there was a bidirectional causal relationship between the variables that were being explored in the context of the United States. This suggests that GDP growth rates are stronger forecasters of ecological footprints than any other element that may be taken into consideration. In addition, empirical evidence from the quantile causality test across all quantile tails reveals a bidirectional causality between the use of non-renewable energy and ecological footprints, which is consistent with the findings of earlier research carried out by and [63,64].

On the other hand, we discovered evidence of a unidirectional causal relationship between FinTech, renewable energy consumption, and ecological footprints across all quantiles. This was the most significant finding. In addition, a one-way causal connection was found between ecological footprints and the utilization of renewable energy sources at the highest quantiles. The conclusions of this study are corroborated by the findings of another study called QARDL, the results of which indicate that the impact of FinTech and the usage of renewable energy is still undervalued in the lower quantiles. It is essential to keep in mind that the ecological footprint left by the United States is not proportional to the amount of energy derived from renewable sources that is used. This shows that governmental initiatives to increase demand for FinTech and promote the use of renewable energy sources in areas with low penetration have not been successful. In addition, this suggests that policy efforts to increase demand for green energy sources in areas with low penetration. After the 0.50 quantile, there is a discernible increase in the amount of speculative demand for these products, which is directly responsible for the growing ecological impact.

Table 6. Granger causality in quantile test results.

Quantiles (τ)	ΔGDP ⇎ ΔEFP	ΔEFP ⇎ ΔGDP	ΔFTEC ⇎ ΔEFP	ΔEFP ⇎ ΔFTEC	ΔREN ⇎ ΔEFP	ΔEFP ⇎ ΔREN	ΔNRE ⇎ ΔEFP	ΔEPF ⇎ ΔNRE
[0.05–0.95]	33.634 *	32.950 *	33.595 *	28.369 *	35.249 *	30.023 *	30.621 *	31.030 *
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0.05	21.770 *	33.009 *	18.541 *	19.553 *	18.541 *	19.553 *	21.225 *	16.697 *
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0.10	29.880 *	19.878 *	23.789 *	20.399 *	23.789 *	20.399 *	19.653 *	21.834 *
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0.20	12.223 *	13.778 *	19.434 *	21.863 *	19.434 *	21.863 *	23.307 *	23.541 *
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0.30	23.853 *	21.689 *	18.786 *	25.047 *	18.786 *	25.997 *	22.951 *	23.014 *
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0.40	15.369 *	20.416 *	23.134 *	23.134 *	22.959 *	24.080 *	29.911 *	31.688 *
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0.50	11.261 *	13.265 *	23.596 *	24.829 *	23.596 *	24.829 *	23.370 *	25.345 *
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0.60	22.674 *	25.085 *	24.461 *	21.192 *	24.461 *	21.192 *	21.904 *	22.006 *
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0.70	31.460 *	27.910 *	27.126 *	28.446 *	27.126 *	29.231 *	24.825 *	26.383 *
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0.80	18.304 *	16.555 *	19.487 *	15.761 *	19.487 *	15.761 *	18.862 *	17.565 *
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0.90	23.712 *	23.098 *	23.514 *	25.184 *	23.514 *	25.184 *	19.758 *	17.291 *
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0.95	29.825 *	32.749 *	28.858 *	23.036 *	27.448 *	22.836 *	31.209 *	31.927 *
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: As the null hypothesis, no granger causality is assumed to exist. Most values suggest rejecting the null hypothesis at the 1% level of significance. * represents level of significance at 1%. Source: Authors' Estimation.

Figure 5 shows the relationships among GDP, non-renewable energy consumption, and the United States' ecological footprint. The findings point to a positive relationship between GDP and ecological footprints from the use of non-renewable energy sources. Ecological footprints, in other words, rise in tandem with both GDP and usage of non-renewable energy. In contrast, green technology, financial innovation, renewable power, and ecological footprint all have a negative relationship with GDP squared. This suggests that a smaller ecological footprint follows a rise in the squares of GDP, financial technology, and renewable energy. These findings point to the existence of competing linkages between these factors and their impact on the United States' ecological footprint. The results of the Granger causality test suggest a positive and negative causal relationship between U.S. gross domestic product and ecological footprint. The use of non-renewable energy sources increases the ecological footprint in both directions. FinTech and renewable energy have a unidirectional causal link with the highest quantiles of the ecological footprint.

