Journal of Cleaner Production 418 (2023) 138146

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

The synergy effect through combination of the digital economy and transition to renewable energy on green economic growth: Empirical study of 18 Latin American and caribbean countries

Young Kyu Hwang

Autonomous University of Madrid, Spain

A R T I C L E I N F O

Handling Editor: Giovanni Baiocchi

Keywords:
Synergistic effect
Renewable energy transition
Digital economy
Green economic
Growth
Latin America

A B S T R A C T

Tremendous effects on the global economy in terms of economic, social and environmental costs remind us of the catastrophic consequences of climate change and global warming caused by CO_2 emissions. Therefore, accelerating decarbonization of the global energy system should be put in place to curb large amount of CO_2 emission from hydrocarbon energy sources on which the current global value chain of production heavily relies.This study focuses on analyzing the effects of renewable energy transition, the digital economy, and the synergy between them on green economic growth in 18 Latin American countries. To capture the multidimensionality of these transitions, the Renewable Energy Transition Index (RETI) and the Digital Economy Index (DEI) are developed using the Principal Component Factor (PCF) technique. The FixedEffect Panel Threshold Regression (FEPTR) substantiates that renewable energy transition has a significant threshold effect on economic growth and environmental sustainability depending on the level of income and carbon emissions. On the other hand, the Method of Moments Quantile Regression (MMQR) shows that both renewable energy transition and the digital economy have a significant positive impact on economic growth in all quantile groups. For the environmental sustainability, only renewable energy transition is found to have a positive impact in all quantile groups. From the synergistic effect perspectives, the CO_2 emissions reduction is observed in both the low and middle quantile groups, but the economic growth promotion is only observed in a low quantile group.

1. Introduction

According to the Intergovernmental Panel on Climate Change's Sixth Assessment Report (IPCC, 2022), the global average temperature has been rising approximately 1.1°C compared with that of the late 1800s. Specifically, the last decade from 2010 to 2019, the average temperature on earth was at a record high without precedents in comparison with the previous decades. The main factors of this global warming can be found in GHG emissions, especially in CO_2 emissions caused by anthropogenic activities and the burning of fossil fuels. Indeed, the average annual GHG emissions during 2010–2019, coinciding with the warmest temperature registered during this decade, were higher than ever even though the average annual growth rate of GHG emissions has been slowed down compared to that of 2000–2009 (1.3% against 2.1%) (IPCC, 2022). It is worth noting that the historical cumulative net CO_2 emissions from 1850 to 2019 account for almost four fifths of the total carbon budget with 50% probability to restrain the increase in global average temperature to well below 1.5°C above preindustrial levels and two thirds of the total carbon budget with a 67% probability to constraint a rise in global average temperature to well below 2°C above pre-industrial levels (IPCC, 2022). Since the remaining carbon budget to meet the Paris Agreement Goals is quite limited in order to avoid catastrophic and irreversible consequences of global warming and climate change, policymakers and researchers agree on taking urgent measures to deal with this issue (World Bank, 2022). As viable alternatives to the issue, they are managing, a paradigm shifts from fossil fuels towards clean and renewable energy sources, known as renewable energy transition, is considered as one of the most prominent and promising option to dealing with global warming and CO_2 emissions reduction (Smil, 2020). This is because the energy supply is the main sector responsible for global GHG emissions which account for approximately 34% of total GHG emissions worldwide in 2019, followed by industry (24%), agriculture, forestry, and other land use (22%), transport (15%), and residential and commercial sectors (6%) (IPCC, 2022), thus the importance of deep decarbonization in energy sector cannot be overemphasized. The key role that renewable energy sources and clean energy

E-mail address: young.hwang@estudiante.uam.es.

https://doi.org/10.1016/j.jclepro.2023.138146
Received 25 February 2023; Received in revised form 12 July 2023; Accepted 16 July 2023
Available online 19 July 2023

technologies can play in achieving global net-zero goals and moving towards a low-carbon economy is also well summarized in the Kaya identity (Kaya, 1990). According to this theory, carbon emissions are determined by three major factors: the carbon intensity of energy sources (C/E), energy intensity (E/Y), and economic output or growth (Y).[1] To mitigate the negative impact of energy use and economic activities on environmental quality, significant changes should be made in terms of the energy mix and sectoral shift, namely moving towards low-carbon energy sources such as renewables and low-energy intensive sectors while maintaining economic growth (Hübner, 2018).

In the new decarbonization scenario, the renewable energy sources are expected to have a prominent role in the coming decades, the digital economy has recently been drawing much attentions from many governments, academics and policymakers who recognized it not only as an important tool for fulfilling a rapid and prompt low-carbon economy transition required to avoid catastrophic consequences on the planet and ensure environmental sustainability, but also as a key enabler to improving countries' competitiveness and productivity in the global market for long-term economic growth (Nwaiwu, 2021). This is because the digital economy has been expecting to greatly facilitate the integration of variable renewables in energy mix by relieving their inherent intermittency and variability through accurate predictions of renewable energy production (Lin and Huang, 2023) and efficient management of energy and resource use via application of smart technologies such as Artificial Intelligence (AI), big data, cloud computing, machine learning and block chain in energy- and emission-intensive sectors (mainly industry, manufacturing and construction, transport, electricity and heating sector) (IEA, 2017). It can also promote green innovations, which allow to save energy enormously and input costs in the production process, reduce energy consumption and GHG emissions, and improve productivity of workers (Asif, 2020). The potential impact of digitalization on decoupling economic growth and energy use from environmental degradation in the process of transition to renewable energy can be closely linked to the Environmental Kuznets Curve (EKC) hypothesis (Grossman and Krueger, 1995). According to this theory, a country's emission level at the initial stage of industrialization increases rapidly due to growing economic activities accompanied by the use of polluting energy sources and low energy efficiency (scale effect). However, after reaching to a certain level of income and technology level, the environmental quality of a country begin to improve due to the gradual adoption of more efficient and environmentally friendly technologies (technical effect) in the production process and a structural transformation from high-energy intensive sectors such as manufacturing towards a more knowledge based service sectors (composition effect). Since the adoption of digital technologies allows countries to greatly improve their total factor productivity and achieve rapid economic growth, it can trigger green innovation efforts and facilitate the adoption of advanced clean energy technologies in the production process. This can ultimately lead to decoupling of economic growth and energy use from environmental degradation as predicted by the EKC hypothesis.

Even though many benefits are expected from the synergy between renewable energy transition and the digital economy on green economic growth in developing countries, most of the previous studies were centered around developed or large emerging countries such as China and India. In this context, this study examines how the combination of renewable energy transition and the digital economy can contribute to a substantial economic growth and reductions in carbon emissions in Latin American and Caribbean (LAC) countries and analyzes the asymmetric and heterogenous impact of transition to renewable energy in association with income and carbon emissions, given that LAC countries are highly different from energy mix, production structure, and natural resources endowment. Thanks to digitalization, accelerating the integration of renewable energy sources into the energy mix can relieve the energy trilemma facing the LAC region; energy affordability, energy security, and energy sustainability (OLADE, 2020). This is due to the fact that application of digital technologies in renewable energy power grids (smart grids) facilitate modern, reliable and affordable energy access by the people living in remote areas, and improve their living conditions (IEA, 2017). Furthermore, it can trigger green innovation efforts and bring about significant improvements in energy productivity and efficiency, cost reductions and energy savings (Luo et al., 2022), which will bring great repercussions upon production capabilities and energy sustainability (Fankhauser and Jotzo, 2018). More on that, the digitalization can provide more flexibility, reliability, and resilience to renewable energy systems through sector coupling, which will facilitate sharing information and data among different sectors, and enhancing energy security (Ren et al., 2021). Based on the critical analysis of observations in the previous studies and the research so far, the main research problems of this study are figured out as follows.

- Does the synergistic effect between the transition to renewable energy and the digital economy for green economic growth exist in the LAC region? In other words, does the synergistic effect between them help to successfully decouple economic growth from environmental degradation?
- Are there any significant non-linear and threshold effect of the transition to renewable energy on economic growth and environmental quality in association with a country's income and emission levels in the LAC region?
- Does the impact of the transition to renewable energy, the digital economy, and the interaction between them on economic growth and environmental quality show significant heterogeneity across different quantile groups in the LAC region?

The salient results from our responses to the research problems above are followed by: First, the Renewable Energy Transition Index (RETI) and the Digital Economy Index (DEI) specific to the LAC region are developed to evaluate the impact on green economic growth by encompassing multidimensional features and complex reality accompanied by renewable energy transition and the digital economy. The previous studies rely on the one-dimensional indicator (renewable energy consumption or renewable energy generation as a proxy for renewable energy transition and Internet penetration rate or mobile subscriptions as a proxy for digital economy) had their limit in describing complex reality and multidimensional features from which renewable energy transition and the digital economy entail. Second, the interaction term between renewable energy transition and the digital economy is incorporated into the regression models to estimate the potential synergistic effect between the digital economy and renewable energy transition on promoting economic growth and enhancing environmental quality in the LAC region. Thanks to ever evolving digital technologies and their popular use in our daily lives, it is right time for this study to get initiated, given that the governments in the LAC region are challenging viable approaches to successful implementation of decarbonization strategy by leveraging potentials of the digital economy. Third, given that the LAC region consisting of many countries with big difference in their income levels, emission intensity, energy system, resource endowments, and structural composition, the impact of transition to renewable energy and the digital economy on economic growth and environmental quality is expected to be quite different. Therefore, the FEPTR and the MMQR econometric techniques are used to analyze asymmetry and non-linearity features of their impact across Latin American and Caribbean economies. The analysis would provide governments and policymakers of each country alike with invaluable information concerning about a specific challenges and opportunities for low-carbon economy transition.

The remaining parts of this paper are organized as follows: Section 2 discusses the potential opportunities and challenges that the LAC region

[1] $C = C/E \times E/Y \times Y$, where C, E and Y denote carbon emissions, energy use and economic output resepectively.

would come across during the process of transition to renewable energy and the digitalization of their economies. Section 3 presents a literature review. Section 4 describes the methodology and the dataset used in this study. Section 5 discusses empirical results and the findings in this study. Section 6 provides conclusions and policy implications.

2. Background

2.1. Renewable energy transition in the LAC

In the LAC region, energy transition is not just simply a shift from high-carbon intensive energy sources such as fossil fuels (coal, oil, and natural gas) to low-carbon intensive ones such as renewable energies (solar, wind, geothermal, tidal, green hydrogen), but also implies a profound and fundamental structural transformation in social, economic, and environmental dimensions which lead to a radical change in the way people produce and consume energy (Guimarães, 2020). This paradigm shifts of renewable energy transition present both opportunities and challenges for the LAC region. The main reasons that renewable energy transition might benefit and offer a great opportunity for the LAC countries to fulfill sustainable development goals (economic, social, and environmental development) are the following. First, renewable energy transition can contribute to achieving the goal of universalization of modern energy access (electricity) in the region, especially in remote areas where network infrastructure does not reach to providing reliable electricity services through decentralized and off-gird renewable energy systems such as distributed solar photovoltaic, wind turbines (Vanegas Cantarero, 2020). Although in the LAC region, 95% of population has already access to electricity (about 18.1 million people were still lacking electricity in 2018), approximately a third of those electricity connections are illegal and electricity theft occurs frequently (Guimarães, 2020). In this aspect, the decentralized and off-grid renewable energy system might be a good alternative to providing reliable electricity services to those people who live in remote and marginalized areas where the electricity cannot reach due to the lack of electricity network and their geographical location (Vanegas Cantarero, 2020). Also, the decentralized and off-grid renewable energy system can encourage consumers to actively participate in energy generation and consumption process (consumers become prosumers), incentivize people to manage their own energy bills more wisely and reduce energy thefts which contributes to more revenue streams and local communities' socioeconomic development (Asif, 2020). Second, Renewable energy transition can contribute to reducing energy dependency of countries and thus enhancing energy security, especially for net importer of crude oil and oil products such as many Caribbean and Central American countries by reducing their vulnerability to high- and volatile oil prices in the global spot market, thus contributing to lower trade and fiscal deficits (Fattouh et al., 2019). Some net oil export countries such as Brazil, Ecuador, and Venezuela can also benefit from renewable energy transition as the increasing participation of renewables in energy system might contribute to diversification of energy mix and thus improving their energy security (Henderson and Sen, 2021). In sum, the renewable energy transition can bring about macroeconomic stability via lowering high vulnerability to commodity prices in the global market and provide more resilience to energy system through diversification of energy mix in the LAC region. Third, renewable energy transition can contribute to sustainability improvement by substituting fossil fuel energy sources with renewable ones, thus raising the share of renewable energy in energy mix which results in reducing CO_2 emissions and environmental degradation (Hampl, 2022). Fourth, renewable energy transition might contribute to reducing energy poverty and inequality in the LAC region through offering affordable energy services to vulnerable population as marginal cost of producing electricity from renewables are close to zero (Urban, 2014). Thanks to this cheaper electricity price, the economic burden of poor households lessens, and consequently their purchasing power also increases (Vanegas Cantarero, 2020). Lastly, due to the high- and untapped renewable energy potential of the LAC region, it might attract huge investments from multinational companies and private investors. Due to the Keynesian multiplier effect of these investments, renewable energy transition might have a positive impact on countries' economic performance as well as on environmental quality promoting green growth in the region (Hafner and Luciani, 2022). On the flip side, renewable energy transition also presents some challenges for the LAC region for the following reasons. First, the large part of government budget of big oil producing and exporting countries in the region such as Brazil, Mexico, Argentina, Colombia, and Venezuela are heavily dependent on revenues stemming from oil, and they might incur huge fiscal deficit due to a drastic loss of revenues during the process of renewable energy transition (Fattouh et al., 2019). Second, high debt burden in many LAC countries constraints severely their fiscal capacity limiting public investments in renewable energy transition, therefore, many investors from private sectors may be reluctant to finance large-scale renewable energy deployment in the LAC region as they perceive high risk and uncertainty regarding their returns on investments (CEPAL, 2022a). Third, fossil fuel subsidies are already common and widespread practice in many LAC countries which makes the price of fossil fuels artificially lower compared to other such as non-conventional renewable energy sources (solar, wind) at their initial stage of development. Consequently, non-conventional renewable energy sources cannot compete with fossil fuels on a level playing field in national energy market hampering a rapid low-carbon energy transition necessary to achieve net-zero emission goals in the region (Urban, 2014). Fourth, large endowment of oil and gas reserves (after Middle East, the LAC region has the second largest reserves of oil and gas in the world) along with existing production system strongly based on hydrocarbons such as fossil-fueled thermal power plants with long lifecycle might lead to lock-in carbon-intensive energy sources and disincentivize efforts towards renewable energy transition in the short- and medium-term in the LAC countries (Hampl, 2022), thus delaying significantly decarbonization of their economies. Furthermore, the lack of affordable energy storage technologies so far (lithium-ion batteries and hydrogen energy are still not cost competitive enough for large-scale application) indispensable to deal with intermittent and variable features of renewable energies makes it even harder to implement a rapid decarbonization in the LAC region (Smil, 2020). Lastly, weak institutional systems characterized by high corruption level, low level of democracy, lack of stringent environmental laws and regulations, high influence of large oil companies on political decision-making process in favor of their benefits, and low awareness of urgency of environmental degradation and climate change issues among policymakers and populations makes it harder to phase out rapidly fossil fuels in their energy systems and prevents LAC countries from moving to renewable energy transition (Vanegas Cantarero, 2020).

As for the energy supply systems in the LAC region, this region has one of the cleanest electricity mixes in the world in large part due to the high share of hydropower (Grottera, 2022). Most energy sources used in electricity generation come from non-polluting renewable energy sources such as hydro, solar, wind, and geothermal (OLADE, 2020). Concretely, in 2019, 58.5% of the total power generation in the LAC region was derived from renewables within which hydro accounts for 45.2% followed by wind (6%), renewable thermal energy (5.1%), Solar (1.5%), and Geothermal (0.7%) while the share of renewables in power generation was 26.8% in worldwide (OLADE, 2020). Furthermore, the total installed capacity of renewables in electricity sector accounted for 58.9% in 2018 with non-conventional renewable energy sources such as wind and solar experiencing remarkable growth from 2010 to 2018 (from 0.5 to 5.9% in case of wind energy and while solar energy reached 2.1% of participation in 2018) (Messina, 2020). From the demand-side perspective, the region is also characterized by a high participation of renewables in terms of total energy consumption (although the figure is much higher from the supply side than from the demand side). For instance, in the LAC region, 29% of total energy consumption came from renewables in 2018 while in worldwide, it only represented by 16% (Pablo Romero et al., 2022). The comparatively high participation of renewable energy in both supply and demand side along with a low energy consumption per capita in relative terms compared with that of other regions in the world makes the LAC region a relatively lower contributor to global net CO_2 emissions (Bárcena Ibarra et al., 2020). According to OLADE (2020), the share of global CO_2 emissions in the LAC region was about 5.02% while other regions in the world, the figure was significantly higher than that of the LAC region except for Africa which accounts for 3.83% of global CO_2 emissions (Asia and Australasia (50.53%), Nort America (16.16%), Middle East (6.33%)).

Fig. 1 shows the changes in the RETI from 2003 to 2019. As can be seen from the maps, some LAC countries have made a noticeable progress in terms of renewable energy transition during the period of study while others have suffered reversal of renewable energy transition. The former group is represented by Argentina, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Honduras, and Paraguay while the latter group is composed of Bolivia, Jamaica, and Nicaragua.

2.2. Digital economy and its impact on energy sector in the LAC region

When it comes to the digital economy in the LAC region, a growing number of countries in the region have been incorporating digitalization as a key objective in their policy agenda to boost productivity growth and energy and material use efficiency in their economy (National Internet of Things in Brazil, Fourth Industrial Centre in Colombia, digital manufacturing laboratory in Uruguay) due to the high potential effect digital economy has on accelerating renewable energy transition, boosting economic growth, and reducing carbon footprint (CEPAL, 2022b; OECD, 2020). However, despite these efforts made so far, the progress of digitalization in the LAC region is somewhat slower than other emerging economies such as Southeast Asian countries and China and lags far behind that of the industrialized countries (ECLAC, 2022). For instance, regarding the Internet penetration rate, parameter frequently used to measure digitalization of economy, was only in 68% in 2018 (CEPAL, 2022b). Although the number is almost twice compared to that of 2010, Internet penetration rate in the LAC region is still far below the OECD average (84%) (OECD, 2020). The lack of qualified workers capable to manage advanced digital technologies constitutes another barrier that prevents digitalization in the LAC region (Jimenez and Gonzalez, 2022). For instance, according to the OECD statistics in 2018, only one-third of workers in the LAC region use digital technology related devices (computers, ICT tools, smartphones) compared to more than half of workers in EU (OECD, 2020). Digital

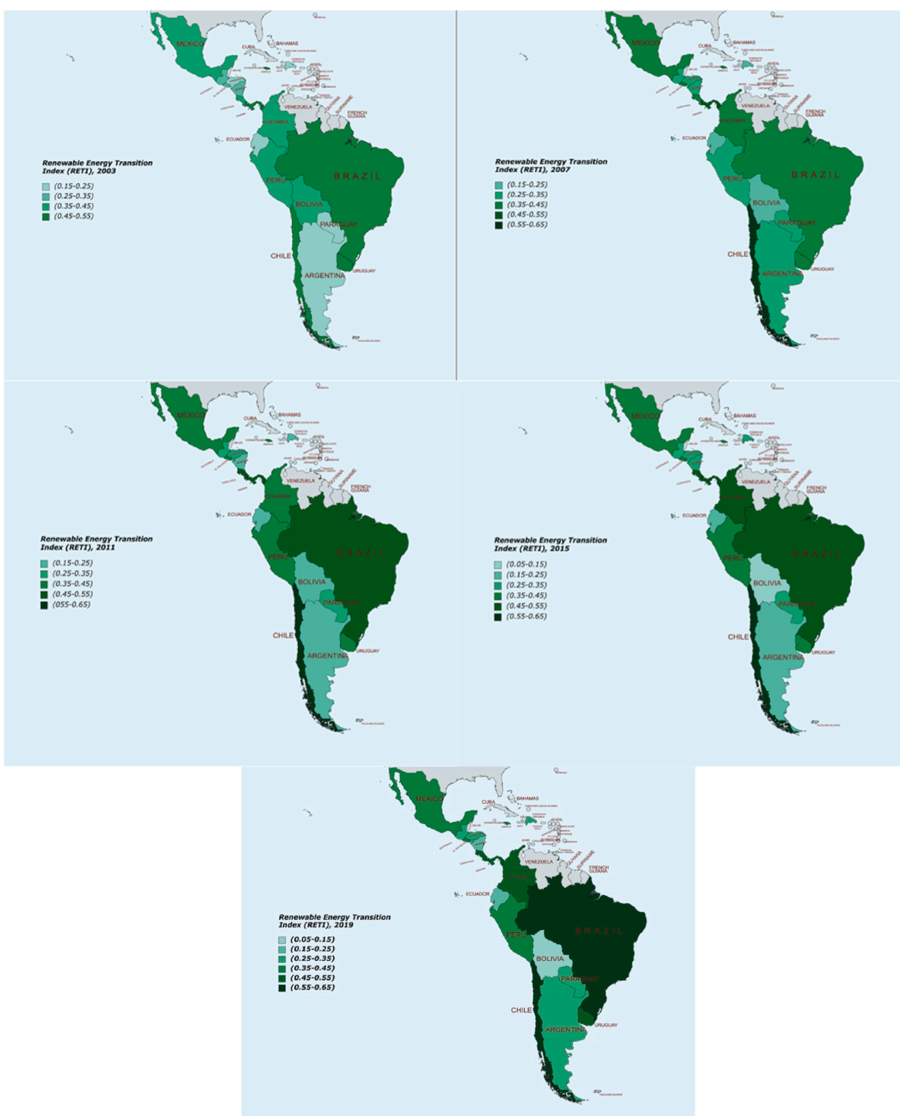

Fig. 1. Spatial distribution of the Renewable Energy Transition Index (RETI) in 2003, 2007, 2011, 2015, and 2019.

economy might offer a great opportunity to accelerate renewable energy transition and decoupling economic growth from environmental degradation in the LAC region for the following reasons: First, the application of advanced digital tools such as AI, machine learning, block chain in energy sectors can facilitate enormously the integration of intermittent and variable renewable energy as it ensures a more reliable electricity supply and enhances energy security and flexibility from renewable energy sources, thus accelerating low-carbon economy transition in the region (ECLAC, 2022). However, it is worth noting that the capabilities of the national energy supply system and the abilities of workers to assimilate advanced digital technologies are key factors for the successful integration of renewable energy sectors. Unlike advanced countries, many Latin American countries face persistent challenges, such as a lack of skilled workers and inefficient energy systems, to handle complex technologies like advanced digital technologies and fully leverage their benefits. Therefore, it is important for governments to provide strong support for enhancing digital literacy and skills, and enabling the development of digital capabilities from the outset (ECLAC, 2022). Second, the application of digital technologies in value chain can significantly improve productivity of workers, energy efficiency and induce technological innovations as well as structural transformation, namely shift from energy-intensive economy to knowledge-intensive and service-based economy (Nagasawa et al., 2017), thus contributing to economic growth and environmental sustainability through less energy consumption, technological progress, and cost savings (Ren et al., 2021). Third, the digital economy can accelerate the development of an integrated energy system where different sectors of an economy will become more interconnected and can freely share energy and data among them, improving the flexibility of national energy system and generating spillover effects on different sectors (Ren et al., 2021). Also, digital economy can significantly reduce the frequent mismatch between supply and demand which is characteristic feature of renewable energy production (Jimenez and Gonzalez, 2022). Lastly, the LAC is one of the most urbanized region worldwide with approximately 80% of population living in the cities which means that the region has high potential to reap benefits from digitalization as costs saving derived by improvement in energy efficiency and productivity are expected to be huge thanks to economies of scale of high urbanization (World Bank, 2022). To take full advantage of the digital economy, issues such as low-quality network infrastructure, scarcity of qualified workers with deep knowledge required to manage advanced digital tools in renewable energy sector, and the high risk of data breaches and hacking in energy sectors should be addressed in LAC countries (Asif, 2020).

3. Literature review

3.1. Renewable energy, economic growth, and environmental sustainability

A large number of studies have analyzed the influence of renewable energy on promoting economic growth in recent years. However, the empirical results obtained from previous studies so far are not as much clear as enough to reach a broad consensus about the positive impact of renewable energy on economic growth. The earlier literatures on the nexus between renewable energy-economic growth have mainly focused on how to determine the direction of causality between renewable energy consumption (REC) and economic growth. Apergis and Payne (2010) examined the causality between REC and economic growth in 20 OECD countries using FMOLS and cointegration test, and they found bidirectional causality between them in both the short- and the long-term. Tugcu et al. (2012) analyzed the impact of REC on economic growth in G-7 economies using ARDL and they found long-run impact of REC on economic growth and bidirectional causality between them. The bidirectional causality between REC and economic growth was confirmed not only in high-income industrialized countries but also demonstrated in emerging BRICS countries alike (Sebri and Ben-Salha, 2014). As for confirmation on the positive impact of REC on economic growth, can also be found in the studies following. Bhattacharya et al. (2016) used FMOLS, found that renewable energy contributes positively to economic growth in 57% of 35 top renewable energy consuming countries in the world. Inglesi-Lotz (2016) used panel cointegration, pooled estimation, and fixed effect estimation and confirmed the positive impact of REC (in absolute and relative terms) on economic growth in 34 OECD countries. Charfeddine and Kahia (2019) found a weak impact of REC on economic growth and CO_2 emissions in 24 MENA countries on the basis of PVAR estimation. On the other hand, there are other studies brought about contradictory results. Ocal and Aslan (2013) estimated the impact of REC on economic growth in Turkey using ARDL and Toda-Yamamoto Granger causality test and they confirmed a negative impact of REC on economic growth. The heterogenous impact of REC on economic growth in terms of country's income level or sectoral composition also has been observed. For example, Ivanovski et al. (2021) examined the impact of REC on economic growth in both OECD and non-OECD countries using Local Linear Dummy Variable Estimation (LLDVE). The estimation results showed that REC had a positive impact on economic growth in non-OECD countries, but non-significant impact was found in OECD ones. Sharma et al. (2021b) studied the relationship between non-renewable and renewable energy consumption and economic development in 27 European countries from 1990 to 2016. The study found a negative relationship between economic growth and renewable energy consumption, and this relationship was two-way. Additionally, the study found that the contribution of renewable energy consumption to economic growth in the 27 EU countries was much smaller compared to that of non-renewable energy consumption.

Doytch and Narayan (2021) observed that REC is particularly effective in promoting high-growth sectors in the economy (service sector in high-income countries and manufacturing sector in middle-income ones), which further enhanced productivity growth and consequently led to economic growth of an economy. Wang and Wang (2020) found a non-linear and positive impact of renewable energy consumption (as a proxy for renewable energy transition) on economic growth in OECD countries using panel threshold regression models. According to the estimation results, when the EU countries were above the threshold value of renewable energy consumption, its impact on economic growth was even stronger and more significant. In a similar vein, Wang et al. (2022a, 2022b, 2022c) investigated the impact of renewable energy on economic growth in 104 countries using threshold regression. The estimation results showed positive, non-linear and heterogenous impacts of renewable energy on economic growth in terms of income level, resource dependence, and anticorruption regulation.

Regarding the impact of renewable energy on environment, there is a general consensus among the researchers about the beneficial impact of renewable energy on improving environmental quality, although the estimation results can be slightly different depending on the indicators used as a proxy for environmental quality,[2] estimation method, countries, and period of the study. For example, Dong et al. (2018) have studied the impact of renewable energy intensity (REI) in 128 countries and found that it effectively contributed to enhancing environmental quality by reducing CO_2 emissions. Furthermore, the results showed that the impact of REI was particularly strong in America, Europe, and Eurasia. Alola et al. (2019) employed Panel Pooled Mean Group ARDL to examine the impact of REC on environmental quality in 16 EU countries and they found that REC contributed to improving environmental quality. Mohsin et al. (2021) used GHG emissions as an indicator of environmental quality and they observed that REC led to a decrease in GHG emissions in 25 developing Asian countries. Destek and Sinha (2020) used FMOLS and DOLS to examine the impact of REC on ecological footprint in 24 OECD countries. The estimation results

[2] the most widely used indicator is CO2 emissions, but GHG emissions and ecological footprint also have been frequently used.

showed that ecological footprint decreased as REC increased (thus positive impact on environmental quality). Sharma et al (2021a) examined the effect of renewable energy adoption in addition to agriculture value added, pesticide use, human capital and economic growth on greenhosuse gas emissions in the countries of the Bay of Bengal Instititute for Multisectoral Technical and Economic Cooperation (BIMSTEC) and found that the interation between renewable energy adoption and pesticide contributed significantly to mitigating the negative impact of pesticide use on environmental quality in agriculture sector. Murshed et al. (2022) investigated the impact of renewable energy in 25 developing Asian countries using Hausman-Taylor regression and observed that renewable energy use did not have a direct impact on carbon productivity. However, energy efficiency gains accompanied by significant mediation effect between renewable energy use and carbon productivity could lead to reducing carbon emissions in seven emerging economies from 2007 to 2018. Trinh et al. (2022) examined the effects of renewable energy consumption, energy efficiency, and financial development in mitigating carbon risk across 180 countries from 1980 to 2018. The study revealed that these factors played a substantial role in significantly reducing carbon risk. Additionally, the authors identified heterogenous impacts of financial development on the energy-environment nexus, as well as a U-shaped relationship between financial development and renewable energy consumption. Dong et al (2022a) studied the effect of renewable energy development on carbon emission efficiency in 32 developed countries using Super Efficiency Slacks-Based Measure (SBM) and Panel threshold regression with fixed effect. The results of the study implied that renewable energy development had a positive impact on carbon emission efficiency, but this impact came in a non-linear feature, and is significantly different from one country to another in terms of the threshold value of energy consumption intensity, financial development, renewable energy development and carbon emission efficiency of an economy. Likewise, Li et al. (2022) examined the impact of renewable energy on economic growth and ecological footprint in 120 countries using panel threshold regression and found a non-linear impact of renewable energy in terms of urbanization and income level of country. As can be seen below, the literature survey on renewable energy-economic growth-environmental sustainability nexus is summarized in Table 1.

3.2. Digital economy, renewable energy transition, economic growth, and environmental sustainability

Regarding the literature on the digital economy, recently a growing body of research has focused on the potential effect it might have on accelerating renewable energy transition and/or on promoting economic growth and enhancing environmental quality in tandem. For instance, Shahbaz et al. (2022) evaluated the relationship between the digital economy and energy transition on panel data of 72 countries during the period 2003–2019. Their estimation showed that the digital economy effectively contributed to promote renewable energy transition by reinforcing governance capabilities of governments and the effect of promotion was larger in high-income countries than in middle-income countries. And the impact of the digital economy on energy transition was came out significantly different across the regions (in Europe and America, the positive effect of the digital economy on renewable generation was higher while in Asia and the Middle East, its positive impact was larger on renewable energy consumption). The investigation of Wang et al. (2022b) in panel data of 72 economies during the period 2010–2019 showed that the positive impact of the digital economy was not only limited to just energy transition due to human capital and financial development but also contributed to improve the justice of economy such as distributional, procedural, and restorative justice. Li et al (2022a) analyzed the impact of the digital economy on green economy efficiency in 281 prefecture-level cities in China using Slacks Based Measure (SBM) and Spatial Autoregressive Regression (SAR) and found that the digital economy exerted a positive effect on green economy efficiency. Moreover, the impact of the digital economy had an important regional heterogeneity feature (its impact was greater in the region with high-income level and well-developed infrastructure and large cities). Liu et al. (2022) investigated the impact of the digital economy on green total factor productivity in 286 cities in China from 2011 to 2019 and they found a significant positive impact. Hao et al. (2023) investigated whether digitalization leads to green economic growth in 30 Chinese provinces and cities during the period 2013–2019 using System of Environmental and Economic Accounting (SEEA) technique. The estimation results confirmed that digitalization had a positive impact on green economic growth through green technology innovation, advanced industrial structure, and the rationalization of industrial structure. Moreover, the existence of spatial effect of the digitalization on green economic growth, regional spatial heterogeneity, and resource endowment heterogeneity were observed. Wang et al. (2023) studied the impact of the digital economy on renewable energy generation (REG) in developed and developing Asian countries from 2003 to 2019. According to the estimation results obtained using IV-GMM, the impact of the digital economy on REG was found positive but its impact was especially stronger in developed Asian economies.

When it comes to the nexus between the digital economy and sustainable development (this is, ensuring economic growth as well as CO_2 emissions reductions), there is no consensus among researchers about whether the digital economy stimulates sustainable development or not. For instance, Lange et al. (2020) argued that the overall impacts of digitalization on improving sustainability (reducing energy consumption and thus, energy related CO_2 emissions) crucially depended on four different aspects which were 1) the direct effect of the Information and Communication Technology (ICT) sector, 2) energy efficiency improvement thanks to digitalization, 3) energy and labor productivities increased by digitalization which leads to economic growth and in turn, generates a growing energy demand and energy consumption, and 4) structural transformation from energy-intensive to knowledge and service-oriented economy motivated by wide spread use of digital technologies and acceleration of digitalization. Authors stated that only if 2) and 4) dominated over the 1) and 3), digitalization ensured sustainability. In a similar vein, Ren et al. (2021) stated that proliferation of digitalization in terms of Internet development not only contributed significantly to increasing energy consumption scale caused by economic growth but also helped to reduce energy consumption intensity and made the energy consumption structure more efficient through economic growth, human capital and financial development, R&D activities, and industrial structure upgrading in 30 Chinese provinces during the period 2006–2017. On the other hand, Santarius et al. (2020) investigated the impact of digitalization on decoupling of environmental degradation from economic growth of 28 European countries, United States, India, and China during the period 1995–2017 and found that digitalization on its own did not automatically lead to decoupling, therefore active political measures along with fundamental changes in consumption patterns and business models were required to take full advantages of energy saving effect of digitalization. The study conducted by Ramzan et al. (2022) examined the impact of ICT on ecological footprint in Pakistan, in addition to financial development, trade openness, and fossil fuel energy. The results indicated that ICT had a negative impact on ecological footprint, meaning it increased environmental degradation. Moreover, the study found that the interaction between ICT and both financial development and trade openness further exacerbated this negative impact on the environment in Pakistan. However, Xu et al. (2022) in their study of 109 countries from 2000 to 2019, found firm evidence of energy saving effect of digitalization (thus less energy related emissions) at the international level and this impact was found to be particularly stronger in low-income developing countries than high-income developed countries. Similarly, Wang et al. (2022a) used a digital economy index of 30 Chinese provinces during the period 2016–2017 to estimate the causal relationship between CO2

Table 1
Literature survey on renewable energy-economic growth-environmental sustainability nexus.

Authors	Year	Countries	Period	Estimation methodology	Key findings
Apergis & Payne	2010	20 OECD countries	1985–2005	Panel unit root and cointegration tests, FMOLS	Presence of short- and long-run bidirectional causality between REC and economic growth.
Tugcu et al.	2012	G7 economies	1980–2009	ARDL	REC had a long-run impact on economic growth. Bidirectional causality (feedback hypothesis) between REC and economic growth.
Ocal & Aslan	2013	Turkey	1990–2014	ARDL, Toda-Yamamoto causality test	REC had a negative impact on economic growth in Turkey.
Sebri & Ben-Salha	2014	BRICS countries	1971–2010	VECM, ARDL bounds testing, FMOLS, DOLS	Feedback hypothesis between economic growth and REC
Bhattacharya et al.	2016	38 top renewable energy consuming countries in the world	1991–2012	FMOLS	REC had a significant positive impact on economic growth for 57% of total selected countries.
Inglesi-Lotz	2016	34 OECD countries	1990–2010	Pedroni cointegration, Pooled estimation, Fixed Effects estimation	Both absolute and relative REC contributed positive and significantly to economic growth in 34 OECD countries.
Dong et al.	2018	128 countries	1990–2014	CCEMG,AMG	REI contributed significantly to reducing CO_2 emissions. The impact of REI was higher in America, Europe, and Eurasia compared to other regions.
Alola et al.	2019	16 EU countries	1997–2014	Panel Pool Mean Group ARDL	REC contributed to improving environmental quality.
Charfeddine & Kahia	2019	24 MENA countries	1980–2015	PVAR	REC had a weak impact on economic growth and CO_2 emissions in 24 MENA countries.
Destek & Sinha	2020	24 OECD countries	1980–2014	FMOLS, DOLS	Ecological footprint decreased when REC rises while NREC led to an increase in ecological footprint. A U-shaped relationship between economic growth and ecological footprint was found and non-existence of the EKC in OECD countries was verified.
Wang & Wang	2020	34 OECD countries	2005–2016	Panel threshold regression	REC had a positive effect on economic growth. Existence of nonlinear effect of REC on economic growth.
Doytch & Narayan	2021	107 countries	1984–2019	Dynamic panel GMM, System GMM, Endogenous growth framework	REC was effective in promoting growth in high-growth sectors (service sectors in high-income countries while in middle-income ones, manufacturing sectors). Complementarity between REC and NREC in high-income countries while in middle-income countries, they were substitutes each other.
Ivanovski et al.	2021	OECD and non-OECD countries	1990–2015	Local linear dummy variable estimation	REC had a positive effect on economic growth in non-OECD countries but not in OECD ones.
Mohsin et al.	2021	25 developing Asian countries	2000–2016	Random effects, Hausman-Taylor regression, ECM	A 1% increase in REC contributed to reducing GHG emissions by about 0,193%. Feedback hypothesis between REC and economic growth. Economic growth and REC were positively correlated in both the short- and the long-run.
Sharma et al.	2021 a	The countries of BIMSTEC (Bangladesh, India, Myanmar, Nepal, Sri Lanka, and Thailand)	1985–2019	Second generation unit root tests, Panel cointegration, Panel quantile regression	An U-shaped relationship between agriculture value added and GHG emissions. The interaction between renewable energy adoption and pesticide use contributed to mitigating the negative effect of pesticide use on environmental quality in agriculture sector.
Sharma et al.	2021 b	27 European countries	1990–2016	Arellano-Bond dynamic panel data estimation, System dynamic panel data estimation, AMG, Quantile regression	Two-way positive relationship between economic growth and non-renewable energy consumption. Two-way negative relationship between economic growth and renewable energy consumption. The contribution of non-renewable energy consumption was much greater than that of renewable energy consumption. Positive impact of non-renewable energy consumption on GDPin all quantile groups except for Q90 in quantile regression.
Dong et al.	2022 a	32 developed countries	2000–2018	Super-efficiency slacks-based measure, Panel threshold model with interactive fixed effects	Renewable energy development led to an improvement in carbon emission efficiency. However, the impact of renewable energy development on carbon emission efficiency was non-linear and differs significantly in terms of energy consumption intensity, financial development, renewable energy development, and carbon emission efficiency level of country.
Li et al.	2022 b	120 countries	1995–2014	Panel threshold regression model, Fixed Effect model	Non-linear impact of renewable energy on economic growth and ecological footprint

(*continued on next page*)

Table 1 (*continued*)

Authors	Year	Countries	Period	Estimation methodology	Key findings
					depending on countries' urbanization and income level. The negative impact of renewable energy on the ecological footprint reduced and then increased when urbanization exceeded the threshold value. Renewable energy had a positive effect on economic growth and its effect became larger as urbanization level increased.
Murshed et al.	2022	7 emerging countries	2007–2018	Mediation regression model	Energy efficiency exerted important mediation effect between carbon productivity and renewable energy use to reduce carbon emission levels in 7 emerging countries. Renewable energy did not have direct impact on carbon productivity.
Trinh et al.	2022	180 countries	1980–2018	OLS, Robust standard errors methods, FE panel methods, GMM (two-step GMM, system GMM), Quantile regression methods (Canay's method, Powell's method, Machado and Silva's method)	REC and improved energy efficiency effectively con- tributed to mitigating climate risk. Inverted U-shape relationship between financial development and REC. Heterogenous impacts of financial development on the energy-environment nexus.
Wang et al.	2022	104 countries	2002–2018	FOLS, Threshold regression	Positive relationship between renewable energy and economic growth. The impact of renewable energy on economic growth in 3 different groups (high-income, middle-income, and low-income groups) varied greatly in terms of resource dependence and anticorruption regulation.

Note: AMG: Augmented Mean Group; ARDL: Autoregressive Distributed Lag; BIMSTEC: Bay of Bengal Initiative for Multisectoral Technical and Economic Cooperation; BRICS: Brazil, Russia, India, China, and South Africa; CCEMG: Common Correlated Effects Mean Group DOLS: Dynamic Ordinary Least Squares; ECM: Error Correction Model; EKC: Environmental Kuznets Curve; EU: European Union; FMOLS: Fully Modified Ordinary Least Squares; GHG: greenhouse gases; GMM: Generalized Method of Moments; MENA: Middle east and North Africa; NEC: nuclear energy consumption; NREC: non-renewable energy consumption; OECD: Organization for Economic Cooperation and Development; REC: renewable energy consumption; REI: renewable energy intensity; VECM: Vector Error Correction Model.

emissions and the digital economy using the System GMM technique. They found that the digital economy negatively affected CO_2 emissions via expansion of tertiary sector which reduced the share of coal consumption and promoted green technology innovation as well. Dong et al (2022b) examined the effect of information infrastructure on urban GHG emissions in 281 prefecture-level cities in China using Difference in Difference (DID) analysis. They found that technological innovation, factor allocation enhancement, and tertiary agglomeration were three major factors through which information infrastructure contributed to reducing GHG emissions in China. Zhang et al. (2022) studied the relationship between the digital economy and carbon emission performance (CEP) in 277 cities in China and found that digital economy improved CEP, but its impact was heterogenous and non-linear in Chinese cities. Ma et al. (2022) analyzed the impact of digitalization on the provincial emission levels in 30 Chinese provinces using Augmented Mean Group (AMG) and Common Correlated Effect Mean Group (CCEMG) estimators. The estimation results indicated that digitalization effectively contributed to reducing emission levels in Chinese provinces. The existence of significant moderating effects of R&D investments and technological innovation between digitalization and CO_2 emissions were also confirmed. Lastly, Zhang (2023) investigated the threshold effect of digital transformation on carbon emissions using the panel data of 29 major exporting countries during the period 2000–2019 to examine the impact of energy consumption on CO_2 emissions. According to their study, when digital transformation went beyond the threshold value, the positive impact of energy consumption on environmental degradation (increases in carbon emissions) began to decrease and the promoting effect of renewable energy on energy saving and carbon emission reduction became larger. As can be seen below, the literature survey on digital economy-economic growth-environmental sustainability nexus is summarized in Table 2.

From the literature review, we came to recognize that there are significant gaps in the extant research. Firstly, regarding the renewable energy, most previous studies have used unidimensional variables of demand or supply on either side, such as renewable energy consumption or renewable energy generation, to assess the impact of renewable energy transition on economic growth and environmental sustainability. Only a few studies have developed multidimensional index of energy transition that accounts for the various facets of complex energy transformation process such as political, institutional, social, economic aspects. Secondly, the LAC region lacks research on the synergistic effect between the digital economy and renewable energy transition. Most previous studies in this research have focused on emerging Asian countries, particularly China (either at the provincial or prefecture level), or industrialized countries (such as EU member countries, the USA, and Canada), to examine the impact of the digital economy on accelerating decarbonization and the decoupling of economic growth from environmental degradation Finally, the extant studies on the impact of renewable energy in the LAC region have failed in considering the heterogeneous and non-linear nature of the renewable energy transition and the digital economy on economic growth and environmental sustainability. The previous studies have mostly used standard linear regression models to analyze this impact, which are unable to capture non-linearity and regional heterogeneity and may bring about biased estimates. Having identified the gaps in extant research through literature review and extensive survey, three different hypotheses are formulated as follows.

Hypothesis 1. Renewable energy transition, when combined with the digital economy, it might bring about synergistic effects and thus contribute greatly to accelerating economic growth and improving environmental quality alike in terms of CO_2 emissions reduction in the LAC region.

Hypothesis 2. The impact of transition to renewable energy on economic growth and environmental quality implies a significant threshold effect in the LAC region. In other words, depending on whether the

Table 2
Literature survey on digital economy-economic growth-environmental sustainability nexus.