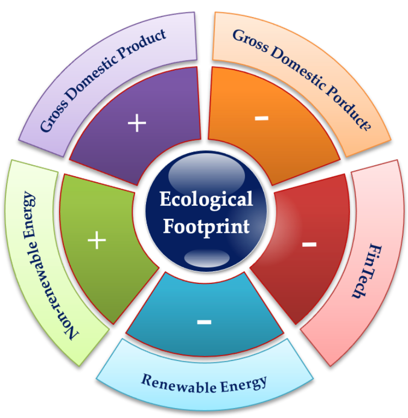

Figure 5. Graphical representation of the empirical analysis.

4.6. Robustness Check

We also employ a complementary regression estimator to check the robustness of the QARDL test results. In this context, we use the standard ARDL method, and the results are shown in Table 7. The effects of GDP, GDP2, FTEC, RNE, and NRE on EFP are reflected similarly in the QARDL and ARDL estimations in this context. GDP has a positive coefficient of 0.5894 in the short run; therefore, we may estimate that a rise of 1% in GDP will lead to a rise of 0.5894% in EFP. A similar positive correlation of 0.4067 is found for GDP in the long run; this means that an increase of 1% in GDP is expected to result in a 0.4067% rise in EFP. GDP2 has negative short-run and long-run coefficients of −0.4219 and −0.3204, respectively. Based on these numbers, it appears that for every 1% growth in GDP2, the EFP is destined to drop by −0.4219 and −0.3204 percentage points. Both the short- and long-term coefficients for FTEC and RNE are negative, suggesting that rising levels of these variables would diminish EFP, whereas rising levels of NRE would enhance it.

Table 7. ARDL test results (Robustness analysis).

Variables	Short Run	Long Run
GDP	0.5894 *	0.4067 *
GDP^2	−0.4219 **	−0.3204 **
FTEC	−0.3920 *	−0.3197 *
RNE	−0.3041 *	−0.2178 *
NRE	0.2954 *	0.2102 *
ECT (−1)	0.1691 *	
Constant	2.9611 *	
Adj. R^2	0.8621	

*, and ** indicate significance at 1%, and 5% levels, respectively. Source: Authors Estimations.

5. Conclusions and Policy Recommendations

5.1. Conclusions

This study evaluates the effects of FinTech, renewable energy, and non-renewable energy use on US Environmental Kuznets Curve (EKC) testing from 2005 Q1 to 2020 Q4. The World Bank's Global Findex, which shows quarterly financial technology growth in the US, is used to create a proxy indicator of FinTech innovation. This study examines quantiles and lagged outcomes using the Quantile Auto Regressive Distributed Lag (QARDL) approach [49]. This method provides a more complete understanding of FinTech, renewable energy, non-renewable energy, and the ecological footprint than typical methods such as OLS or quantile regression. Based on [54], the analysis examines causation within quantiles to determine the causes and effects of GDP, FinTech, renewable energy, non-renewable energy, and ecological footprint. The QARDL model confirms the expected negative link between the error correction parameter and the quantiles, suggesting a long-term relationship between these variables and the US ecological footprint. FinTech and renewable energy have a smaller long-term ecological footprint across quantiles. Economic growth and non-renewable energy usage improve the ecological footprint from the lower to the upper quantiles. Economic growth rates affect the environment differently over time. The data show that greater energy usage over time improves the ecological footprint. Short-term dynamics show that FinTech, renewables, and economic expansion have different impacts on the ecological footprint. The QARDL approach experimentally tests the environmental Kuznets curve hypothesis. The QARDL study supports the EKC hypothesis by showing that economic growth increases the ecological footprint, while economic growth squared decreases it. This conclusion supports the emerging evidence of an inverted U-shaped link between economic growth and environmental degradation. The Wald test also revealed that the long-term parameters show significant fluctuation between quantiles, suggesting that the null hypothesis of constant parameters across quantiles is rejected. The Granger causality study in quantiles shows bidirectional causal linkages between economic growth, FinTech, renewable energy, non-renewable energy, and the US ecological footprint.