Authors	Year	Countries	Period	Estimation methodology	Key findings
Lange et al.	2020	EU countries, Norway, Switzerland, Australia, Brazil, Canada, China, India, Japan, South Korea, Russia, Taiwan, USA	1995–2016	Theoretical formulation based on Brock and Taylor (2005)	Digitalization did not contribute to decoupling of economic growth form energy consumption. ICT sector led to an increase in energy consumption.
Santarius et al.	2020	28 EU countries, US, India, China	1995–2017	Theoretical approach	Digitalization on its own did not automatically lead to a decoupling of economic growth from environmental degradation.
Ren et al.	2021	30 provinces in China	2006–2007	OLS, System-GMM	Positive correlation between China's energy consumption and Internet development. Internet development could promote the energy consumption scale via economic growth, but it could also contribute to reducing energy consumption intensity through channels of economic growth, R&D investments, financial development, industrial structural upgrading, and human capital. Important regional differences regarding the effect of Internet development on energy consumption scale, structure, and intensity.
Dong et al.	2022 b	281 prefecture-level cities in China	2003–2018	DID analysis	Information infrastructure had a significant effect on reducing urban greenhouse gases emission levels. Technological innovation, industrial structural upgrading, factor allocation enhancement, and tertiary agglomeration were the mechanisms through which information infrastructure improved environmental performance.
Li et al.	2022 a	277 cities in China	2011–2018	SBM,SAR	Digital economy had a significant positive impact on green economy efficiency. Impact of the digital economy differed significantly across the regions. Stronger impact in the Eastern region and large cities while in the Central, Western regions and small cities, the impact of the digital economy was smaller.
Liu et al.	2022	286 cities in China	2011–2019	DDF, GML, Tobit, Quantile regression, Impulse response function, Intermediary effect model	Digital economy improved significantly green total factor productivity. Important regional heterogeneity observed. Digital economy promoted green total factor productivity through industrial structure upgrading.
Ma et al.	2022	30 Chinese provinces	2006–2017	AMG,CCEMG	Digitalization contributed to curbing the provincial emission levels. Significant moderating effect of R&D investments and technological innovation between digitalization and CO_2 emissions. Economic growth, financial development, and energy use contributed significantly to increasing CO_2 emissions.
Ramzan et al.	2022	Pakistan	1960 Q1 to 2019 Q4	Non-parametric causality in quantile techniques, Diks and Panchenko nonlinear Granger causality test	The interaction between ICT and FID increased significantly the ecological footprint. The interaction between ICT and trade openness increased significantly the ecological footprint. ICT, financial development and fossil fuel energy had a significant impact on ecological footprint.
Shahbaz et al.	2022	72 countries	2003–2019	System-GMM, Panel quantile regression	Digital economy had a positive impact on energy transition (in terms of both REC and REG). Governments' governance capabilities played a key role in promoting energy transition through digital economy. Strong impact of the digital economy on energy transition at higher quantiles. Existence of regional heterogeneities regarding the impact of the digital economy on energy transition.
Wang et al.	2022 a	30 Provinces in China	2006–2017	System-GMM	Digital economy had a negative effect on CO_2 emissions. The infrastructure, innovation and application, economic growth, and jobs of the digital economy contributed to reducing CO_2 emissions.
Wang et al.	2022 b	72 countries	2010–2019	System-GMM, Mediating effect model	Digital economy promoted a just transition. Human capital and financial development were the two mechanisms through which the digital economy indirectly enhanced just transition.
Xu et al.	2022	109 Countries in Asia Pacific, Europe, Africa	2000–2019	System-GMM, Mediating effect model	Digitalization contributed to reducing energy consumption, energy intensity, and optimizing energy structure. Technological innovation, human capital, and industrial structure were the three main mechanisms through which the digitalization indirectly affects energy. In low-income and developing countries, digitalization had a greater impact on the energy.

(*continued on next page*)

Table 2 (*continued*)

Authors	Year	Countries	Period	Estimation methodology	Key findings
Zhang et al.	2022	277 cities in China	2011–2019	EBM, SDM, OLS, Mediation effect model, Threshold regression model	Digital economy enhanced carbon emission performance. The main mechanisms through which the digital economy affected carbon emission performance were energy intensity, energy consumption scale, and urban afforestation. Non-linear and different impact of the digital economy on carbon emission performance depending on the levels of energy intensity, energy consumption structure, government intervention, and urban afforestation. Existence of spatial effect of the digital economy on carbon emission performance.
Hao et al.	2023	30 Chinese provinces and cities	2013–2019	SEEA	Digitalization significantly led to green economic growth. Green technology innovation, advanced industrial structure and the rationalization of industrial structure have important mediation effects between digitalization and green economic growth. The existence of positive local and neighboring effect of digitalization on green economic growth. The existence of regional spatial heterogeneity and resource endowment heterogeneity.
Wang et al.	2023	Developed and developing Asian countries	2003–2019	IV-GMM	Digital economy had a positive impact on REG. The impact was particularly strong in developed economies in Asia. Existence of regional heterogeneity as the impact of the digital economy on REG was positive and significant only in East and South Asian countries.
Zhang et al.	2023	29 major exporting countries in the world	2000–2019	Multivariate threshold regression	High digitalization contributed to reducing the promotion effect of per capita energy consumption on carbon emissions. The promotion effect of renewable energy on energy conservation and carbon emission reductions increased when digital infrastructure development, digital trade competitiveness, and digital technology exceeded each threshold value.

Note: DDF: Direction Distance Function; DFI: Digital Financial Inclusion; DID: Difference In Difference; EBM: Epsilon Based Measure; EEP: Energy-Environment Performance; FID: Financial Development; ICT: Information and Communication Technologies; GML: Global Marmquist-Luenberger; IV-GMM: Instrumental Variable- Generalized Method of Moments; REG: Renewable Energy Generation; R&D: Research and Development; SAR: Spatial Autoregressive; SBM: Slacks Based Measure; SDM: Spatial Durbin Model; SEEA: System of Environmental and Economic Accounting.

countries are below or above the threshold value,[3] its impact will be very different.

Hypothesis 3. The impact of renewable energy transition and the digital economy on economic growth and environmental quality shows a significant heterogeneity across the quantile distribution. In other words, depending on whether countries belong to one quantile or another, the impact of renewable energy transition on economic growth and environmental quality will be significantly different in the LAC region.

4. Methodology and data

In this section, we provide both empirical and theoretical framework on which our analysis is based.

4.1. *Principal factor analysis (PFA) to elaborate renewable energy transition index (RETI) and digital economy index (DEI)*

As principal objectives of this investigation are focused on estimating the impact of renewable energy transition on economic growth as well as environmental degradation in the LAC countries and analyzing the synergistic effect of the digital economy on renewable energy transition from the perspective of economic growth and environmental degradation, the Principal Factor Analysis (PFA) is used to elaborate both the Renewable Energy Transition Index (RETI) and Digital Economy Index (DEI). The main reason why we use the composite index instead of the single-dimension indicator is that both renewable energy transition[4] and digital economy imply multidimensional and complex aspects such as economic,social, political and technical components, so, using one single-dimension indicator cannot reflect well the complex reality of the energy transition and the digital economy.

4.1.1. *Renewable energy transition index (RETI)*

Eleven indicators are selected to construct the RETI based on the data availability and previous studies by Kuc- Czarnecka et al., (2021), Singh et al. (2019), and Višković et al. (2022). Prior to application of the PFA, the stationarity and the normalization or the standardization of the indicators should be done to avoid spurious results and to ensure that all of the indicators are at the same scale. The stationarity of each indicator used in the RETI is examined with the unit root test and the test results indicate that all of them are stationary, therefore only the standardization of the data is required to be done. Based on the results of the PFA, four factors identified are grouped into four dimensions to construct the RETI. The weights of each dimension are assigned based on the eigenvalues obtained from the PFA. (see Appendix). Table 3 illustrates the RETI and its four principal dimensions.

[3] In this study, both per capita income and per capita CO_2 emissions are used as threshold variables.

[4] In previous studies, both renewable energy consumption and renewable energy supply are more frequently used variables to capture the progress of energy transition.

Table 3
Renewable energy transition index (RETI).

Renewable Energy Transition Index				
Dimension	Indicator (factor)	Unit	Data source	Attribute
Institutions, regulations, and governance (41%)	Control of Corruption Index (factor 1)		World Bank	+
	Government Effectiveness Index (factor 1)		World Bank	+
	Regulatory Quality Index (factor 1)		World Bank	+
	Investment freedom index (factor 1)		The Global Economy.com	+
Energy system structure (17%)	RE share of electricity generation (factor 4)	% Of total electricity generation	IRENA	+
	Manufacturing, value added (factor 4)	% Of GDP	World Bank	+
	Energy use (Energy efficiency) (factor 4)	$2017 PPP GDP/MJ	British Petroleum (BP), Energy Information Administration (EIA)	+
Universal energy access, facility to start-up new business (20%)	Access to electricity, rural (factor 3)	% Of rural population	WB	+
	Financial freedom index (factor 3)		The Global Economy.com	+
Human capital, large-scale projects funding opportunities (22%)	Scientific and technical journal articles (factor 2)	% Of GDP	World Bank	+
	Bank credit to the public sector (factor 2)	% Of GDP	World Bank	+

4.1.2. Digital economy index (DEI)

Developing the DEI is based on a set of 13 indicators in consideration of data availability and previous studies by Muhammad Shahbaz et al. (2022), Wang et al. (2022a), and Wang et al. (2022b). Most indicators used in constructing the DEI are non-stationary ones unlike those used in constructing the RETI. Therefore, they are first differenced and normalized before conducting the PFA. A total of six factors is identified and then reduced to three dimensions for their use in constructing the DEI (see in Table A.0 in Appendix). Table 4 shows the DEI and its three dimensions.

4.2. Control variables

To mitigate potential omitted variable bias, the following variables have been chosen as control variables.

- Total natural resource rents: Many Latin American economies' fiscal capacity and gross domestic product heavily rely on revenues obtained from the extraction of non-renewable natural resources: oil, natural gas, and critical minerals required for low-carbon energy transition, such as copper, lithium, and cobalt (CEPAL,N 2022 a). However, this dependence on natural resource exploitation can also lead to significant environmental costs as the extractive industries in the region are often energy-intensive, and emit high levels of CO2, contributing to increased carbon emissions in the LAC region (Alvarado et al., 2021).
- Inflation level:The economies in the LAC region have been experiencing persistent inflationary pressures. From an economic growth standpoint, high levels of inflation can result in significant negative effects on household purchasing power, production costs, and create uncertainty of future levels of price, which can undermine investments and savings (CEPAL,N 2022 a). From an environmental perspective, high levels of inflation can influence consumption behavior, and lead individuals and households to opt for cheaper and less sustainable energy sources. For example, traditional biomass energy, which may be more affordable during periods of high inflation, can aggravate environmental degradation and pollution (Urban, 2014). Additionally, high levels of inflation can impact

Table 4
Digital economy index (DEI)[a].

Digital Economy Index				
Dimension	Indicator (factor)[b]	Unit	Data source	Attribute
Digital Economy Infrastructure (58%)	E-Participation Index (factor 1)		United Nations (UN)	+
	Online Service Index (factor 1)		United Nations (UN)	+
	Mobile cellular subscriptions (factor 2)	per 100 people	International Telecommunication Union (ITU)	+
	Fixed broadband subscriptions (factor 2)	per 100 people	International Telecommunication Union (ITU)	+
	Services, value added per worker (factor 2)	constant 2015 US$	World Bank (WB)	+
	Fixed telephone subscriptions (factor 3)	per 100 people	International Telecommunication Union (ITU)	+
	Telecommunication Infrastructure Index (factor 3)		United Nations (UN)	+
Quality of workers & possession of communication appliances (26%)	Human Capital Index (factor 5)	% Of total population	International Telecommunication Union (ITU)	+
	Internet Users (factor 6)		United Nations (UN)	+
	Wage and salaried workers (factor 6)	% Of total employment	World Bank (WB)	+
	Services, value added (factor 6)	% Of GDP	World Bank (WB)	+
Technology-intensive goods trade (16%)	ICT goods exports (factor 4)	% Of total goods exports	World Bank (WB)	+
	ICT goods imports (factor 4)	% Of total goods imports	World Bank (WB)	+

[a] Before performing Principal Factor Analysis, each components of the DEI are first differenced and normalized.
[b] Factor refers to the factor assigned during the PCF analysis.

government fiscal capacity and restrict the availability of public funds for environmental protection efforts.

- Foreign Direct Investment (FDI): FDI might have an ambiguous effect on both economic growth and environmental sustainability in the LAC region. On the one hand, FDI can facilitate the transfer of advanced technologies and managerial expertise, which can enhance productivity and stimulate economic growth in the region (Ben Jebli et al., 2019). On the other hand, FDI can also attract investments in natural resource exploitation and energy-intensive industries (Doytch and Narayan, 2016). This can result in the lock-in of carbon-intensive technologies and practices, and lead to negative environmental impacts. The focus on resource extraction and energy-intensive sectors may cause increased pollution, deforestation, and carbon emissions, thereby posing challenges to environmental sustainability in the LAC region.
- Globalisation: Globalisation is another variable to consider when examining economic growth and environmental degradation. The process of globalisation in the LAC region has been accelerating since the Washington Consensus in 1992 and brought about significant changes in the economic structure of many LAC countries, including privatization and market liberalization (Santiago et al., 2020). From an economic growth perspective, globalisation has been facilitating greater trade and investment flows, as well as the integration of many Latin American countries into the global markets. However, it has exposed many economies in the region to global competitiveness and increased vulnerability to external shocks as well. From an environmental perspective, increased economic activities and trade might lead to higher energy consumption and CO2 emissions, thereby worsening environmental quality. However, it is important to note that globalisation can also facilitate the transfer of cleaner technologies and knowledge transfers, which can contribute to environmental improvement.
- Agriculture, Forestry, and Fishing Value added: Unlike other regions in the world, a significant share of greenhouse gas (GHG) emissions in the LAC region stems from agricultural production and land use change, such as the expansion of agricultural lands and deforestation (OLADE, 2020). Specifically, in Latin America, 42.2% of the total GHG emissions come from agriculture, livestock, land use change, and forestry, whereas these sectors account for only 17.4% of the total GHG emissions globally (Bárcena Ibarra et al., 2020).

4.3. Variables and data descriptions

In this study, a balanced panel of 18 Latin American and Caribbean countries during the period 2003–2019 is used, namely Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, and Uruguay, to investigate the impact of transition to renewable energy on economic growth and environmental degradation and the synergistic effect of the digital economy on renewable energy transition from the perspective of economic growth and environmental degradation. For this purpose, a set of 10 variables are used (see Table 5). The key independent variable are the Renewable Energy Transition Index (RETI), the Digital Economy Index (DEI), and the interaction term between the RETI and DEI (RETIxDEI). Before proceeding to the analysis, all variables are transformed into logarithmic form to deal with Skewness and make them conform to normality (see Table 6). Furthermore, the log-transformation of the variables will facilitate the interpretation of the coefficients in regression model in terms of elasticity. Before conducting the analysis, it is worth noting that the LAC region has been facing three serious issues of data use: availability, quality and quality. The national data of most countries in the LAC region required for this research employ the System of National Accounts (SNA, 1993) standard for measuring GDP. However, this standard does not properly take into account the informal economy, which is prevalent in the LAC region. To alleviate the issues of data facing this study: availability, quality and quantity, the World Bank database was used for this research.

Table 5
Variable description.

Variable	Explanation	Unit	Data Source
GDPpc	Per capita Gross Domestic Production. Proxy for economic growth	constant 2015 (US$)	World Bank (WB)
CO2pc	Per capita CO_2 emissions. Proxy for environmental degradation or environmental quality	metric tons per capita	World Bank (WB)
RETI	Renewable Energy Transition Index	–	Various
DEI	Digital Economy Index	–	Various
RETIxDEI	Interaction term between Renewable Energy Transition Index and Digital Economy Index	–	Various
TNRR	Total Natural Resource Rents	% Of GDP	World Bank (WB)
Inflation	Inflation, GDP deflator	annual %	World Bank (WB)
FDI	Foreign Direct Investment, net inflows	% Of GDP	World Bank (WB)
GI	Globalization Index	–	The Global Economy.com
AFFVadd	Agriculture, Forestry, and Fishing Value added	% of GDP	World Bank (WB)

Table 6
Descriptive statistics.

Variable	Obs	Mean	Std. dev.	Min	Max
LnGDPpc	306	8.661	0.6131	7.2944	9.6827
LnCO2pc	306	0.5806	0.5335	−0.4778	1.573
LnRETI	306	−1.0853	0.3574	−2.0480	−0.4947
LnDEI	306	−0.7314	0.1330	−1.2987	−0.1361
LnRETIxLnDEI[a]	306	0.0099	0.0430	−0.1499	0.2558
LnTNRR	306	0.7943	1.1333	−2.3308	2.937
LnInflation	306	2.3224	0.5209	−2.5333	4.0186
LnFDI	306	1.7651	0.6381	−6.7944	2.9301
LnGI	306	4.1669	0.0853	3.8979	4.362
LnAFFVadd	306	1.9393	0.4667	0.7825	2.9384

[a] To avoid issues of multicollinearity in our estimation, the interaction term is previously centered. This involves subtracting the mean values of both LnRETI and LnDEI from their respective variables. Then, LnRETI and LnDEI are multiplied to obtain the interaction term, LnRETIxLnDEI.

4.4. Preliminary tests

Before proceeding the linear- and non-linear regression, a set of preliminary tests is required to examine issues of correlation and multicollinearity, cross sectional dependence, the presence of unit root, cointegration relationships among the variables, and the existence of fixed or random effects in regression model (Fuinhas and Marques, 2019). Furthermore, when applying the Methods of Moments Quantile Regression (MMQR), Swamey, Shapiro-Wilk and Skewness-Kurtosis test are conducted to examine whether the slope homogeneity and the residuals of the dependent variables in regression models, namely LnGDPpc and LnCO2pc, follow a normal distribution or not (Fuinhas and Marques, 2019; Machado and Silva, 2019). In case of the Fixed-Effect Panel Threshold Regression (FEPTR), the threshold test is previously done to analyze the existence of meaningful threshold points and thus the applicability of the FEPTR.

4.5. Standard regression models (Pooled Ordinary Least Squares (POLS), random effects (RE) estimator, Driscoll-Kraay Fixed Effects (D-K FE) estimator, Fixed Effects Two Stage Least Squares (FE-2SLS))

The standard linear regressions, namely POLS, RE, the D-K FE, and

Table 7
Standard linear regressions.

Dependent variable: LnGDPpc								
Estimation technique	POLS		RE		Driscoll-Kraay FE		FE-2SLS	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
LnTNRR	−0.013 (0.022)	−0.010 (0.022)	−0.047*** (0.014)	−0.047*** (0.014)	−0.046*** (0.010)	−0.046*** (0.011)	−0.060*** (0.015)	−0.062*** (0.015)
LnInflation	0.206*** (0.046)	0.204*** (0.046)	−0.055*** (0.015)	−0.055*** (0.015)	−0.059** (0.026)	−0.058** (0.025)	−0.055*** (0.015)	−0.053*** (0.015)
LnFDI	−0.102 (0.041)	−0.104** (0.041)	−0.002 (0.012)	−0.002 (0.012)	−0.003 (0.017)	−0.003 (0.017)	−0.009 (0.012)	−0.008 (0.012)
LnGI	4.012*** (0.339)	4.070*** (0.341)	2.144*** (0.149)	2.141*** (0.152)	2.099*** (0.129)	2.088*** (0.133)	2.163*** (0.188)	2.145*** (0.187)
LnRETI	**0.336*** (0.082)**	**0.334*** (0.081)**	**0.022 (0.047)**	**0.022 (0.047)**	**0.006 (0.034)**	**0.004 (0.033)**	**−0.037 (0.062)**	**−0.046 (0.062)**
LnDEI	**0.800*** (0.187)**	**0.796*** (0.187)**	**0.115** (0.049)**	**0.116** (0.050)**	**0.110* (0.056)**	**0.110* (0.056)**	**0.412** (0.178)**	**0.399** (0.174)**
LnRETIxLnDEI		**0.742 (0.568)**		**−0.053 (0.151)**		**−0.069 (0.213)**		**−0.380** (0.179)**
Constant	−7.395*** (1.473)	−7.644*** (1.483)	0.003 (0.649)	0.018 (0.659)	0.177 (0.610)	0.220 (0.632)	0.101 (0.847)	0.159 (0.840)
Country FE	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No	No	No
R^2	0.540	0.543	0.405	0.405	0.396	0.395	0.410	0.405
Number of obs.	306	306	306	306	306	306	288	288
Dependent variable: LnCO2pc								
Estimation technique	POLS		RE		Driscoll-Kraay FE		FE-2SLS	
	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4
LnAFFVadd	−0.974*** (0.051)	−0.976*** (0.051)	−0.347*** (0.052)	−0.347*** (0.052)	−0.286*** (0.069)	−0.290*** (0.068)	−0.246*** (0.057)	−0.252*** (0.057)
LnInflation	0.174*** (0.033)	0.175*** (0.033)	−0.039** (0.017)	−0.038** (0.017)	−0.046** (0.018)	−0.045** (0.018)	−0.048*** (0.017)	−0.047*** (0.017)
LnFDI	0.003 (0.028)	0.006 (0.028)	0.034** (0.014)	0.034** (0.014)	0.034*** (0.006)	0.034** (0.034)	0.032** (0.014)	0.033** (0.014)
LnGI	1.599*** (0.258)	1.542*** (0.259)	0.578*** (0.188)	0.540*** (0.191)	0.580*** (0.105)	0.543*** (0.121)	0.607** (0.235)	0.576** (0.235)
LnRETI	**−0.638*** (0.064)**	**−0.636*** (0.064)**	**−0.145*** (0.054)**	**−0.148*** (0.054)**	**−0.140** (0.048)**	**−0.144*** (0.048)**	**−0.130* (0.073)**	**−0.139* (0.073)**
LnDEI	**0.228* (0.132)**	**0.230* (0.132)**	**0.079 (0.058)**	**0.079 (0.057)**	**0.073 (0.052)**	**0.073 (0.054)**	**0.224 (0.197)**	**0.209 (0.192)**
LnRETIxLnDEI		**−0.651 (0.398)**		**−0.186 (0.175)**		**−0.178 (0.211)**		**−0.359* (0.205)**
Constant	−5.130*** (1.136)	−4.887*** (1.143)	−1.224 (0.853)	−1.070 (0.863)	−1.333** (0.512)	−1.177* (0.558)	−1.390 (1.098)	−1.271 (1.101)
Country FE	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No	No	No
R^2	0.698	0.700	0.593	0.598	0.574	0.582	0.559	0.578
Number of obs.	306	306	306	306	306	306	288	288

Note: *, **, and *** denote significance level at 10%, 5%, and 1% respectively; Model 1–4 correspond to equation (1)-(4) respectively in section 4.4. The values in parentheses indicate the standard error.

FE-2SLS estimators are performed before the non-linear regression models (the FEPTR and the MMQR) to detect the effect of transition to renewable energy as well as the interaction term between the RETI and DEI on economic growth and environmental degradation. The results obtained from the standard linear regression models will be compared with those of the MMQR and FEPTR models to see whether the estimated coefficients effectively show the non-linear and heterogenous behaviors in our panel data.

The benchmark regression models are constructed as follows:

$$LnGDPpc_{it} = b_{10} + b_{11}LnTNRR_{it} + b_{12}LnInflation_{it} + b_{13}LnFDI_{it} + b_{14}LnGI_{it} + c_{11}LnRETI_{it} + c_{12}LnDEI_{it} + a_{1i} + e_{1it} \tag{1}$$

$$LnGDPpc_{it} = b_{20} + b_{21}LnTNRR_{it} + b_{22}LnInflation_{it} + b_{23}LnFDI_{it} + b_{24}LnGI_{it} + c_{21}LnRETI_{it} + c_{22}LnDEI_{it} + c_{23}(LnRETI * LnDEI)_{it} + a_{2i} + e_{2it} \tag{2}$$

When the LnCO2pc is considered as an outcome variable:

$$LnCO2pc_{it} = b_{30} + b_{31}LnAFFVadd_{it} + b_{32}LnInflation_{it} + b_{33}LnFDI_{it} + b_{34}LnGI_{it} + c_{31}LnRETI_{it} + c_{32}LnDEI_{it} + a_{3i} + e_{3it} \tag{3}$$

$$LnCO2pc_{it} = b_{40} + b_{41}LnAFFVadd_{it} + b_{42}LnInflation_{it} + b_{43}LnFDI_{it} + b_{44}LnGI_{it} + c_{41}LnRETI_{it} + c_{42}LnDEI_{it} + c_{43}(LnRETI * LnDEI)_{it} + a_{4i} + e_{4it} \tag{4}$$

Where the subscript i denotes the country, t represents year, b_{k0}, b_{k1}, b_{k2}, b_{k3}, and b_{k4} represent a constant and the coefficients of control variables respectively, c_{k1}, c_{k2}, and c_{k3} represent coefficients of the independent variables LnRETI, LnDEI, and LnRETIxLnDEI respectively, a_{ki} denotes country fixed effects, and e_{kit} represents the error term. The variables LnGDPpc, LnCO2pc, LnTNRR, LnInflation, LnFDI, LnGI, LnAFFVadd, LnRETI,LnDEI, and LnRETIxLnDEI denote per capita gross domestic product, per capita carbon dioxide emissions, total natural resource rents, inflation level, foreign direct investment, globalization index, agriculture, forest, and fishery value added, renewable energy transition index, digital economy index, and the interaction term between the renewable energy transition index and the digital economy index respectively (synergistic effect between renewable energy transition and the digital economy). The interaction term is incorporated in regression models to see whether the digital economy has a meaningful synergistic effect with renewable energy transition on promoting economic growth and improving environmental sustainability by reducing CO_2 emissions. It is worth noting that to obtain LnRETIxLnDEI, both LnRETI and LnDEI are previously centralized (demeaned), and then multiplied them to finally obtain the interaction term. In this way, the potential multi-collinearity issue can be addressed. Finally, all variables are transformed into logarithmic forms to reduce the variability and to facilitate the interpretation of the coefficients estimated in terms of elasticities.

Both coefficients c_{23} and c_{43} are required to evaluate the synergistic effect. If the parameter c_{23} in equation (2) is positive and statistically significant, the synergistic effect on economic growth exists. Similarly, if the parameter c_{43} in equation (4) is negative and statistically significant, this means that the digital economy combined with renewable energy transition effectively contributes to enhancing environmental quality.

4.6. FixedEffect Panel Threshold Regression (FEPTR)

The FEPTR is used to analyze whether the impacts of energy transition on economic growth and environmental degradation are different and show non-linearity and asymmetry depending on whether country's per capita income or per capita CO_2 emissions are above or below the threshold values.

The FEPTR model with a single threshold can be formulated as follows:

$$Y_{it} = \mu_i + \delta_1 R_{it} * I(Q_{it} \le \gamma_1) + \delta_2 R_{it} * I(Q_{it} > \gamma_1) + \sum \theta_m Z_{it} + V_t + \varepsilon_{it} \tag{5}$$

In case of multiple thresholds:

$$Y_{it} = \mu_i + \delta_1 R_{it} * I(Q_{it} \le \gamma_1) + \delta_2 R_{it} * I(Q_{it} > \gamma_1) + \delta_n R_{it} * I(Q_{it} \ge \gamma_k) \ldots + \sum_{n=1}^{m} \theta_m Z_{it} + V_t + \varepsilon_{it} \tag{6}$$

Where μ_i and V_t denote a country and time fixed effect, R_{it}, Z_{it} , and , Q_{it} denote a regime-dependent, independent, and threshold variable respectively, I (.) represents an indicative function, θ_i and δ_i denote the coefficients of the independent and the regime-dependent variables in different intervals respectively (below and above the threshold value), γ_k represents a critical value of threshold variable Q_{it}, and ε_{ki} is the independent and identically distributed error term.

Adapting the FEPTR to our regression models, the FEPTR can be formulated as follows:

$$\begin{aligned} LnGDPpc_{it} = {} & \alpha_{1i} + \theta_{11} LnTNRR_{it} + \theta_{12} LnInflation_{it} + \theta_{13} LnFDI_{it} + \theta_{14} LnGI_{it} \\ & + \theta_{15} LnDEI_{it} + \theta_{16} LnRETIxLnDEI_{it} + \delta_{11} LnRETI_{it} * I(Q_{it} \le \gamma_1) \\ & + \delta_{12} LnRETI_{it} * I(Q_{it} > \gamma_1) + V_{1t} + \varepsilon_{1it} \end{aligned} \tag{7}$$

$$\begin{aligned} LnGDPpc_{it} = {} & \alpha_{2i} + \theta_{21} LnTNRR_{it} + \theta_{22} LnInflation_{it} + \theta_{23} LnFDI_{it} + \theta_{24} LnGI_{it} \\ & + \theta_{25} LnDEI_{it} + \theta_{26} LnRETIxLnDEI_{it} + \delta_{21} Ln\,RETI_{it} * I(Q_{it} \le \gamma_1) \\ & + \delta_{22} Ln\,RETI_{it} * I(\gamma_1 < Q_{it} \le \gamma_2) + \delta_{23} Ln\,RETI_{it} * I(LnGDPpc_{it} > \gamma_2) \\ & + V_{2t} + \varepsilon_{2it} \end{aligned} \tag{8}$$

When the LnCO2pc is considered as an outcome variable:

$$\begin{aligned} LnCO2pc_{it} = {} & \alpha_{3i} + \theta_{31} LnAFFVadd_{it} + \theta_{32} LnInflation_{it} + \theta_{33} LnFDI_{it} \\ & + \theta_{34} LnGI_{it} + \theta_{35} LnDEI_{it} + \theta_{36} LnRETIxLnDEI_{it} + \delta_{31} LnRETI_{it} \\ & * I(Q'_{it} \le \gamma'_1) + \delta_{32} LnRETI_{it} * I(Q'_{it} > \gamma'_1) + V_{3t} + \varepsilon_{3it} \end{aligned} \tag{9}$$

$$\begin{aligned} LnCO2pc_{it} = {} & \alpha_{4i} + \beta_{41} LnAFFVadd_{it} + \beta_{42} LnInflation_{it} + \beta_{43} LnFDI_{it} \\ & + \beta_{44} LnGI_{it} + \beta_{45} LnDEI_{it} + \beta_{46} LnRETIxLnDEI_{it} \\ & + \delta_{41}\, Ln\,RETI_{it} * I(Q'_{it} \le \gamma'_1) + \delta_{42} LnRETI_{it} * I(\gamma'_1 < Q'_{it} \le \gamma'_2) \\ & + \delta_{43}\, Ln\,RETI_{it} * I(Q'_{it} > \gamma'_2) + V_{4t} + \varepsilon_{4it} \end{aligned} \tag{10}$$

Where the threshold variable (Q_{it}), can be either LnGDPpc or LnCO2pc. As can be seen from equation (7) to equation (10), the Renewable Energy Transition Index (RETI) is used as a regime-dependent variable (R_{it}) in all the regressions in the framework of FEPTR.[5] However, the independent variables (Z_{it}) used can be slightly different depending on whether the outcome variable is LnGDPpc or LnCO2pc. In former case, the variables LnTNRR, LnInflation, LnFDI, LnGI, LnDEI, and the interaction term LnRETIxLnDEI are used as covariates while in the latter case, all the variables maintain exactly the same except for LnTNRR, which is replaced by LnAFFVadd.

4.7. Methods of Moments Quantile Regression (MMQR)

After the FEPTR analysis, the MMQR econometric technique is used to measure the non-linear and heterogenous impact of the determinants of economic growth (LnGDPpc) and environmental degradation (LnCO2pc) across the quantile distribution. According to Alvarado et al. (2021) and Machado and Silva (2019), the advantages of using the MMQR are the following: 1) The MMQR is consistent and efficient in the presence of endogenous regressors and fixed effects. Since it utilizes a triangular structure with respect to the model parameters, it enables the sequential calculation of the one-step Generalized Method of Moments (GMM) estimator (Machado and Silva, 2019), 2) The MMQR allows to estimate marginal effect of each regressor on outcome variable across the entire quantile distribution, 3) The MMQR considers heterogeneity within countries when estimating the coefficients.

The MMQR model has the following structure:

$$Q_{Dv}(\tau | X_{it}) = (\alpha_i + \delta_i q(\tau)) + X'_{it}\beta + Z'_{it}\gamma q(\tau) \tag{11}$$

Where $Q_{Dv}(\tau|X_{it})$ denotes the conditional quantile distribution of the dependent variable, τ denotes quantile level, X'_{it} represents the independent and control variables jointly, $\alpha, \delta, \beta, \gamma$ represent the parameters of interest, the term $(\alpha_i + \delta_i q(\tau))$ is the scalar coefficient which denotes the quantile fixed effect for individual country (Machado and Silva, 2019), and finally Z'_{it} represents a k-vector of known components of X_{it} normalized to satisfy the moment conditions (Machado and Silva, 2019).

Adapting to our regression models, the MMQR can be formulated as follows:

$$\begin{aligned} Q_{LnGDPpc}(\tau | \alpha_{1i}, \vartheta_{1t}, X_{1it}) = {} & \alpha_{1i} + \beta_{11} LnTNRR_{it} + \beta_{12} LnInflation_{it} + \beta_{13} LnFDI_{it} \\ & + \beta_{14} LnGI_{it} + \beta_{15} LnRETI_{it} + \beta_{16} LnDEI_{it} + v_{1t} + \varepsilon_{1it} \end{aligned} \tag{12}$$

$$\begin{aligned} Q_{LnGDPpc}(\tau | \alpha_{2i}, \vartheta_{2t}, X_{2it}) = {} & \alpha_{2i} + \beta_{21} LnTNRR_{it} + \beta_{22} LnInflation_{it} + \beta_{23} LnFDI_{it} \\ & + \beta_{24} LnGI_{it} + \beta_{25} LnRETI_{it} + \beta_{26} LnDEI_{it} \\ & + \beta_{27} (LnRETI * LnDEI)_{it} + v_{2t} + \varepsilon_{2it} \end{aligned} \tag{13}$$

When the LnCO2pc is considered as an outcome variable:

[5] The reason why we do not use the interaction term LnRETIxLnDEI as a regime-dependent variable is that when it is used as such, we cannot find any evidence of the threshold effect in any of the cases.

$$Q_{LnCO2pc}(\tau|\alpha_{3i},\vartheta_{3t},X_{3it}) = \alpha_{3i} + \beta_{31}LnAFFVadd_{it} + \beta_{32}LnInflation_{it} + \beta_{33}LnFDI_{it} + \beta_{34}LnGI_{it} + \beta_{35}LnRETI_{it} + \beta_{36}LnDEI_{it} + v_{3t} + \varepsilon_{3it} \quad (14)$$

$$Q_{LnCO2pc}(\tau|\alpha_{4i},\vartheta_{4t},X_{4it}) = \alpha_{4i} + \beta_{41}LnAFFVadd_{it} + \beta_{42}LnInflation_{it} + \beta_{43}LnFDI_{it} + \beta_{44}LnGI_{it} + \beta_{45}LnRETI_{it} + \beta_{46}LnDEI_{it} + \beta_{47}(LnRETIxLnDEI)_{it} + v_{4t} + \varepsilon_{4it} \quad (15)$$

Where $Q_{LnGDPpc}(\tau|X_{it})$ and $Q_{LnCO2pc}(\tau|X_{2it})$ denote the quantile distribution of LnGDPpc and LnCO2pc respectively, α_{ki} and v_{kt} represent an unobserved country and time fixed effect respectively, β_{ki} denotes the coefficients to estimate, and ε_{kit} represents the error term.

By applying the MMQR, the heterogenous impacts of renewable energy transition, the digital economy, and the synergistic effect between them can be assessed across the different quantiles of country's per capita GDP and per capita CO_2 emissions. In other words, the MMQR enables to examine whether the impacts of the RETI, DEI, and RETIxDEI differ across the conditional distribution of per capita income or per capita carbon emission level. In the MMQR analysis, the effects of renewable energy transition and other key independent variables on conditional distribution of dependent variable are evaluated at percentiles of 0.20, 0.40, 0.60, 0.80 and 0.90 respectively.

5. Empirical results

5.1. Preliminary tests

5.1.1. Correlation matrix and VIF test

From the results of the correlation matrix (see Table A.1 in Appendix), we cannot find any evidence of the collinearity issue among the independent variables as all of they have a coefficient of correlation below 0.7. After analyzing the correlation matrix, the Variance Inflation Factor (VIF) test are carried out to examine the multicollinearity issue among the variables. The results of the test indicate that there are no multicollinearity problems (see Table A.2 in Appendix) as the individual VIF as well as the mean value of VIF are less than 10 in which they are generally accepted benchmark (Fuinhas et al., 2021).

5.1.2. Cross-sectional dependence (CSD) test

To check the presence of CSD between the variables in our panel data, Pesaran Cross Sectional Dependence (CD-test) Test is used (Pesaran et al., 2006). The results indicate that all the variables, except the interaction term LnRETIxLnDEI, present the cross-sectional dependence at the 1% significance level, rejecting the null hypothesis of cross-sectional independence (see Table A.3 in Appendix), meaning that all the LAC countries in this study share some common shocks or characteristics that make them dependent on each other.

5.1.3. Panel unit root test

After confirming the existence of the CSD in panel data, the stationarity of the variables is examined. For this purpose, both the first- (Maddala and Wu, 1999) and second-generation panel unit root test (CIPS) developed by Pesaran (2007) are conducted with two different specifications: with and without trend (see Table A.4 in Appendix). The first-generation Maddala and Wu Panel Unit Root test shows that, without trend, all the variables are stationary at level, but with trend, LnGDPpc, LnCO2pc, and LnTNRR are found to have a unit root. However, after the first difference, they all become stationary at the 1% significance level regardless of the specification. On the other hand, the CIPS test indicates that the variables LnGDPpc, LNCO2pc, and LnTNRR are not stationary irrespective of considerations on trend.[6] With trend, the variable LnAFFVadd is stationary at the 5% significance level but shows unit root problem without trend. However, after the first difference, all of them become stationary at the 1% significance level, so, the tests indicate that the data consists of variables with I (0) and I (1) and the unit root problem disappears when they are transformed into first difference.

5.1.4. Panel cointegration test

After the unit root test, the next step accompanies verifying the evidence of cointegration among the variables. This is a crucial step before implementing the non-linear regression models, such as the FEPTR and MMQR, because we cannot use the variables at first difference to get rid of the unit root problem. However, the use of non-stationary variables might pose a serious problem since it might produce a spurious regression, and we should deal with it before carrying out the estimation. As an alternative to this issue, the cointegration test is performed to see whether the variables in regression model jointly show the evidence of a long-run equilibrium and stable relationship or not. In other words, the cointegration test allows to examine whether a combination of non-stationary variables is stationary or not and jointly shows a stable pattern in the long run. If the evidence of a cointegration relationship between the variables with a unit root (non-stationary at levels) is confirmed, the estimation can proceed without generating spurious estimation results. Thus, we proceed to check the cointegration among the variables in regression models by using two different types of panel cointegration tests: Pedroni (first-generation cointegration test) and Westerlund cointegration tests (second-generation cointegration test). The former does not consider the cross-sectional dependence (CSD) while the latter takes into account CSD and is robust in the presence of CSD. In all the regression models (see equations (1)–(4)), the results strongly support the evidence of cointegration relationships among the variables, as second-generation Westerlund cointegration test rejects the null hypothesis of no cointegration at 1% significance level against the alternative of cointegration of all panels[7] (see Table A.5 in Appendix).

5.1.5. Hausman test

To verify the existence of fixed or random effects in our regression models, Hausman test is performed. According to Hausman test, the null hypothesis of not systematic difference in coefficients (random-effect regression model is more appropriate) is rejected at the 1% significance level in all the cases. Therefore, the fixed effects should be incorporated in regression models (see Table A.6 in Appendix).

5.2. Standard linear regression models (POLS, RE, Driscoll-Kraay FE,FE-2SLS)

The standard linear regression models, namely Pooled Ordinary Least Squares (POLS), Random Effects (RE), Driscoll-Kraay Fixed Effects (D-K FE), and Fixed Effects Two Stage Least Squares (FE-2SLS) estimators are performed before the non-linear ones, namely MMQR and FEPTR for comparison purposes. Prior to estimation of linear regression models, several tests are conducted. These include Breusch and Pagan multiplier test, Wooldridge autocorrelation test, and Modified Wald test.

[6] Among the variables which are shown to be stationary at level, only LnGI and LnAFFVadd are weakly stationary at the 10% and 5% significance level according to the CIPS test.

[7] The time trend is included in all the cointegration tests. Furthermore, the option "all panels" is included after the command xtcointest westerlund in Stata to establish the alternative hypothesis of cointegration of all panels because when this option is not included, the Westerlund cointegration test evaluates the null hypothesis of no cointegration versus an alternative one that some panels are cointegrated.

The purpose of the tests is to determine whether static panel is preferred over Pooled OLS (POLS), the presence of autocorrelation of order 1, and heteroskedasticity respectively (Labra and Torrecillas, 2014). The results of the tests indicate that the panel static model is preferred over POLS and there is the existence of autocorrelation of order 1, and groupwise heteroskedasticity in our panel data, since the null hypotheses are rejected at the 1% significance level in all the tests (see Table A.7-Table A.9 in Appendix). After confirmation on the existence of heteroskedasticity, autocorrelation of order 1, cross-sectional dependence, and fixed effects in previous tests, the D-K estimator with FE is preferred as our main econometric technique to estimate the coefficients in linear regression models since it is robust in the presence of autocorrelation, heteroskedasticity, and cross-sectional dependence. Additionally, FE-2SLS was performed to address potential endogeneity issues in linear regression models by using instrumental variables. In this regard, the lagged terms of the endogenous variables LnRETI and LnDEI were employed as instrumental variables, as they satisfied with the relevance and exogeneity conditions (the lagged terms of LnRETI and LnDEI are correlated with LnRETI and LnDEI respectively, as they represent their past values, and they only affect the outcome variables through LnRETI and LnDEI respectively since the lagged terms of LnRETI and LnDEI are uncorrelated with the error term).

Table 7 shows that renewable energy transition (LnRETI) has a significant positive impact on economic growth (LnGDPpc) only in POLS. In other static panel regressions remaining, its impact is not statistically significant. This finding is somewhat similar to the previous study of Charfeddine and Kahia (2019), who found that renewable energy consumption had only a weak impact on the economic growth in resource-rich middle-income countries such as 24 MENA nations. On the other hand, renewable energy transition is found to have a negative effect on CO_2 emissions in the LAC region at the significance level of at least 5% level in all standard linear regression models. Unlike the nexus between energy transition and economic growth, there is a broad consensus among the researchers about the beneficial impact of renewable energy sources on improving environmental quality and reducing air pollution levels. The study of Dong et al. (2018) demonstrated that renewable energy consumption contributed significantly to reducing carbon emissions in 128 countries in the globe. Mohsin et al. (2021) reached a similar conclusion that renewable energy consumption led to a significant reduction of GHG emissions in 25 Asian countries.

As for the digital economy, its positive effect on economic growth is found in all linear regression models, although the significance level of LnDEI is somewhat lower in Driscoll-Kraay FE estimator (statistically significant at the 10% level). With regard to the impact of the digital economy on CO_2 emissions, the positive and significant impact at 10% level is found only in POLS while in other panel static models, the coefficient of LnDEI is not statistically significant. Regarding the synergistic effect between renewable energy transition and the digital economy on economic growth and environmental sustainability, this impact is not observed in any of the estimations, except for FE-2SLS. In FE-2SLS estimation, the elasticity of LnRETIxLnDEI is found to be negative and statistically significant at the 5% level in both cases, indicating that the synergistic effect has a negative impact on economic growth but a positive impact on environmental sustainability. In sum, the results of standard linear regressions indicate that the positive impacts of the transition to renewable energy on enhancing environmental quality and the digital economy on promoting economic growth are observed consistently when considering the LAC region as a whole. However, when it comes to the synergistic effect, its significant impact is only observed in FE-2SLS estimation.

5.3. Fixed-Effect Panel Threshold Regression (FEPTR)

5.3.1. FEPTR estimation results without interaction term (LnRETIxLnDEI)

Before conducting the FEPTR, a threshold effect test is performed to determine whether the relationship between renewable energy transition and economic growth or environmental degradation shows non-linearity (see Appendix).

When considering per capita GDP as the dependent and threshold variable (with $Y_{it} = Ln\ GDPpc_{it}, Q_{it} = Ln\ GDPpc_{it}$), a double-threshold effect is found at the 10% significance level (see Table A.11 and A.12 in Appendix). Table 8 shows that the impact of renewable energy transition on economic growth is not statistically significant when per capita income is below the first threshold (LnGDPpc <8.530). However, when LnGDPpc is in between the first and second threshold (8.530 ≤LnGDPpc <9.362), the impact of renewable energy transition becomes significant and negatively affects economic growth with a coefficient of −0.086. When LnGDPpc crosses the second threshold value (9.362), the coefficient of LnRETI becomes even more negative (−0.245) and statistically significant at the 1% significance level.

Table 8
FEPTR models regression results with $R_{it} = Ln\ RETI_{it}$.