More in-depth studies of the elements affecting environmental contamination proxies are possible in the future. Among the technological and socioeconomic factors that could be investigated are the effects of FinTech, demographic dynamics, green growth, and others. These linkages can be better understood in their entirety if taken into account alongside environmental proxies. Expanding the EKC argument, thoroughly analyzing influencing factors, conducting nation and sector-wise evaluations, and examining the indirect impact of FinTech and renewable energy on ecological footprints in the US are all examples of how future research can add to the existing body of knowledge and tackle the gaps in our current understanding. Insights gained from these lines of inquiry can improve our knowledge of the interconnections among economic growth, technological advances in management of resources, and ecological sustainability, and so guide better policy and decision making.

5.2. Policy Recommendations

Several policy implications for long-term sustainability emerge from a detailed analysis of the empirical results. Since environmental quality tends to deteriorate with increasing income, it can be safely inferred that the United States' current economic trajectory is unsustainable. The use of fossil fuels for energy is a key contributor, as shown by observational data. However, the ineffectiveness of policy levels in disseminating green FinTech and renewable energy solutions demonstrates that the low penetration of green FinTech and renewable energy solutions is having little to no effect on the ecological footprint. Simple solutions include switching to green technology and renewable energy sources instead of those that rely on fossil fuels, but this may not be feasible because it could slow economic growth. Therefore, the solution can be created in a phase-by-phase approach at the policy level, taking into account the various quantiles.

Starting from the lower-income quantiles, it is observed that the turning points of the environmental Kuznets curve (EKC) are comparatively lower compared to the higher quantiles. Since the presence of EKC with lower turning points may help mitigate the negative externalities caused by the rising emphasis on economic growth, conducting policy-oriented assessments at this level may prove beneficial. This can be accomplished by assisting the use of green FinTech and renewable energy to attain its full potential by increasing its adoption among consumers and industry. This can be accomplished through public–private partnerships that aim to raise the residents' level of environmental awareness in order to achieve the desired results [65,66]. While doing so, the government is in a position to offer assistance in the form of FinTech and solutions for renewable energy to the people that are being subsidized by these facilities for a fixed period of time. It is possible that the acceptance of FinTech and renewable energy solutions among households may progressively increase as a result of this decision [67]. After these policy-level changes are made, the United States will become less reliant on fossil fuels and air pollution will go down. This will help the country catch up with SDG 9, SDG 13, SDG 14, and SDG 15.

The effects of exceeding the ecological footprint threshold and ways to lower it can be explained. This discussion may illuminate the effects of extensive deployment on industry dynamics using new economic geography. Sustainable practices, resource efficiency, policy interventions and regulatory frameworks that reward environmentally friendly actions, and raising individual and corporate awareness of environmental repercussions of decision are needed to reduce the ecological footprint [68,69]. New economic geography can also help firms adapt to greener practices [70]. Thinking about the consequences of crossing the ecological footprint threshold and applying new economic geography can help us create a more sustainable and environmentally conscious future.

Promoting environmentally conscious behaviors and facilitating the transition to cleaner energy sources, respectively, are two ways in which FinTech and renewable energy can make a substantial contribution to environmental improvement. FinTech platforms can use carbon neutrality mechanisms in digital payment systems, sophisticated analytics of data for sustainability, creative fundraising models to support renewable energy development, streamlined energy trading, specialized loans, and financing possibilities to promote enhancements to energy efficiency, and bridged access to financial services. Fostering a more environmentally conscious society and accelerating the transition to clean energy sources can be accomplished through the integration of the cutting-edge capabilities of FinTech with the sustainable and environmentally friendly nature of renewable energy.

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