Y_{it} = $LnGDPpc_{it}$				
Variables	Q_{it} = $LnGDPpc_{it}$		Q_{it} = $LnCO2pc_{it}$	
LnTNRR	0.039*** (0.010)	0.039*** (0.010)	0.018* (0.010)	0.017* (0.010)
LnInflation	−0.020** (0.010)	−0.020** (0.010)	−0.006 (0.009)	−0.005 (0.010)
LnFDI	0.009 (0.007)	0.009 (0.007)	−0.000 (0.007)	0.000 (0.007)
LnGI	0.395*** (0.148)	0.396*** (0.149)	0.280* (0.146)	0.267* (0.147)
LnDEI	−0.028 (0.031)	−0.028 (0.031)	0.005 (0.031)	0.005 (0.031)
LnRETIxLnDEI		0.002 (0.091)		−0.093 (0.089)
cat#c.LnRETI				
0	**0.000 (0.029)**	**0.000 (0.029)**	**0.132*** (0.036)**	**0.130*** (0.036)**
1	**−0.086*** (0.031)**	**−0.086*** (0.032)**	**0.038 (0.029)**	**0.035 (0.029)**
2	**−0.245*** (0.036)**	**−0.245*** (0.036)**		
Constant	6.780*** (0.608)	6.779*** (0.611)	7.343*** (0.602)	7.395*** (0.604)
R^2 (within)	0.837	0.837	0.836	0.836
Number of Obs.	306	306	306	306
Y_{it} = $LnCO2pc_{it}$				
Variables	**Q_{it} = $LnGDPpc_{it}$**		**Q_{it} = $LnCO2pc_{it}$**	
LnAFFVadd	−0.240*** (0.047)	−0.238*** (0.047)	−0.144*** (0.043)	−0.147*** (0.043)
LnInflation	−0.005 (0.016)	−0.005 (0.016)	−0.018 (0.014)	−0.016 (0.014)
LnFDI	0.031*** (0.012)	0.031*** (0.012)	0.000 (0.011)	0.000 (0.011)
LnGI	−0.065 (0.236)	−0.055 (0.238)	−0.050 (0.206)	−0.076 (0.207)
LnDEI	−0.008 (0.052)	−0.009 (0.052)	0.001 (0.045)	0.001 (0.045)
LnRETIxLnDEI		0.069 (0.152)		−0.147 (0.130)
cat#c.LnRETI				
0	**0.046 (0.069)**	**0.046 (0.069)**	**0.142*** (0.050)**	**0.138*** (0.050)**
1	**−0.102** (0.049)**	**−0.101** (0.049)**	**−0.103** (0.042)**	**−0.107** (0.042)**
2			**−0.575*** (0.064)**	**−0.578*** (0.064)**
Constant	1.014 (0.992)	0.969 (0.998)	0.906 (0.868)	1.019 (0.874)
R^2 (within)	0.503	0.503	0.610	0.612
Number of Obs.	306	306	306	306

Note: *, **, and *** denote significance level at 10%, 5%, and 1% respectively and time dummies were included during the estimation; Y_{it} denotes the dependent variable. The values in parentheses indicate the standard error.

When considering per capita GDP and per capita CO_2 emissions as the dependent and the threshold variable respectively ($Y_{it} = Ln\ GDPpc_{it}$, $Q_{it} = Ln\ CO2pc_{it}$), a single-threshold model is found to be appropriate at the 5% significance level based on the threshold effect test (see Table A.17 and A.18 in Appendix). Table 8 shows that the impact of renewable energy transition on economic growth is positive and statistically significant when $LnCO_2$ is less than 0.545, but as LnCO2pc exceeds the threshold value, its positive impact becomes statistically not significant. Specifically, when LnCO2pc is below the threshold (1.076), the coefficient of LnRETI is 0.132 but when LnCO2pc is above the threshold, the positive effect of renewable energy transition on economic growth disappears.

When considering per capita CO_2 emissions and per capita GDP as the dependent and threshold variable respectively ($Y_{it} = Ln\ CO2pc_{it}$, $Q_{it} = Ln\ GDPpc_{it}$), a single-threshold effect is found at the 1% significance level (see Table A.23 and A.24 in Appendix). According to the FEPTR estimates shown in Table 8, the impact of LnRETI on LnCO2pc is not significant when LnGDPpc is less than 8.516. However, when LnGDPpc exceeds the threshold value, the coefficient of LnRETI turns negative and statistically significant at the 5% level (−0.102).

When considering per capita CO_2 emissions as the dependent and threshold variable ($Y_{it} = Ln\ CO2pc_{it}$, $Q_{it} = Ln\ CO2pc_{it}$), a double-threshold effect is found at the 1% significance level (see Table A.29 and A.30 in Appendix). According to the FETHR estimates in Table 8, when LnCO2pc is below the first threshold (0.123), the coefficient of LnRETI is 0.142, indicating that renewable energy transition leads to environmental deterioration. However, when LnCO2pc is between 0.123 and 1.153, the coefficient of LnRETI turns negative and is statistically significant at the 5% level (−0.103), which means that renewable energy transition contributes to improving environmental sustainability in the LAC region within this range of CO_2 values. When LnCO2pc exceeds the second threshold (1.153), the coefficient of LnRETI becomes even more negative than the previous one and statistically significant at the 1% significance level (−0.575), thus showing the gradual increasing effect of renewable energy transition on environmental and air quality improvement in terms of CO_2 emissions reduction when countries' emission level is already high.

Lastly, when interaction term, namely LnRETIxLnDEI is included in regression models, the estimates of LnRETI obtained are practically the same as previous FEPTR analysis without LnRETIxLnDEI as shown in Table 8, confirming the robustness of our empirical findings.

5.3.2. FEPTR estimation results with the regime-dependent variable replaced

To further ensure the robustness and reliability of our empirical findings, additional FEPTR analysis is conducted by replacing LnRETI with LnREShareTFEC (which denotes the renewable energy share in total final energy consumption) as a regime-dependent variable. In the previous studies, important authors have used the share of renewable energy consumption in the energy mix as a proxy for the clean energy transition in their seminal works (Doytch and Narayan, 2021; Inglesi-Lotz, 2016). Therefore, LnREShareTFEC can be a good proxy for LnRETI. Table 9 shows that even with the change of regime-dependent variable in regression models, the main estimation results remain stable. LnREShareTFEC, like LnRETI, shows an important threshold effect on economic growth in terms of per capita income and per capita CO_2 emission levels. The negative impact of LnREShareTFEC on economic growth is observed, and its elasticity decreases as a country's LnGDPpc or LnCO2pc increases. The only difference is that when LnCO2pc is considered as a threshold variable, no threshold effect is detected or the negative impacts of LnREShareTFEC on economic growth gradually attenuates. On the other hand, LnREShareTFEC negatively affects CO_2 emissions and shows an important threshold effect depending on a country's income or emission levels, which is consistent with the previous estimation results when using LnRETI as a regime-dependent variable. The only difference is that the beneficial impact of

Table 9
FEPTR model regression results with $R_{it} = Ln\ REShareTFEC_{it}$.

Y_{it} = $LnGDPpc_{it}$				
Variables	Q_{it} = $LnGDPpc_{it}$		Q_{it} = $LnCO2pc_{it}$	
LnTNRR	0.038*** (0.009)	0.038*** (0.009)	0.024** (0.010)	0.024** (0.010)
LnInflation	−0.006 (0.008)	−0.005 (0.008)	−0.005 (0.010)	−0.005 (0.010)
LnFDI	−0.001 (0.006)	−0.000 (0.006)	−0.005 (0.007)	−0.004 (0.007)
LnGI	0.428*** (0.125)	0.446*** (0.125)	0.640*** (0.147)	0.653*** (0.148)
LnDEI	0.016 (0.026)	0.028 (0.028)	0.019 (0.031)	0.029 (0.033)
LnREShareTFECxLnDEI		−0.053 (0.040)		−0.045 (0.047)
cat#c.LnREShareTFEC				
0	**−0.207*** (0.021)**	**−0.207*** (0.021)**	**No threshold effect**	**−0.136*** (0.025)**
1	**−0.173*** (0.021)**	**−0.174*** (0.021)**		**−0.103*** (0.026)**
2	**−0.118*** (0.021)**	**−0.118*** (0.021)**		**−0.059** (0.029)**
Constant	7.346*** (0.500)	7.283***	6.263*** (0.601)	6.214*** (0.604)
R^2 (within)	0.883	0.884	0.838	0.838
Number of Obs.	306	306	306	306
Y_{it} = $LnCO2pc_{it}$				
Variables	**Q_{it} = $LnGDPpc_{it}$**		**Q_{it} = $LnCO2pc_{it}$**	
LnAFFVadd	−0.095** (0.039)	−0.100** (0.039)	−0.198*** (0.036)	−0.170*** (0.036)
LnInflation	0.011 (0.012)	0.011 (0.012)	0.011 (0.012)	0.013 (0.012)
LnFDI	0.021** (0.009)	0.022** (0.009)	0.014 (0.009)	0.015* (0.009)
LnGI	−0.229 (0.181)	−0.239 (0.181)	−0.070 (0.171)	−0.048 (0.171)
LnDEI	−0.008 (0.040)	−0.021 (0.042)	0.011 (0.039)	−0.006 (0.041)
LnREShareTFECxLnDEI		0.050 (0.061)		−0.084 (0.060)
cat#c.LnREShareTFEC				
0	**−0.444*** (0.032)**	**−0.444*** (0.032)**	**−0.516*** (0.031)**	**−0.532*** (0.032)**
1	**−0.390*** (0.033)**	**−0.389*** (0.033)**	**−0.465*** (0.030)**	**−0.465*** (0.030)**
2			**−0.421*** (0.031)**	**−0.420*** (0.031)**
Constant	2.920*** (0.748)	2.960*** (0.746)	2.659*** (0.710)	2.474*** (0.710)
R^2 (within)	0.698	0.702	0.713	0.715
Number of Obs.	306	306	306	306

Note: *, **, and *** denote significance level at 10%, 5%, and 1% respectively and time dummies were included during the estimation; Y_{it} denotes the dependent variable. The values in parentheses indicate the standard error.

LnREShareTFEC decreases when LnGDPpc or LnCO2pc increases. However, the sign and the significance level do not differ significantly when the regime-dependent variable changes, confirming the robustness of the empirical findings.

5.4. Method of Moments Quantile Regression (MMQR)

5.4.1. MMQR without time fixed effect

The standard linear regression models may not properly account for the heterogenous distribution of panel data and can lead to biased estimation results when outliers are present or when the elasticity of the variable of interest differ significantly across different points of the outcome variable (Alvarado et al., 2021). To address this issue, the MMQR is used in our analysis for estimating the asymmetric and non-linear effect of renewable energy transition and other covariates on economic growth and CO_2 emissions across the quantile distribution. Before estimating the MMQR, a battery of tests, including Swamey's test (Pesaran and Yamagata, 2008), Shapiro-Wilk W test (Royston, 1983), Skewness-Kurtosis test (D'agostino et al., 1990; Royston, 1992) are carried out to evaluate slope homogeneity and the normal distribution of the dependent variable (see Table A.59-A.61 and Figure A.1 in Appendix). The results confirm slope heterogeneity and non-normality of LnGDPpc and LnCO2pc as the null hypotheses of Swamey, Shapiro-Wilk and Skewness-Kurtosis tests are rejected at the 1% significance level respectively, satisfying prerequisites for the application of the MMQR to our analysis objective (Fuinhas and Marques, 2019). Table 10 shows the estimation results of the MMQR without time fixed effects. The MMQR is conducted at the 20th,40th,60th, 80th, and 90th percentiles of the conditional distribution. The results indicate a significant and positive impact of renewable energy transition on economic growth across all quantiles, but this promotional effect of LnRETI is especially stronger at lower quantiles. However, as one moves along the quantile distribution, the positive effect of renewable energy transition on economic growth gradually decreases. These findings highlight the fact that in the LAC region, the beneficial impacts of renewable energy transition on economic growth in lower-income countries are much larger than high-income countries. The possible explanation is that the integration of renewable energy sources in the electricity mix can greatly contribute to improving energy access and reducing energy poverty for a large share of vulnerable populations living in low-income countries through off-grid and distributed electricity generation, which might eventually lead to improving standard of livings of poor households and local economic development (Urban, 2014). The evidence of the beneficial impact of renewable energy-based off-grid electricity generation on economic growth and poverty alleviation can be found in the study conducted by Wirawan and Gultom (2021). The researchers investigated the potential effects of renewable energy-based rural electrification on poverty alleviation in 217 remote non-grid villages in Indonesia. The findings of their study indicate that renewable-based off-grid electrification has significant positive effects. Specifically, it reduces the poverty level, decreases the number of individuals relying on health insurance, and contributes to an increase in the number of small industries, which ultimately has a positive impact on the local economy. Furthermore, the potential marginal benefits in low-income countries that can be obtained from renewable energy transition at its early stage of development is much larger than high-income countries, this is because the lack of infrastructure and low-quality electricity networks predominant in low-income countries can be greatly reduced or enhanced by the integration of renewables in the electricity mix (Vanegas Cantarero, 2020). But for high-income countries in the LAC region, the relatively small impact of renewable energy transition on economic growth can be explained by the fact that in these countries, non-renewable and polluting fossil fuels are the major energy sources responsible for their energy needs, to carry out economic activities in a cost-effective way and to ensure economic growth in the short-term, which prevents the successful implementation of renewable energy transition requiring long-term period (Henderson and Sen, 2021). Also in high-income countries, the existing energy system and infrastructures are already highly adapted to fossil fuel energy sources (large thermal power plants, large gas pipelines in Argentina and Chile), and in case these economies decide to phase out fossil-fuels and move to renewable energy transition, a significant part of these assets has a high risk of becoming stranded (ECLAC, 2022). For this reason, relatively wealthy countries in the LAC region may decide to postpone renewable energy transition and remain locked in legacy technologies (fossil fuel-based technologies). Regarding the impact of the digital economy on economic growth, this study finds a positive and statistically significant effect of LnDEI at the 1% significance level on LnGDPpc in all quantiles. However, this effect decreases as the quantile increases. These findings demonstrated that the process of digitalization contributes to accelerating economic growth in all countries of the Latin American and the Caribbean region, but its impact is particularly strong for the countries belonging to the lower quantile. This is because the marginal benefits of the digital economy in low-income countries are greater than high-income countries due to the lower degree of digitalization. Therefore, the potential gains from incorporating digital technologies into their workspace and production processes might be enormous in terms of improving labor productivity, thus resulting in economic growth for the country. It is worth noting that the coefficient of LnDEI is systematically larger than that of LnRETI in MMQR1 and MMQR2 as shown in Table 10, which means that the digital economy has a much larger impact on promoting economic growth than renewable energy transition in the LAC region.

Regarding the effect of the interaction term (LnRETIxLnDEI) on economic growth, we can only verify its significant impact at the 20th quantile (1.815 at the 5% significance level). This finding indicates that in low-income LAC countries, the synergistic effect between the digital economy and renewable energy transition on accelerating economic growth is especially high. On the other hand, the finding also suggests that most LAC countries are still far from taking full advantages of the synergy effect between the digital economy and renewable energy transition to accelerate economic growth as the coefficient of LnRETIxLnDEI is statistically not significant at other quantile groups. With respect to the control variables, we found no significant impact of total natural resources rents on economic growth across all quantiles. The finding is somewhat unexpected since the fiscal revenues derived from the exploitation of natural resources occupy a significant portion of governments' budgets in many LAC countries. The possible explanation is that heavy reliance on revenues obtained from exploitation of natural resources in their fiscal capacity, such as production of oil and natural gas and extraction of minerals, makes LAC countries highly vulnerable and susceptible to changes in global commodity market prices, which worsens the macroeconomic stability of these nations and acts as a stumbling block to the successful diversification of their economy. With regard to LnInflation, its impact on economic growth is positive and statistically significant at the 1% significance level across all quantiles. The positive effect of inflation on economic growth in the LAC region is somewhat surprising, given that a high price level is generally expected to have a detrimental impact on economic growth. This is due to the reduction in the real purchasing power of consumers, which can result in decreased consumption and lower aggregate demand. Moreover, high inflation can generate uncertainty among investors, potentially leading to reduced savings and investments, thereby further dampening economic growth. The possible explanation for the positive effect of inflation on economic growth is that many LAC countries are net exporters of commodities, and a high level of inflation, to some extent, might benefit them in terms of trade since they can sell commodities like oil, gas, agricultural goods, and minerals at a much higher price to other countries, as happened in Commodity boom period from 2000 to 2014. Also we came to recognize that the real impact of inflation on economic growth in the LAC region may not be fully captured due to the limited number of varibles used in the regression model or the specific model specifications used in this study. As for the potential of globalization, a

Table 10
MMQR estimation results (without time fixed effects).

LnGDPpc

Variables	Location		Scale		Q20		Q40		Q60		Q80		Q90	
	MMQR 1	MMQR 2	MMQR 1	MMQR 2	MMQR 1	MMQR 2	MMQR 1	MMQR 2	MMQR 1	MMQR 2	MMQR 1	MMQR 2	MMQR 1	MMQR 2
LnTNRR	−0.013	−0.010	−0.006	−0.007	−0.006	−0.001	−0.012	−0.008	−0.016	−0.013	−0.020	−0.018	−0.022	−0.020
	(0.020)	(0.021)	(0.011)	(0.012)	(0.028)	(0.031)	(0.021)	(0.023)	(0.019)	(0.019	(0.019)	(0.019)	(0.020)	(0.020)
LnInflation	0.206***	0.204***	0.004***	0.005	0.202***	0.199***	0.205***	0.203***	0.207***	0.207***	0.210***	0.210***	0.211***	0.211***
	(0.052)	(0.052)	(0.029)	(0.031)	(0.073)	(0.076)	(0.055)	(0.057)	(0.048)	(0.047)	(0.050)	(0.047)	(0.052)	(0.050)
LnFDI	−0.102	−0.104	−0.042	−0.040	−0.052	−0.056	−0.094	−0.093	−0.123*	−0.123*	−0.151**	−0.150**	−0.165**	−0.162**
	(0.074)	(0.075)	(0.040)	(0.044)	(0.103)	(0.109)	(0.077)	(0.081)	(0.068)	(0.068)	(0.070)	(0.068)	(0.074)	(0.071)
LnGI	4.012***	4.070***	−0.612***	−0.615***	4.743***	4.800***	4.134***	4.237***	3.712***	3.786***	3.301***	3.364***	3.112***	3.190***
	(0.337)	(0.345)	(0.185)	(0.202)	(0.471)	(0.505)	(0.362)	(0.383)	(0.315)	(0.315)	(0.322)	(0.315)	(0.336)	(0.326)
LnRETI	**0.336*** **	**0.334*** **	**−0.078*** **	**−0.073**	**0.429*** **	**0.421*** **	**0.351*** **	**0.354*** **	**0.297*** **	**0.300*** **	**0.245*** **	**0.249*** **	**0.220** **	**0.229** **
	(0.092)	**(0.095)**	**(0.050)**	**(0.056)**	**(0.128)**	**(0.139)**	**(0.097)**	**(0.104)**	**(0.085)**	**(0.086)**	**(0.087)**	**(0.086)**	**(0.092)**	**(0.091)**
LnDEI	**0.800*** **	**0.796*** **	**−0.199*** **	**−0.166**	**1.037*** **	**0.993*** **	**0.839*** **	**0.841*** **	**0.702*** **	**0.720*** **	**0.568*** **	**0.606*** **	**0.507** **	**0.559*** **
	(0.197)	**(0.193)**	**(0.108)**	**(0.113)**	**(0.275)**	**(0.283)**	**(0.209)**	**(0.211)**	**(0.184)**	**(0.175)**	**(0.188)**	**(0.175)**	**(0.198)**	**(0.185)**
LnRETIxLnDEI		**0.742**		**−0.905*** **		**1.815** **		**0.988**		**0.324**		**−0.297**		**−0.552**
		(0.617)		**(0.361)**		**(0.902)**		**(0.679)**		**(0.561)**		**(0.561)**		**(0.585)**
Constant	−7.395***	−7.644***	2.734***	2.781***	−10.663***	−10.945	−7.942***	−8.402***	−6.504***	−6.362***	−4.215***	−4.452	−3.372**	−3.666***
	(1.454)	(1.493)	(0.798)	(0.874)	(2.030)		(1.562)	(1.658)	(1.359)	(1.360)	(1.390)		(1.450)	(1.410)
Number of Obs.	306	306	306	306	306	306	306	306	306	306	306	306	306	306

LnCO2pc

Variables	Location		Scale		Q20		Q40		Q60		Q80		Q90	
	MMQR 3	MMQR 4	MMQR 3	MMQR 4	MMQR 3	MMQR 4	MMQR 3	MMQR 4	MMQR 3	MMQR 4	MMQR 3	MMQR 4	MMQR 3	MMQR 4
LnAFFVadd	−0.974***	−0.976***	−0.054*	−0.047	−0.916***	−0.927***	−0.956***	−0.961***	−0.991***	−0.989***	−1.031***	−1.023***	−1.056***	−1.051***
	(0.051)	(0.051)	(0.031)	(0.031)	(0.057)	(0.057)	(0.051)	(0.050)	(0.053)	(0.053)	(0.064)	(0.063)	(0.075)	(0.076)
LnInflation	0.174***	0.175***	−0.077**	−0.086**	0.256***	0.264***	0.199***	0.201***	0.149***	0.151*	0.093	0.087	0.056	0.036
	(0.054)	(0.057)	(0.033)	(0.035)	(0.061)	(0.065)	(0.054)	(0.057)	(0.057)	(0.060)	(0.069)	(0.072)	(0.080)	(0.086)
LnFDI	0.003	0.006	−0.010	−0.012	0.014	0.018	0.007	0.009	−0.000	0.002	−0.008	−0.006	−0.013	−0.013
	(0.033)	(0.034)	(0.020)	(0.021)	(0.037)	(0.038)	(0.032)	(0.033)	(0.034)	(0.035)	(0.041)	(0.042)	(0.048)	(0.050)
LnGI	1.599***	1.542***	0.078	0.064	1.516***	1.477***	1.573***	1.523***	1.625***	1.560***	1.682***	1.608***	1.720***	1.645***
	(0.246)	(0.252)	(0.151)	(0.155)	(0.275)	(0.282)	(0.244)	(0.251)	(0.257)	(0.261)	(0.311)	(0.315)	(0.360)	(0.378)
LnRETI	**−0.638*** **	**−0.636*** **	**−0.044**	**−0.037**	**−0.591*** **	**−0.598*** **	**−0.624*** **	**−0.625*** **	**−0.653*** **	**−0.647*** **	**−0.685*** **	**−0.674*** **	**−0.707*** **	**−0.696*** **
	(0.069)	**(0.070)**	**(0.043)**	**(0.043)**	**(0.078)**	**(0.078)**	**(0.069)**	**(0.069)**	**(0.073)**	**(0.072)**	**(0.088)**	**(0.087)**	**(0.102)**	**(0.105)**
LnDEI	**0.228***	**0.230***	**−0.015**	**0.026**	**0.243***	**0.203**	**0.233***	**0.222***	**0.223***	**0.237***	**0.212**	**0.257**	**0.205**	**0.273**
	(0.124)	**(0.126)**	**(0.076)**	**(0.077)**	**(0.138)**	**(0.141)**	**(0.123)**	**(0.125)**	**(0.129)**	**(0.131)**	**(0.156)**	**(0.157)**	**(0.181)**	**(0.189)**
LnRETIxLnDEI		**−0.651***		**0.083**		**−0.737***		**−0.676***		**−0.627**		**−0.565**		**−0.515**
		(0.380)		**(0.234)**		**(0.425)**		**(0.378)**		**(0.394)**		**(0.475)**		**(0.570)**
Constant	−5.130***	−4.887***	0.148	0.256	−5.288***	−5.151***	−5.179***	−4.965***	−5.081***	−4.816***	−4.793***	−4.624***	−4.902***	−4.472***
	(1.081)	(1.108)	(0.663)	(0.681)	(1.209)	(1.236)	(1.074)	(1.101)	(1.130)	(1.147)	(1.365)	(1.382)	(1.582)	(1.659)
Number of Obs.	306	306	306	306		306	306	306	306	306	306	306	306	306

Note: *, **, and *** denote significance level at 10%, 5%, and 1% respectively and time dummies were included during the estimation; MMQR 1- MMQR 4 correspond to equation 12–15 without time fixed effects in section 4.6 respectively. The values in parentheses indicate the standard error.

very strong positive and statistically significant effect at the 1% level on economic growth is found in all quantiles. The results are consistent with the previous findings of Koengkan and Fuinhas (2022), who confirmed that globalization had a positive impact on the improvement of the income level in LAC countries. Regarding FDI, we cannot find any significant impact on economic growth across the quantile distribution.

When considering LnCO2pc as a dependent variable, a negative and statistically significant effect of LnRETI at the 1% significance level is found across all quantiles, and its negative impact on CO_2 emissions gradually increases as the quantile increases. The finding indicates that the positive contribution of renewable energy transition to improving environmental sustainability in the LAC region is very robust, and its impact on improving environmental quality in countries with high per capita CO_2 emissions is particularly stronger than those with low per capita CO_2 emissions. When it comes to the digital economy, a positive and statistically significant impact at the 10% significance level is found at the 40th and 60th quantiles but no meaningful effect is found in other quantile groups. The finding shows that the potential benefits derived from the digital economy in terms of energy and resource use efficiency improvement (thus less energy demand) are not sufficiently exploited in the LAC region and the negative impact of the digital economy on the environment is especially noticeable in middle-emission countries. Concerning the synergistic effect between the digital economy and renewable energy transition, LnRETIxLnDEI is found to have a negative and statistically significant impact at the 10% significance level on LnCO2pc at the 20th and 40th quantiles. The finding indicates that renewable energy transition if combined with the digital economy, might lead to a large reduction in carbon dioxide emissions in the region, which is especially true for economies with a moderate level of CO_2 emissions in the LAC region. With respect to the control variables, the results indicate that globalization leads to significantly increase carbon dioxide emissions in all quantiles, and this effect increases as ones move along the quantile distribution. Meanwhile, agriculture, forestry, and fishing activities significantly reduce CO_2 emissions at all quantile groups. These findings suggest that globalization is not effective in improving environmental quality in the LAC region through the import of clean energy technologies or attracting environmentally friendly firms. The negative coefficient of LnAFFVadd indicates that the activities related to the production of crops, livestock, and fishing are relatively environmentally friendly in the LAC region.

Regarding inflation, a positive and statistically significant effect on carbon dioxide emissions is found at the 20th, 40th, and 60th quantiles. The possible explanation can be attributed to the fuel stacking problem, which implies the simultaneous use of traditional biomass energy sources with modern energy sources (electricity) in many households in the LAC region. As the energy price increases, many households opt for cheaper energy sources such as firewood and organic wastes (which is highly polluting) to cooking and heating rather than expensive modern energy sources. Lastly, no significant impact of FDI on carbon dioxide emissions in the LAC region is found across the quantile distribution.

5.4.2. MMQR with time fixed effect

To confirm the robustness of our empirical findings in MMQR analysis, time fixed effects are included in regression models. The estimation results of MMQR with time fixed effects shown in Table 11 indicate that the empirical findings of this study are robust since no significant changes are observed in the signs and elasticities of variables compared to the previous estimation results of the MMQR without time fixed effects.

5.5. Discussion of findings

Based on the previous estimation results, several important outcomes can be highlighted as follows:

First, the synergistic effect between renewable energy transition and the digital economy in the LAC region is not widely confirmed, and its impact on economic growth and environmental sustainability is interdependent in income and emission levels, thus verifying only partially the Hypothesis 1 of this study. Linear regressions estimate that the synergy between them is not significant to economic growth or environmental sustainability in 18 combined LAC countries. However, the non-linearity and heterogeneity of the synergistic effect between renewable energy transition and the digital economy are found through the MMQR analysis, showing that the synergistic effect on promoting economic growth is found at the 20th quantile only (i.e., low-income countries), while the synergistic effect on improving environmental quality is found at the 40th, the 60th and the 80th quantiles[8] (i.e., low-, middle-, and high- CO2 emitting countries). The estimation results are somewhat contrary to the findings in the study of Shahbaz et al. (2022), who confirmed that the digital economy positively affected energy transition in 72 countries, and its impact was especially strong in high-income countries. The contradiction can be explained by the fact that many LAC economies' lacks high-quality energy and digital infrastructure, as well as qualified workers with specialized knowledge and engineering skills capable of managing advanced clean energy and digital technologies (important skill gaps), which are stumbling blocks to broad application of advanced digital technologies in the energy system of many LAC countries. This in turn, impedes the rapid integration of renewable energy sources in the energy mix, as their high unpredictability features such as intermittency and variability are not properly addressed. Consequently, the process of renewable energy transition is significantly delayed. Furthermore, the fiscal capacity of many LAC governments limited in funding large-scale renewable energy deployment and renovating extant digital infrastructure, above all things the production process and local value chain heavily locked-in to fossil fuel technologies, makes it difficult to create the synergy between renewable energy transition and the digital economy in the LAC region. The strong impact of the synergistic effect between renewable energy transition and the digital economy on promoting economic growth found in low-income LAC countries due to the fact that the marginal benefits derived from additional energy access and digitalization in these countries are significantly higher than in high-income countries in terms of productivity gains, improvements in standards of living and reduction of energy poverty reduction. Xu et al. (2022) also found, in their study of 109 countries, that the impact of digitalization on reducing energy intensity and optimizing energy system structure was especially strong in low-income and developing countries. The finding of synergistic effect between renewable energy transition and the digital economy on reducing CO_2 emissions in low- and middle-emission LAC countries in this study contrasts with that of Lange et al. (2020), who argued that digitalization had no effect on the decoupling of economic growth from energy consumption due to the rebound effect in high-energy- consuming and industrialized countries.

Second, this study reveals an important threshold effect of renewable energy transition on economic growth and CO_2 emissions in the LAC region, and certainly proved the validity of Hypothesis 2. The FEPTR analysis shows that the negative effect of renewable energy transition on economic growth becomes larger as income levels increases. The positive impact of renewable energy transition on economic growth is observed only when emissions levels are below the threshold, and this positive impact disappears when emissions levels exceed the threshold. This is because LAC countries with relatively high-income levels have higher per capita energy consumption compared with low-income countries. As the major sources of total final energy consumption in high-income countries in the LAC region are hydrocarbons and given the intermittency of renewables, the relative importance of renewable energy as its contribution to economic growth decreases. Doytch and

[8] This is when the time fixed effects were considered in regression models. However, when they were not taken into account, the synergistic effect was found at the 20th and the 40th quantiles.

Table 11
MMQR estimation results (with time fixed effects).

LnGDPpc

Variables	Location		Scale		Q20		Q40		Q60		Q80		Q90	
	MMQR 1	MMQR 2	MMQR 1	MMQR 2	MMQR 1	MMQR 2	MMQR 1	MMQR 2	MMQR 1	MMQR 2	MMQR 1	MMQR 2	MMQR 1	MMQR 2
LnTNRR	−0.000	0.003	−0.010	−0.012	0.011	0.018	0.002	0.006	−0.005	−0.003	−0.011	−0.011	−0.014	−0.015
	(0.021)	(0.021)	(0.011)		(0.029)	(0.030)	(0.022)		(0.020)	(0.020)	(0.020)	(0.021)	(0.021)	(0.022)
LnInflation	0.232***	0.233***	0.003	0.005	0.228***	0.227***	0.231***	0.232	0.234***	0.235***	0.236***	0.238***	0.237***	0.240***
	(0.060)	(0.059)	(0.032)		(0.083)	(0.081)	(0.063)		(0.056)	(0.055)	(0.058)	(0.058)	(0.061)	(0.061)
LnFDI	−0.085	−0.087	−0.035	−0.034	−0.042	−0.045	−0.077	−0.078	−0.103	−0.104	−0.125*	−0.125*	−0.136*	−0.136***
	(0.071)	(0.072)	(0.038)		(0.099)	(0.099)	(0.075)		(0.067)	(0.068)	(0.069)	(0.071)	(0.073)	(0.075)
LnGI	4.134***	4.162***	−0.694***	−0.718	4.987***	5.049***	4.294***	4.346	3.786***	3.801***	3.338***	3.354***	3.132***	3.124***
	(0.366)	(0.373)	(0.197)		(0.506)	(0.512)	(0.397)		(0.346)	(0.356)	(0.354)	(0.367)	(0.369)	(0.385)
LnRETI	**0.307*** **	**0.308*** **	**−0.058**	**−0.057**	**0.378*** **	**0.378*** **	**0.320*** **	**0.323**	**0.278*** **	**0.280*** **	**0.240*** **	**0.245** **	**0.223** **	**0.226** **
	(0.094)	**(0.098)**	**(0.051)**		**(0.131)**	**(0.134)**	**(0.100)**		**(0.088)**	**(0.092)**	**(0.091)**	**(0.096)**	**(0.096)**	**(0.102)**
LnDEI	**0.902*** **	**0.896*** **	**−0.141**	**−0.098**	**1.075*** **	**1.017*** **	**0.934*** **	**0.921**	**0.831*** **	**0.847*** **	**0.740*** **	**0.785*** **	**0.698*** **	**0.754*** **
	(0.204)	**(0.196)**	**(0.110)**		**(0.283)**	**(0.269)**	**(0.216)**		**(0.191)**	**(0.185)**	**(0.197)**	**(0.192)**	**(0.207)**	**(0.205)**
LnRETIxLnDEI		**0.717**		**−1.086**		**2.059** **		**0.996**		**0.170**		**−0.506**		**−0.854**
		(0.607)				**(0.833)**				**(0.580)**		**(0.598)**		**(0.628)**
Constant	−7.831***	−7.977***	3.094***	3.240***	−11.633***	−11.980***	−8.543***	−8.810***	−6.283***	−6.347***	−4.285***	−4.331***	−3.368**	−3.291**
	(1.545)	(1.561)	(0.830)	(0.848)	(2.136)	(2.144)	(1.680)	(1.698)	(1.462)	(1.496)	(1.495)	(1.540)	(1.557)	(1.612)
Number of Obs.	306	306	306	306	306	306	306	306	306	306	306	306	306	306

LnCO2pc

Variables	Location		Scale		Q20		Q40		Q60		Q80		Q90	
	MMQR 3	MMQR 4	MMQR 3	MMQR 4	MMQR 3	MMQR 4	MMQR 3	MMQR 4	MMQR 3	MMQR 4	MMQR 3	MMQR 4	MMQR 3	MMQR 4
LnAFFVadd	−0.970***	−0.972***	−0.081**	−0.073**	−0.880***	−0.890***	−0.947***	−0.955***	−0.995***	−0.996***	−1.053***	−1.052***	−1.099***	−1.090***
	(0.051)	(0.050)	(0.031)	(0.030)	(0.064)	(0.061)	(0.052)	(0.051)	(0.052)	(0.052)	(0.059)	(0.061)	(0.070)	(0.071)
LnInflation	0.165***	0.165**	−0.089**	−0.100**	0.265***	0.279***	0.191***	0.188***	0.138**	0.132**	0.074	0.055	0.023	0.002
	(0.061)	(0.064)	(0.037)	(0.039)	(0.076)	(0.078)	(0.062)	(0.065)	(0.062)	(0.066)	(0.071)	(0.079)	(0.084)	(0.091)
LnFDI	0.010	0.014	−0.014	−0.015	0.027	0.030	0.015	0.017	0.006	0.009	−0.004	−0.003	−0.013	−0.010
	(0.036)	(0.036)	(0.022)	(0.022)	(0.045)	(0.044)	(0.037)	(0.036)	(0.037)	(0.037)	(0.042)	(0.044)	(0.050)	(0.051)
LnGI	1.924***	1.885***	0.379**	0.363**	1.502***	1.471***	1.817***	1.800***	2.042***	2.002***	2.313***	2.284***	2.529***	2.473***
	(0.284)	(0.281)	(0.172)	(0.170)	(0.350)	(0.340)	(0.289)	(0.284)	(0.287)	(0.289)	(0.327)	(0.342)	(0.386)	(0.397)
LnRETI	**−0.683*** **	**−0.685*** **	**−0.111** **	**−0.104** **	**−0.560*** **	**−0.566*** **	**−0.652*** **	**−0.660*** **	**−0.718*** **	**−0.718*** **	**−0.797*** **	**−0.799*** **	**−0.860*** **	**−0.853*** **
	(0.074)	**(0.074)**	**(0.045)**	**(0.045)**	**(0.092)**	**(0.090)**	**(0.076)**	**(0.075)**	**(0.075)**	**(0.077)**	**(0.086)**	**(0.091)**	**(0.101)**	**(0.105)**
LnDEI	**0.267* **	**0.273** **	**−0.017**	**0.019**	**0.286* **	**0.252**	**0.272* **	**0.269* **	**0.262* **	**0.280** **	**0.250**	**0.294* **	**0.241**	**0.304**
	(0.137)	**(0.138)**	**(0.083)**	**(0.084)**	**(0.168)**	**(0.166)**	**(0.140)**	**(0.139)**	**(0.138)**	**(0.141)**	**(0.158)**	**(0.167)**	**(0.187)**	**(0.196)**
LnRETIxLnDEI		**−0.810* **		**−0.046**		**−0.758**		**−0.799* **		**−0.825* **		**−0.860* **		**−0.884**
		(0.426)		**(0.259)**		**(0.513)**		**(0.429)**		**(0.436)**		**(0.517)**		**(0.604)**
Constant	−6.321***	−6.126***	−0.972	−0.856	−5.239***	−5.152***	−6.046***	−5.926***	−6.624***	−6.403***	−7.318***	−7.067***	−7.871***	−7.514***
	(1.179)	(1.175)	(0.717)	(0.713)	(1.456)	(1.417)	(1.205)	(1.184)	(1.194)	(1.204)	(1.366)	(1.427)	(1.611)	(1.663)
Number of Obs.	306	306	306	306	306	306	306	306	306	306	306	306	306	306

Note: *, **, and *** denote significance level at 10%, 5%, and 1% respectively and time dummies were included during the estimation; MMQR 1- MMQR 4 correspond to equation 12–15 in section 4.6 respectively. The values in parentheses indicate the standard error.

Narayan (2021) also argued that renewable energy transition was only effective in promoting high-growth sectors of an economy, which corresponds to the agriculture and mining (extractive) sectors of most LAC nations. However, these two sectors are resource- and energy-intensive sectors with a high reliance on hydrocarbon energy sources, such as oil and gas, which impedes the use of renewable energy sources and potential gains that can be reaped from renewable energy transition, such as low-electricity generating costs and new jobs creation in clean energy sector. The positive and significant impact of renewable energy transition on economic growth in countries with low levels of CO_2 emissions (thus lower per capita energy consumption due to either high energy efficiency or low access to energy) can be explained by the fact that in both cases, the transition to renewable energy can boost economic growth in terms of improving further energy efficiency or offering affordable energy services to poor segments of population of an economy. Regarding the effect of renewable energy transition on improving environmental sustainability, the estimation results of FEPTR also indicate a significant threshold effect. When a country's income level is below the threshold, no significant impact of renewable energy transition is found. However, when a country's per capita GDP exceeds the threshold value, the impact of renewable energy transition on CO_2 emissions becomes significant, leading to an improvement in environmental quality by reducing CO_2 emissions. This finding is in accord with that of Li et al. (2022. b), who found a non-linear and significant threshold effect of renewable energy on the ecological footprint in 120 countries. They verified a positive impact of renewable energy on environmental sustainability and emphasized that renewable energy only became effective in improving environmental quality when a country's development of urbanization or income level reached a certain threshold. The estimation results also confirmed that the effect of renewable energy transition on environmental sustainability was non-linear and varied significantly depending on a country's level of emissions. When per capita CO_2 emissions of an economy are below the first threshold, renewable energy transition leads to a decline in environmental quality by increasing emissions. However, when per capita CO_2 emissions are above the first threshold, the effect of renewable energy transition on environmental quality turns to positive, and it becomes even more profound when a country's emission levels exceed the second threshold. This finding can be explained by the fact that low per capita CO_2 emission countries in the LAC region are mainly low-income countries, where per capita energy consumption is significantly lower than in high-income countries due to a large share of population lacking access to affordable and reliable energy services, who are unable to pay for high energy bills because of their low purchasing power (Urban, 2014). As a result, a popular use of cheaper traditional biomass energy sources (also known as conventional renewables), such as fuelwoods and organic wastes for cooking and heating, is quite common in these countries, ultimately leading to air pollution and environmental degradation. On the contrary, countries with high per capita CO_2 emissions in the LAC region are mostly upper-middle and high-income nations characterized by considerably higher energy consumption (both total and per capita) and larger production activities than their low-income counterparts. Due to their superior macroeconomic and fiscal capacities, high-income countries in the LAC region are better in financing the high upfront costs required to carry out large-scale deployment of renewable energy sources (utility-scale solar and wind farms). As a result, the benefits from renewable energy transition in high-income countries with high level of emissions and energy consumption will be significantly greater than in low-income countries, particularly in terms of reducing CO_2 emissions. Dong et al. (2022. a), in their study of 32 developed countries, also found a significant positive relationship between renewable energy development and carbon emission efficiency when country's income level was high.

Finally, the estimates of MMQR in this study confirm the heterogenous impact of renewable energy transition and the digital economy on economic growth and environmental sustainability in 18 LAC countries, verifying that the validity of the Hypothesis 3 of this study also hold. Unlike standard linear regressions and threshold regressions, the positive impact of renewable energy transition on economic growth is found at all quantile groups. Its impact is stronger at lower quantiles and gradually decreases across the quantile distribution. Renewable energy transition is also found to have a positive and significant impact at the 1% significance level on environmental sustainability at all quantiles and its impact gradually increases at higher quantiles. The results are consistent with the study of Li et al. (2022b), who affirmed that renewable energy had a beneficial impact on economic growth. Wang et al. (2022a, 2022b, 2022c) also confirmed a positive effect of renewable energy on economic growth and its heterogenous impact in terms of resource dependence and anticorruption regulation. With regard to the digital economy, its impact on promoting economic growth is found at the 1% significance level at all quantiles. Similar to renewable energy transition, the digital economy has a strong impact at lower quantiles, but its impact gradually decreases along the quantile distribution. It is worth noting that the digital economy has a much stronger impact on promoting economic growth than renewable energy transition in the LAC region as the coefficients of LnDEI is systematically greater than that of LnRETI across all quantile distribution. The results are consistent with the findings of Hao et al. (2023), who found a significant positive and spillover effects of digitalization on green economic growth in 277 cities in China. No evidence is found to support enough the robust positive impact of the digital economy on improving environmental quality in this study, as the coefficients of LnDEI are positive (more CO_2 emissions) and statistically significant at the 10% significance level at different quantile groups. Lange et al. (2020) reached a similar conclusion that the digitalization might not contribute to reducing CO_2 emissions due to a significant rebound effect and increased electricity consumption by the ICT sectors. Main empirical findings of this study are summarized with their impacts in Table 12. And the overview of this research is illustrated in Fig. 2 by the categories: hwo to approach, what are done, what outcomes are, and policy implications.

6. Conclusion and policy implications

In this study, the synergistic effect between renewable energy and the digital economy was investigated in 18 Latin American and the Caribbean countries during the period 2003–2019 from the perspective of economic growth and environmental sustainability. New multidimensional indices, the Renewable Energy Transition Index (RETI) and the Digital Economy Index (DEI) specific to the LAC region were developed to encompass multidimensional features and complex reality accompanied by renewable energy transition and the digital economy in evaluating the impact on green economic growth. Furthermore, the FEPTR and the MMQR techniques were used to estimate the non-linear and heterogenous impact of renewable energy transition and the digital economy. Based on the estimation results, this study substantiated that the synergistic effect improved environmental sustainability in various quantile groups in the LAC region. However, the effect on boosting economic growth could be observed only at the lowest-quantile (20th quantile) using the MMQR. The robustness test was carried out by incorporating time fixed effects into the MMQR and also confirmed the validity of the estimation results. On the other hand, the FEPTR analysis indicated that renewable energy transition had an important threshold effect in association with the levels of income and CO_2 emissions in the LAC region. Regarding the threshold effect, renewable energy transition did negatively affect economic growth when per capita GDP of the country was above the first and second thresholds, and its negative impact became larger as income level increased. Nevertheless, no significant effect of renewable energy transition on economic growth was found in low-income countries (i.e., those countries with per capita GDP below the first threshold). For countries with per capita CO_2 emissions below the threshold, renewable energy transition led to their economic growth, but meaningful impact was not confirmed when country's

Table 12
Summary of empirical findings.

Countries	Impacts confirmed	Reasoning basis
The LAC countries with relatively low levels of income	1) Strong synergistic effect between RET and DE on promoting economic growth at the 1% level at Q20. 2) Strong effect of RET and DE on promoting economic growth at the 1% level at Q20 and Q40.	MMQR with time fixed effects
	No significant effect of RET on economic growth and CO_2 emissions below the first threshold.	FEPTR
The LAC countries with relatively low levels of CO_2 emissions	1) Weak synergistic effect between RET and the DE on improving environmental sustainability at the 10% level at Q40.[a] 2) Strong effect of RET on improving environmental quality at the 1% level at Q20 and Q40. 3) Weak negative effect of DE on environmental quality at the 10% level at Q20 and Q40.	MMQR with time fixed effects
	1) Strong positive effect of RET on economic growth at the 1% level below the first threshold. 2) Strong negative effect of RET on environmental quality at the 1% level below the first threshold.	FEPTR
The LAC countries with relatively high levels of income	1) No synergistic effect between RET and DE on promoting economic growth. 2) Strong effect of RET and DE on promoting economic growth at the 1% level at Q60, Q80 and Q90	MMQR with time fixed effects
	1) Strong negative effect of RET on economic growth at the 1% level above the first and the second threshold (increasing effect) 2) Moderate positive effect of RET on environmental quality at the 5% level above the first threshold.	FEPTR
The LAC countries with relatively high levels of CO_2 emissions	1) Weak synergistic effect between RET and the DE on improving environmental sustainability at the 10% level at Q60 and Q80. 2) Strong effect of RET on improving environmental quality at the 1% level at Q60,Q80, and Q90. 3) Negative effect of DE on environmental quality at the 5% and 10% level at Q60 and Q80 respectively.	MMQR with time fixed effects
	1) No significant effect of RET on economic growth above the first threshold. 2) Positive effect of RET on environmental quality (increasing effect) at the 5% and the 1% level above the first and the second threshold respectively.	FEPTR

Note: DE: Digital Economy; FEPTR: Fixed Effects Panel Threshold Regression; MMQR: Methods of Moments Quantile Regression; RET: Renewable Energy Transition.

[a] When the time fixed effects are not considered, the synergistic effect is found at the 10% significance level at Q20 and Q40.

emissions levels were above the threshold. When it comes to the threshold effect of renewable energy transition on environmental sustainability, renewable energy transition had a positive effect only when country's income levels were above the threshold, but significant effect was not found in the countries with income level below the threshold. On the other hand, the negative effect of renewable energy transition was found when the level of country's CO_2 emissions were below the first threshold, but renewable energy transition led to improved environmental quality when per capita CO_2 emissions exceeded the first and second thresholds. This study also found the heterogenous impacts of renewable energy transition and the digital economy in the LAC region. Unlike the synergistic effect, the positive effect of renewable energy transition on both economic growth and environmental sustainability was verified across all quantile groups, and its impact was particularly stronger at lower quantile. The digital economy had a positive effect on economic growth in all quantile groups and its impact was much stronger at lower quantile. However, the digital economy did not lead to improved environmental sustainability as it increased CO_2 emissions in some quantile groups.

The following policy implications could be drawn from the empirical results obtained in this research.

First, as far as the high potential benefits of the synergy between renewable energy transition and the digital economy are concerned, the governments in the LAC region should prioritize the integration of renewable energy promoted by digitalization as urgent implementation strategies in order to achieve a rapid decarbonization of their economies and sustainable development in the region. The broad application of digital technologies in power grids dominated by renewables such as smart grids can bring important energy saving costs thanks to more efficient energy management and can provide more flexibility, reliability, and resilience to energy systems alike by reducing a mismatch between supply and demand and by accurate weather forecasting. Given that many countries in the LAC region are suffering from a lack of efficient energy system infrastructure, qualified workforce, and technological and innovation capabilities to assimilate the advantages of digitalization in power grids, consolidating regional energy system integration and close collaboration between public and private sectors, as well as establishing strong cooperation with the Global North (group formed by advanced economies) can be a good alternative for the LAC region to fully exploit the potential benefits from decarbonization and digitalization process on economic growth because they can deliver important energy security and cost savings thanks to more resilience to price volatility of oil and gas, the economy of scale and can generate spillover effects by promoting sharing of technical knowledge and skills as well as facilitating transfer of advanced green technology from developed countries.

Second, given that each country in the LAC region has been facing different challenges in terms of renewable energy transition and digitalization of their economy to achieve net-zero goals and sustainable development goals, one-size-fits-all strategy is not adequate anymore. Therefore, the governments in the region are encouraged to take feasible measures adaptable to their specific context. Four different measures are recommended, taking into consideration the country's level of income and CO2 emissions: First, for the LAC countries with relatively lower income levels, policymakers should exert great efforts to mobilize domestic private capital to finance costly digitalization of renewable energy power system and to create favorable financial conditions to attract large capital investments from foreign and domestic investors. Given the fact that fiscal capacities of governments to finance high capital-intensive renewable energy deployment and the development of digital infrastructures in these countries are quite limited, specific funds devised by international development banks for clean energy deployment projects in developing countries such as green bonds can be of great help. It is also recommended that the governments in low-income countries in the LAC should proactively support and incentivize renewable energy deployment and digitalization of their economies to lower the high poverty level, accelerate economic growth, improve living standards of their citizens, and reduce carbon emissions. Second, for the LAC countries with relatively low levels of CO_2 emissions, goal-oriented policy measures should be taken by the governments to strengthen their efforts towards a more sustainable pathways so that the benefits of digitalization of energy mix can be fully exploited in terms of environmental preservation. In this regard, it can be of great help to

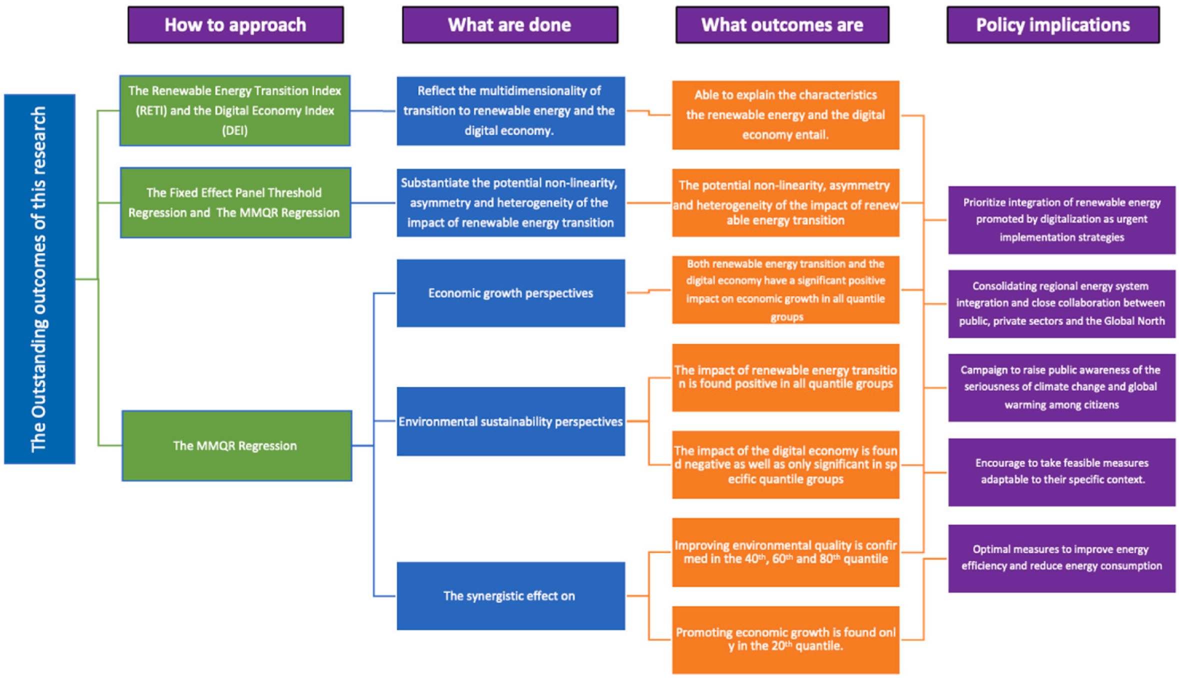

Fig. 2. Summary of the reserch.

offer specific skill trainings and development programs to train highly competitive workers for managing complex digital tools in advanced renewable energy sector. The governments and policymakers in the LAC countries with low level of CO_2 emissions should pay careful attention to avoid potential rebound effects due to digitalization. Third, for the LAC countries with relatively high levels of income, governments should implement policy measures to reduce their high dependence on hydrocarbons in their economic structure and facilitate the integration of renewables in their energy mix in order to achieve Sustainable Development Goals. To this end, governments can establish favorable fiscal incentives such as tax credit to private investors and firms who actively invest and adopt green energy technology in their production line, offer Power Purchase Agreements (PPA) for low-carbon energy producers to guarantee electricity prices in longer term and remove political barriers which might hinder a prompt and successful renewable energy transition such as vested interest of large oil and gas companies in influencing political decisions in favor of them and streamline unnecessary bureaucratic process to facilitate rapid renewable energy deployment. Lastly, for the LAC countries with relatively high levels of CO_2 emissions, the policymakers should increase their efforts towards decoupling of economic growth from environmental degradation with special focus on energy-intensive and high-emitting sectors such as steel and cement industries, transport sector which is heavily reliant on oil and its derivatives as fuels for internal combustion engine cars. In this respect, the use of green hydrogen and promotion of electromobility (electric cars) can be a good alternative. The governments in these countries also should take optimal measures to improve energy efficiency and reduce energy consumption (product labelling to induce sustainable production and consumption patterns, retrofit in buildings and old power system infrastructure to increase their energy efficiency) accompanied by an effective demand side management to induce consumers' behavioral change in order to optimize their energy use and avoid potential rebound effects. It is also recommended that governments in the LAC countries with high level of CO_2 emissions campaign to raise public awareness of the seriousness of climate change and global warming among citizens. These campaigns should be focused on behavioral changes towards the use of cleaner energy sources for heating and cooking and restrain the public to use high-polluting biomass energy sources.

Given that some of the important indicators of the digital economy in the LAC region were unavailable during the research, such as medium and high-tech manufacturing value added, Internet bandwidth and speed, and diffusion rate of 5G networks, it was not possible to incorporate them into the design of the DEI. If these indicators were available, we could make the DEI more concrete. It would also have been interesting to investigate the effects of sub-dimensions of the RETI and DEI to see what aspect of them has a greater influence on boosting economic growth and improving environmental sustainability in the LAC region.

The study can be further extended to find the salient mechanisms through which renewable energy transition and the digital economy can be of a great contribution to green economic growth in the LAC region. Furthermore, it will also be interesting to analyze the spatial spillover effects of renewable energy transition and the digital economy on economic growth and carbon emissions in the LAC countries in association with their geographical location (country's proximity to critical minerals reserves for clean energy transition and tec hubs).

Financial disclosure

None reported.

CRediT authorship contribution statement

Young Kyu Hwang: Conceptualization, Methodology, Software, Writing – original draft, Writing – review & editing, Investigation, Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix

Table A.0
Principal Factor Analysis

RETI				
Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	3.58625	1.50593	0.3260	0.3260
Factor2	2.08032	0.68130	0.1891	0.5151
Factor3	1.39903	0.21466	0.1272	0.6423
Factor4	1.18437	0.20917	0.1077	0.7500
DEI				
Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	1.84872	0.34834	0.1422	0.1422
Factor2	1.50038	0.04470	0.1154	0.2576
Factor3	1.45568	0.11883	0.1120	0.3696
Factor4	1.33685	0.21515	0.1028	0.4724
Factor5	1.12170	0.10554	0.0863	0.5587
Factor6	1.01617	0.03970	0.0782	0.6369

Table A.1
Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) LnGDPpc	1.000									
(2) LnCO2pc	0.736***	1.000								
(3) LnRETI	0.490***	0.247***	1.000							
(4) LnDEI	0.329***	0.203**	0.210**	1.000						
(5) LnRETIxLnDEI	−0.020	−0.101	−0.025	−0.010	1.000					
(6) LnTNRR	−0.079	0.141	−0.186*	−0.020	−0.114	1.000				
(7) LnInflation	0.153	0.149	−0.045	0.004	0.021	0.030	1.000			
(8) LnFDI	0.137	0.112	0.294***	0.132	0.022	−0.215***	−0.006	1.000		
(9) LnGI	0.668***	0.537***	0.524***	0.229***	−0.123	−0.077	−0.025	0.284***	1.000	
(10) LnAFFVadd	−0.736***	−0.738***	−0.628***	−0.206**	0.039	0.120	0.039	−0.191**	−0.582***	1.000

Table A.2
VIF test

Model 1			Model 2		
Variable	VIF	1/VIF	Variable	VIF	1/VIF
LnRETI	1.47	0.681	LnRETI	1.47	0.681
LnGI	1.44	0.692	LnGI	1.47	0.681
LnFDI	1.16	0.859	LnFDI	1.16	0.859
LnDEI	1.07	0.933	LnTNRR	1.08	0.922
LnTNRR	1.07	0.934	LnDEI	1.07	0.933
LnInflation	1.00	0.997	LnRETIxLnDEI	1.03	0.968
Mean VIF	1.20		LnInflation	1.00	0.997
			Mean VIF	1.19	
Model 3			**Model 4**		
Variable	**VIF**	**1/VIF**	**Variable**	**VIF**	**1/VIF**
LnAFFVadd	1.94	0.514	LnAFFVadd	1.94	0.514
LnRETI	1.83	0.546	LnRETI	1.83	0.546
LnGI	1.68	0.595	LnGI	1.71	0.585
LnFDI	1.13	0.884	LnFDI	1.13	0.882
LnDEI	1.07	0.931	LnDEI	1.07	0.931
LnInflation	1.00	0.998	LnRETIxLnDEI	1.02	0.979
Mean VIF	1.44		LnInflation	1.00	0.997
			Mean VIF	1.39	

Note: Model 1–4 correspond to equation (1)- (4) respectively in section 4.4.

Table A.3
Cross-section dependence test

Variable	CD-test	p-value	corr	abs (corr)
LnGDPpc	38.44***	0.000	0.754	0.869
LnCO2pc	12.07***	0.000	0.237	0.509
LnTNRR	13.02***	0.000	0.255	0.381
LnInflation	12.42***	0.000	0.244	0.379
LnFDI	6.51***	0.000	0.128	0.268
LnGI	32.76***	0.000	0.642	0.676
LnRETI	6.87***	0.000	0.135	0.497
LnDEI	6.00***	0.000	0.118	0.313
LnRETIxLnDEI	1.45	0.147	0.028	0.310
LnAFFVadd	10.56***	0.000	0.207	0.450

Note: ***, **, * denote statistical significance level at 1%,5%, and 10% respectively; H_0: cross-section independence.

Table A.4
Unit root test

Maddala and Wu Panel Unit Root test (MW)				
At levels				
Variable	Specification without trend		Specification with trend	
	Chi-sq	p-value	Chi-sq	p-value
LnGDPpc	69.761***	0.001	14.974	0.999
LnCO2pc	56.374**	0.017	25.202	0.911
LnTNRR	46.523	0.112	44.461	0.157
LnInflation	90.067***	0.000	145.549***	0.000
LnFDI	170.085***	0.000	139.881***	0.000
LnGI	184.769***	0.000	54.990**	0.022
LnRETI	34.608	0.535	66.730***	0.001
LnDEI	173.777***	0.000	109.980***	0.000
LnRETIxLnDEI	244.892***	0.000	150.424***	0.000
LnAFFVadd	64.335***	0.003	82.204***	0.000
At first difference				
Variable	**Specification without trend**		**Specification with trend**	
	Chi-sq	**p-value**	**Chi-sq**	**p-value**
DLnGDPpc	116.046***	0.000	114.868***	0.000
DLnCO2pc	193.850***	0.000	158.079***	0.000
DLnTNRR	212.432***	0.000	171.350***	0.000
DLnInflation	435.686***	0.000	334.921***	0.000
DLnFDI	482.563***	0.000	400.023***	0.000
DLnGI	184.801***	0.000	247.834***	0.000
DLnRETI	262.613***	0.000	225.039***	0.000
DLnDEI	264.095***	0.000	183.361***	0.000
DLnRETIxDLnDEI	274.792***	0.000	196.996***	0.000
DLnAFFVadd	284.125***	0.000	226.529***	0.000
Second generation Pesaran CIPS test				
At levels				
Variable	Specification without trend		Specification with trend	
	Zt-bar	p-value	Zt-bar	p-value
LnGDPpc	1.884	0.970	4.718	1.000
LnCO2pc	0.328	0.628	2.318	0.990
LnTNRR	−0.679	0.249	0.385	0.650
LnInflation	−5.142***	0.000	−3.632***	0.000
LnFDI	−5.155***	0.000	−4.210***	0.000
LnGI	−1.307*	0.096	−3.031***	0.001
LnRETI	−1.144***	0.126	−1.757**	0.039
LnDEI	−6.236***	0.000	−4.197***	0.000
LnRETIxLnDEI	−5.380***	0.000	−3.541***	0.000
LnAFFVadd	−1.860**	0.031	−0.169	0.433
At first difference				
Variable	**Specification without trend**		**Specification with trend**	
	Zt-bar	**p-value**	**Zt-bar**	**p-value**
DLnGDPpc	−3.120***	0.001	−2.602***	0.005
DLnCO2pc	−7.246***	0.000	−6.601***	0.000
DLnTNRR	−8.422***	0.000	−7.445***	0.000
DLnInflation	−10.304***	0.000	−7.796***	0.000
DLnFDI	−12.614***	0.000	−10.411***	0.000
DLnGI	−10.933***	0.000	−8.846***	0.000
DLnRETI	−9.038***	0.000	−7.516***	0.000

(*continued on next page*)

Table A.4 (*continued*)

Second generation Pesaran CIPS test				
At levels				
Variable	Specification without trend		Specification with trend	
	Zt-bar	p-value	Zt-bar	p-value
DLnDEI	−9.842***	0.000	−7.142***	0.000
DLnRETIxDLnDEI	−9.192***	0.000	−6.459***	0.000
DLnAFFVadd	−8.195***	0.000	−6.604***	0.000

Note: ***, **, * denote statistical significance level at 1%,5%, and 10% respectively; H_0: series is I (1); the prefix D represents first difference.

Table A.5
Cointegration test

Pedroni cointegration test				
	Model 1	Model 2	Model 3	Model 4
	Statistic	Statistic	Statistic	Statistic
Modified Phillips–Perron t	6.8510***	7.6340***	6.6399***	7.2500***
Phillips–Perron t	0.7732	0.4867	0.4252	−0.8973
Augmented Dickey–Fuller t	1.6949**	1.2535	−0.2237	−0.9155
Westerlund cointegration test				
	Model 1	**Model 2**	**Model 3**	**Model 4**
	Statistic	Statistic	Statistic	Statistic
Variance ratio	7.1719***	9.4704***	2.4929***	3.7122***

Note: ***, **, * denote statistical significance level at 1%,5%, and 10% respectively; Model 1–4 correspond to equations (1)–(4) respectively in section 4.4; both trend and the option 'all panels' were included in Westerlund cointegration test. If the option 'all panels' was not set, it has a H_a: cointegration of some panels, thus H_0:of no cointegration of all panels, H_a: cointegration of all panels.

Table A.6
Hausman test

	Model 1	Model 2	Model 3	Model 4
Statistics	chi2 (6) = 27.37***	chi2 (7) = 31.72***	chi2 (6) = 30.24***	chi2 (7) = 28.46***

Note: ***, **, * denote statistical significance level at 1%,5%, and 10% respectively; Model 1–4 correspond to equations (1)–(4) respectively in section 4.4; H_0: not systematic difference in coefficients (presence of RE).

Table A.7
Breusch & Pagan Lagrangian multiplier test

	Model 1	Model 2	Model 3	Model 4
Statistics	chibar2 (01) = 1389.52***	chibar2 (01) = 1369.88***	chibar2 (01) = 830.90***	chibar2 (01) = 820.08***

Note: ***, **, * denote statistical significance level at 1%,5%, and 10% respectively; Model 1–4 correspond to equations (1)–(4) respectively in section 4.4; H_0: POLS is preferred rather than static panel.

Table A.8
Wooldridge test

	Model 1	Model 2	Model 3	Model 4
Statistics	F (1,17) = 279.389***	F (1,17) = 296.260***	F (1,17) = 52.890***	F (1,17) = 55.322***

Note: ***, **, * denote statistical significance level at 1%,5%, and 10% respectively; Model 1–4 correspond to equations (1)–(4) respectively in section 4.4; H_0: no first-order autocorrelation.

Table A.9
Modified Wald test for groupwise heteroskedasticity

	Model 1	Model 2	Model 3	Model 4
Statistics	chi2 (18) = 622.44***	chi2 (18) = 592.66***	chi2 (18) = 762.90***	chi2 (18) = 751.76***

Note: ***, **, * denote statistical significance level at 1%,5%, and 10% respectively; Model 1–4 correspond to equations (1)–(4) respectively in section 4.4; H_0: no heteroskedasticity.

Table A.10
Temporal effect (Wald test)

	Model 1	Model 2	Model 3	Model 4
Statistics	F (16, 266) = 17.60***	F (16, 265) = 17.63***	F (16,266) = 1.72**	F (16,265) = 1.71**

Note: ***, **, * denote statistical significance level at 1%,5%, and 10% respectively; Model 1–4 correspond to equation (1)- (4) respectively in section 4.4; H_0: time fixed effect not significant.

FEPTR

- FEPTR with $Y_{it} = Ln\ GDPpc_{it},\ R_{it} = Ln\ RETI_{it}\ , Q_{it} = Ln\ GDPpc_{it}$.

Table A.11
Threshold effect test ($Y_{it} = Ln\ GDPpc_{it}, ;\ R_{it} = Ln\ RETI_{it}\ , Q_{it} = Ln\ GDPpc_{it}$)

model	Threshold	Lower	Upper
Th-1	9.362	9.305	9.370
Th-21	9.362	9.305	9.370
Th-22	8.530	8.521	8.534

Table A.12
Double Threshold effect test ($Y_{it} = Ln\ GDPpc_{it}, ;\ R_{it} = Ln\ RETI_{it}\ , Q_{it} = Ln\ GDPpc_{it}$)

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	1.157	0.004	57.200	0.133	62.431	73.869	89.254
Double	0.960	0.003	59.620	0.070	51.953	65.297	75.772

Table A.13
FEPTR estimation results ($Y_{it} = Ln\ GDPpc_{it}, ;\ R_{it} = Ln\ RETI_{it}, Q_{it} = Ln\ GDPpc_{it}$)

LnGDPpc	Coefficient	Std.err	t	P > t	[95% Confidence interval]	
LnTNRR	0.039***	0.010	3.880	0.000	0.019	0.059
LnInflation	−0.020**	0.010	−2.050	0.041	−0.038	−0.001
LnFDI	0.009	0.007	1.280	0.203	−0.005	0.023
LnGI	0.395***	0.148	2.660	0.008	0.103	0.688
LnDEI	−0.028	0.031	−0.900	0.367	−0.089	0.033
_cat#c.LnRETI						
0	0.000	0.029	0.010	0.991	−0.056	0.057
1	−0.086***	0.031	−2.730	0.007	−0.148	−0.024
2	−0.245***	0.036	−6.760	0.000	−0.316	−0.173
_cons	6.780***	0.608	11.150	0.000	5.582	7.977
sigma_u	0.542					
sigma_e	0.060					
rho	0.988	(Fraction of variance due to u_i)				
R^2 (within)	0.837					
Number of obs.	306					

Note: *, **, and *** denote significance level at 10%, 5%, and 1% respectively and time dummies were included during the estimation.

Table A.14
Threshold effect test ($Y_{it} = Ln\ GDPpc_{it}, ;\ R_{it} = Ln\ RETI_{it}\ , Q_{it} = Ln\ GDPpc_{it}$)

model	Threshold	Lower	Upper
Th-1	9.362	9.280	9.370
Th-21	9.362	9.305	9.370
Th-22	8.530	8.521	8.534

Table A.15
Double Threshold effect test ($Y_{it} = Ln\ GDPpc_{it}$, ; $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ GDPpc_{it}$)

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	1.147	0.004	59.040	0.073	56.272	64.251	75.865
Double	0.960	0.003	56.470	0.057	46.759	58.537	75.224

Table A.16
FEPTR estimation results ($Y_{it} = Ln\ GDPpc_{it}$, ; $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ GDPpc_{it}$)

LnGDPpc	Coefficient	Std.err	t	P > t	[95% Confidence interval]	
LnTNRR	0.039	0.010	3.860	0.000	0.019	0.059
LnInflation	−0.020	0.010	−2.050	0.042	−0.038	−0.001
LnFDI	0.009	0.007	1.270	0.204	−0.005	0.023
LnGI	0.396	0.149	2.660	0.008	0.102	0.689
LnDEI	−0.028	0.031	−0.900	0.368	−0.089	0.033
LnRETIxLnDEI	0.002	0.091	0.020	0.983	−0.177	0.181
_cat#c.LnRETI						
0	0.000	0.029	0.010	0.990	−0.056	0.057
1	−0.086	0.032	−2.720	0.007	−0.148	−0.024
2	−0.245	0.036	−6.750	0.000	−0.316	−0.173
_cons	6.779	0.611	11.100	0.000	5.577	7.981
sigma_u	0.542					
sigma_e	0.061					
rho	0.988	(Fraction of variance due to u_i)				
R^2 (within)	0.837					
Number of obs.	306					

Note: *, **, and *** denote significance level at 10%, 5%, and 1% respectively and time dummies were included during the estimation.

- FEPTR with $Y_{it} = Ln\ GDPpc_{it}$, $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ CO2pc_{it}$.

Table A.17
Threshold effect test ($Y_{it} = Ln\ GDPpc_{it}$, ; $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ CO2pc_{it}$)

model	Threshold	Lower	Upper
Th-1	1.076	1.046	1.145
Th-21	1.076	1.046	1.145
Th-22	0.545	0.540	0.546

Table A.18
Double Threshold effect test ($Y_{it} = Ln\ GDPpc_{it}$, ; $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ CO2pc_{it}$)

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	1.093	0.004	77.490	0.010	45.986	57.257	75.783
Double	0.973	0.003	35.810	0.167	42.965	53.287	74.653

Table A.19
FEPTR estimation results ($Y_{it} = Ln\ GDPpc_{it}$, ; $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ CO2pc_{it}$)

LnGDPpc	Coefficient	Std.err	t	P > t	[95% Confidence interval]	
LnTNRR	0.018	0.010	1.750	0.081	−0.002	0.038
LnInflation	−0.006	0.009	−0.640	0.524	−0.025	0.013
LnFDI	−0.000	0.007	0.000	0.996	−0.014	0.014
LnGI	0.280	0.146	1.910	0.057	−0.008	0.569
LnDEI	0.005	0.031	0.160	0.873	−0.056	0.066
_cat#c.LnRETI						
0	0.132	0.036	3.710	0.000	0.062	0.202
1	0.038	0.029	1.300	0.194	−0.019	0.095
2	−0.245	0.043	−5.680	0.000	−0.330	−0.160
_cons	7.343	0.602	12.190	0.000	6.157	8.529
sigma_u	0.515					
sigma_e	0.061					
rho	0.986	(Fraction of variance due to u_i)				
R^2 (within)	0.836					
Number of obs.	306					

Note: *, **, and *** denote significance level at 10%, 5%, and 1% respectively and time dummies were included during the estimation.

Table A.20
Threshold effect test ($Y_{it} = Ln\ GDPpc_{it}$, ; $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ CO2pc_{it}$)

model	Threshold	Lower	Upper
Th-1	1.076	1.046	1.145
Th-21	1.076	1.046	1.145
Th-22	0.545	0.540	0.546

Table A.21
Double Threshold effect test ($Y_{it} = Ln\ GDPpc_{it}$, ; $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ CO2pc_{it}$)

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	1.091	0.004	76.930	0.010	49.926	58.093	72.051
Double	0.969	0.003	36.490	0.147	42.008	50.710	72.484

Table A.22
FEPTR estimation results ($Y_{it} = Ln\ GDPpc_{it}$, ; $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ CO2pc_{it}$)

LnGDPpc	Coefficient	Std.err	t	P > t	[95% Confidence interval]	
LnTNRR	0.017	0.010	1.720	0.086	−0.002	0.037
LnInflation	−0.005	0.010	−0.540	0.591	−0.024	0.014
LnFDI	0.000	0.007	0.010	0.994	−0.014	0.014
LnGI	0.267	0.147	1.820	0.070	−0.022	0.557
LnDEI	0.005	0.031	0.160	0.871	−0.056	0.066
LnRETIxLnDEI	−0.093	0.089	−1.050	0.294	−0.268	0.081
_cat#c.LnRETI						
0	0.130	0.036	3.650	0.000	0.060	0.200
1	0.035	0.029	1.210	0.227	−0.022	0.093
2	−0.246	0.043	−5.700	0.000	−0.331	−0.161
_cons	7.395	0.604	12.240	0.000	6.206	8.585
sigma_u	0.516					
sigma_e	0.061					
rho	0.986	(Fraction of variance due to u_i)				
R^2 (within)	0.836					
Number of obs.	306					

Note: *, **, and *** denote significance level at 10%, 5%, and 1% respectively and time dummies were included during the estimation.

- FEPTR with $Y_{it} = Ln\ CO2pc_{it}$, $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ GDPpc_{it}$.

Table A.23
Threshold effect test ($Y_{it} = Ln\ CO2pc_{it}$, ; $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ GDPpc_{it}$)

model	Threshold	Lower	Upper
Th-1	8.516	8.511	8.518
Th-21	8.516	8.511	8.518
Th-22	7.824	7.810	7.830

Table A.24
Double Threshold effect test ($Y_{it} = Ln\ CO2pc_{it}$, ; $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ GDPpc_{it}$)

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	2.843	0.010	70.110	0.007	47.235	54.830	66.128
Double	2.615	0.009	25.190	0.410	40.608	47.875	68.522

Table A.25
FEPTR estimation results ($Y_{it} = Ln\ CO2pc_{it}$, ; $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ GDPpc_{it}$)

LnCO2pc	Coefficient	Std.err	t	P > t	[95% Confidence interval]	
LnAFFVadd	−0.240	0.047	−5.100	0.000	−0.332	−0.147
LnInflation	−0.005	0.016	−0.290	0.774	−0.035	0.026
LnFDI	0.031	0.012	2.640	0.009	0.008	0.055
LnGI	−0.065	0.236	−0.270	0.784	−0.530	0.401
LnDEI	−0.008	0.052	−0.160	0.874	−0.111	0.094

(continued on next page)

Table A.25 (*continued*)

LnCO2pc	Coefficient	Std.err	t	P > t	[95% Confidence interval]	
_cat#c.LnRETI						
0	0.046	0.069	0.670	0.500	−0.089	0.181
1	−0.102	0.049	−2.070	0.039	−0.199	−0.005
2	−0.275	0.054	−5.060	0.000	−0.382	−0.168
_cons	1.014	0.992	1.020	0.307	−0.938	2.966
sigma_u	0.391					
sigma_e	0.101					
rho	0.938	(Fraction of variance due to u_i)				
R^2 (within)	0.503					
Number of obs.	306					

Note: *, **, and *** denote significance level at 10%, 5%, and 1% respectively and time dummies were included during the estimation.

Table A.26
Threshold effect test ($Y_{it} = Ln\ CO2pc_{it}$, ; $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ GDPpc_{it}$)

model	Threshold	Lower	Upper
Th-1	8.516	8.511	8.518
Th-21	8.516	8.511	8.518
Th-22	7.824	7.810	7.830

Table A.27
Double Threshold effect test ($Y_{it} = Ln\ CO2pc_{it}$, ; $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ GDPpc_{it}$)

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	2.837	0.010	69.610	0.020	44.686	55.718	71.540
Double	2.614	0.009	24.670	0.433	40.632	48.006	62.463

Table A.28
FEPTR estimation results ($Y_{it} = Ln\ CO2pc_{it}$, ; $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ GDPpc_{it}$)

LnCO2pc	Coefficient	Std.err	t	P > t	[95% Confidence interval]	
LnAFFVadd	−0.238	0.047	−5.050	0.000	−0.331	−0.145
LnInflation	−0.005	0.016	−0.310	0.754	−0.036	0.026
LnFDI	0.031	0.012	2.640	0.009	0.008	0.055
LnGI	−0.055	0.238	−0.230	0.817	−0.523	0.413
LnDEI	−0.009	0.052	−0.180	0.860	−0.112	0.094
LnRETIxLnDEI	0.069	0.152	0.460	0.647	−0.229	0.368
_cat#c.LnRETI						
0	0.046	0.069	0.670	0.502	−0.089	0.182
1	−0.101	0.049	−2.040	0.043	−0.198	−0.003
2	−0.276	0.054	−5.060	0.000	−0.383	−0.169
_cons	0.969	0.998	0.970	0.332	−0.996	2.934
sigma_u	0.391					
sigma_e	0.101					
rho	0.937	(Fraction of variance due to u_i)				
R^2 (within)	0.503					
Number of obs.	306					

Note: *, **, and *** denote significance level at 10%, 5%, and 1% respectively and time dummies were included during the estimation.

- FEPTR with $Y_{it} = Ln\ CO2pc_{it}$, $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ CO2pc_{it}$.

Table A.29
Threshold effect test ($Y_{it} = Ln\ CO2pc_{it}$, ; $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ CO2pc_{it}$)

model	Threshold	Lower	Upper
Th-1	0.302	0.298	0.326
Th-21	0.123	0.121	0.151
Th-22	1.153	1.095	1.210

Table A.30
Double Threshold effect test ($Y_{it} = Ln\ CO2pc_{it}$, ; $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ CO2pc_{it}$)

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	2.737	0.009	84.010	0.020	47.540	61.671	92.674
Double	2.103	0.007	87.150	0.000	26.227	29.826	36.125

Table A.31
FEPTR estimation results ($Y_{it} = Ln\ CO2pc_{it}$, ; $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ CO2pc_{it}$)

LnCO2pc	Coefficient	Std.err	t	P > t	[95% Confidence interval]	
LnAFFVadd	−0.144	0.043	−3.370	0.001	−0.228	−0.060
LnInflation	−0.018	0.014	−1.270	0.205	−0.045	0.010
LnFDI	0.000	0.011	0.040	0.971	−0.021	0.022
LnGI	−0.050	0.206	−0.240	0.810	−0.455	0.355
LnDEI	0.001	0.045	0.030	0.979	−0.088	0.090
_cat#c.LnRETI						
0	0.142	0.050	2.850	0.005	0.044	0.240
1	−0.103	0.042	−2.430	0.016	−0.186	−0.020
2	−0.575	0.064	−8.960	0.000	−0.702	−0.449
_cons	0.906	0.868	1.040	0.298	−0.804	2.616
sigma_u	0.282					
sigma_e	0.089					
rho	0.909	(Fraction of variance due to u_i)				
R^2 (within)	0.610					
Number of obs.	306					

Note: *, **, and *** denote significance level at 10%, 5%, and 1% respectively and time dummies were included during the estimation.

Table A.32
Threshold effect test ($Y_{it} = Ln\ CO2pc_{it}$, ; $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ CO2pc_{it}$)

model	Threshold	Lower	Upper
Th-1	0.302	0.298	0.326
Th-21	0.123	0.121	0.151
Th-22	1.153	1.095	1.210

Table A.33
Double Threshold effect test ($Y_{it} = Ln\ CO2pc_{it}$, ; $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ CO2pc_{it}$)

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	2.707	0.009	86.800	0.007	42.760	53.294	78.122
Double	2.093	0.007	84.810	0.000	25.643	31.131	41.783

Table A.34
FEPTR estimation results ($Y_{it} = Ln\ CO2pc_{it}$, ; $R_{it} = Ln\ RETI_{it}$, $Q_{it} = Ln\ CO2pc_{it}$)

LnCO2pc	Coefficient	Std.err	t	P > t	[95% Confidence interval]	
LnAFFVadd	−0.147	0.043	−3.450	0.001	−0.232	−0.063
LnInflation	−0.016	0.014	−1.170	0.243	−0.043	0.011
LnFDI	0.000	0.011	0.040	0.965	−0.021	0.022
LnGI	−0.076	0.207	−0.370	0.713	−0.484	0.331
LnDEI	0.001	0.045	0.030	0.979	−0.088	0.090
LnRETIxLnDEI	−0.147	0.130	−1.130	0.260	−0.403	0.109
_cat#c.LnRETI						
0	0.138	0.050	2.760	0.006	0.040	0.237
1	−0.107	0.042	−2.530	0.012	−0.191	−0.024
2	−0.578	0.064	−9.010	0.000	−0.705	−0.452
_cons	1.019	0.874	1.170	0.244	−0.701	2.739
sigma_u	0.283					
sigma_e	0.089					
rho	0.909	(Fraction of variance due to u_i)				
R^2 (within)	0.612					
Number of obs.	306					

Note: *, **, and *** denote significance level at 10%, 5%, and 1% respectively and time dummies were included during the estimation.

- FEPTR with $Y_{it} = Ln\ GDPpc_{it},\ R_{it} = Ln\ REShareTFEC_{it}\ , Q_{it} = Ln\ GDPpc_{it}$.

Table A.35
Threshold effect test ($Y_{it} = Ln\ GDPpc_{it},;\ R_{it} = Ln\ REShareTFEC_{it}\ , Q_{it} = Ln\ GDPpc_{it}$)

model	Threshold	Lower	Upper
Th-1	9.481	9.460	9.481
Th-21	9.454	9.450	9.466
Th-22	8.580	8.577	8.581

Table A.36
Double Threshold effect test ($Y_{it} = Ln\ GDPpc_{it},;\ R_{it} = Ln\ REShareTFEC_{it}\ , Q_{it} = Ln\ GDPpc_{it}$)

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	0.865	0.003	107.730	0.003	53.284	65.879	92.792
Double	0.686	0.002	75.330	0.007	48.880	56.280	69.400

Table A.37
FEPTR estimation results ($Y_{it} = Ln\ GDPpc_{it},;\ R_{it} = Ln\ REShareTFEC_{it}\ , Q_{it} = Ln\ GDPpc_{it}$)

LnGDPpc	Coefficient	Std.err	t	P > t	[95% Confidence interval]	
LnTNRR	0.038	0.009	4.480	0.000	0.021	0.055
LnInflation	−0.006	0.008	−0.680	0.500	−0.022	0.011
LnFDI	−0.001	0.006	−0.150	0.881	−0.013	0.011
LnGI	0.428	0.125	3.430	0.001	0.182	0.674
LnDEI	0.016	0.026	0.620	0.537	−0.035	0.068
_cat#c.LnREShareTFEC						
0	−0.207	0.021	−10.050	0.000	−0.247	−0.166
1	−0.173	0.021	−8.240	0.000	−0.215	−0.132
2	−0.118	0.021	−5.580	0.000	−0.159	−0.076
Constant	7.346	0.500	14.700	0.000	6.362	8.330
Sigma u	0.509					
Sigma e	0.051					
rho	0.990	(Fraction of variance due to u_i)				
R^2 (within)	0.883					
Number of obs.	306					

Note: *, **, and *** denote significance level at 10%, 5%, and 1% respectively and time dummies were included during the estimation.

Table A.38
Threshold effect test ($Y_{it} = Ln\ GDPpc_{it},;\ R_{it} = Ln\ REShareTFEC_{it}\ , Q_{it} = Ln\ GDPpc_{it}$)

model	Threshold	Lower	Upper
Th-1	9.481	9.460	9.481
Th-21	9.454	9.450	9.466
Th-22	8.580	8.577	8.581

Table A.39
Double Threshold effect test ($Y_{it} = Ln\ GDPpc_{it},;\ R_{it} = Ln\ REShareTFEC_{it}\ , Q_{it} = Ln\ GDPpc_{it}$)

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	0.856	0.003	111.130	0.010	60.167	73.671	108.201
Double	0.682	0.002	73.590	0.007	45.576	54.512	72.747

Table A40
FEPTR estimation results ($Y_{it} = Ln\ GDPpc_{it},;\ R_{it} = Ln\ REShareTFEC_{it}\ , Q_{it} = Ln\ GDPpc_{it}$)

LnGDPpc	Coefficient	Std.err	t	P > t	[95% Confidence interval]	
LnTNRR	0.038	0.009	4.410	0.000	0.021	0.054
LnInflation	−0.005	0.008	−0.670	0.505	−0.021	0.011
LnFDI	−0.000	0.006	−0.070	0.941	−0.012	0.011

(*continued on next page*)

Table A40 (*continued*)

LnGDPpc	Coefficient	Std.err	t	P > t	[95% Confidence interval]	
LnGI	0.446	0.125	3.550	0.000	0.199	0.693
LnDEI	0.028	0.028	1.010	0.313	−0.026	0.082
LnREShareTFECxLnDEI	−0.053	0.040	−1.340	0.181	−0.131	0.025
_cat#c.LnREShareTFEC						
0	−0.207	0.021	−10.090	0.000	−0.248	−0.167
1	−0.174	0.021	−8.290	0.000	−0.216	−0.133
2	−0.118	0.021	−5.610	0.000	−0.159	−0.077
Constant	7.283	0.501	14.530	0.000	6.296	8.270
Sigma u	0.508					
Sigma e	0.051					
rho	0.990	(Fraction of variance due to u_i)				
R^2 (within)	0.884					
Number of obs.	306					

Note: *, **, and *** denote significance level at 10%, 5%, and 1% respectively and time dummies were included during the estimation.

- FEPTR with $Y_{it} = Ln\ GDPpc_{it},\ R_{it} = Ln\ REShareTFEC_{it}, Q_{it} = Ln\ CO2pc_{it}$.

Table A.41
Threshold effect test ($Y_{it} = Ln\ GDPpc_{it},;\ R_{it} = Ln\ REShareTFEC_{it}\ , Q_{it} = Ln\ CO2pc_{it}$)

model	Threshold	Lower	Upper
Th-1	0.545	0.542	0.546
Th-21	0.545	0.542	0.546
Th-22	1.346	1.323	1.349

Table A.42
Double Threshold effect test ($Y_{it} = Ln\ GDPpc_{it},;\ R_{it} = Ln\ REShareTFEC_{it}\ , Q_{it} = Ln\ CO2pc_{it}$)

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	1.079	0.004	29.190	0.473	50.814	60.320	73.644
Double	0.948	0.003	39.740	0.120	41.685	49.629	67.403

Table A.43
FEPTR estimation results ($Y_{it} = Ln\ GDPpc_{it},;\ R_{it} = Ln\ REShareTFEC_{it}, Q_{it} = Ln\ CO2pc_{it}$)

LnGDPpc	Coefficient	Std.err	t	P > t	[95% Confidence interval]	
LnTNRR	0.024	0.010	2.430	0.016	0.005	0.043
LnInflation	−0.005	0.010	−0.560	0.576	−0.024	0.013
LnFDI	−0.005	0.007	−0.680	0.497	−0.019	0.009
LnGI	0.640	0.147	4.340	0.000	0.349	0.930
LnDEI	0.019	0.031	0.610	0.540	−0.042	0.080
_cat#c.LnREShareTFEC						
0	−0.136	0.025	−5.500	0.000	−0.184	−0.087
1	−0.103	0.026	−4.000	0.000	−0.154	−0.052
2	−0.058	0.029	−2.050	0.042	−0.115	−0.002
_cons	6.263	0.601	10.420	0.000	5.079	7.447
sigma_u	0.528					
sigma_e	0.060					
rho	0.987	(Fraction of variance due to u_i)				
R^2 (within)	0.834					
Number of obs.	306					

Note: *, **, and *** denote significance level at 10%, 5%, and 1% respectively and time dummies were included during the estimation.

Table A.44
Threshold effect test ($Y_{it} = Ln\ GDPpc_{it},;\ R_{it} = Ln\ REShareTFEC_{it}\ , Q_{it} = Ln\ CO2pc_{it}$)

model	Threshold	Lower	Upper
Th-1	0.545	0.542	0.546
Th-21	0.545	0.542	0.546
Th-22	1.346	1.323	1.349

Table A.45
Double Threshold effect test ($Y_{it} = Ln\ GDPpc_{it}$, ; $R_{it} = Ln\ REShareTFEC_{it}$, $Q_{it} = Ln\ CO2pc_{it}$)

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	1.077	0.004	29.090	0.483	55.697	67.590	86.996
Double	0.946	0.003	40.000	0.090	37.522	49.941	78.450

Table A.46
FEPTR estimation results ($Y_{it} = Ln\ GDPpc_{it}$, ; $R_{it} = Ln\ REShareTFEC_{it}$, $Q_{it} = Ln\ CO2pc_{it}$)

LnGDPpc	Coefficient	Std.err	t	P > t	[95% Confidence interval]	
LnTNRR	0.024	0.010	2.380	0.018	0.004	0.043
LnInflation	−0.005	0.010	−0.550	0.586	−0.024	0.014
LnFDI	−0.004	0.007	−0.630	0.532	−0.018	0.009
LnGI	0.653	0.148	4.410	0.000	0.362	0.945
LnDEI	0.029	0.033	0.880	0.380	−0.035	0.093
LnREShareTFECxLnDEI	−0.045	0.047	−0.950	0.341	−0.136	0.047
_cat#c.LnREShareTFEC						
0	−0.136	0.025	−5.510	0.000	−0.184	−0.087
1	−0.103	0.026	−4.010	0.000	−0.154	−0.053
2	−0.059	0.029	−2.050	0.042	−0.115	−0.002
_cons	6.214	0.604	10.290	0.000	5.025	7.402
sigma_u	0.527					
sigma_e	0.060					
rho	0.987	(Fraction of variance due to u_i)				
R^2 (within)	0.838					
Number of obs.	306					

Note: *, **, and *** denote significance level at 10%, 5%, and 1% respectively and time dummies were included during the estimation.

- FEPTR with $Y_{it} = Ln\ CO2pc_{it}$, $R_{it} = Ln\ REShareTFEC_{it}$, $Q_{it} = Ln\ GDPpc_{it}$.

Table A.47
Threshold effect test ($Y_{it} = Ln\ CO2pc_{it}$, ; $R_{it} = Ln\ REShareTFEC_{it}$, $Q_{it} = Ln\ GDPpc_{it}$)

model	Threshold	Lower	Upper
Th-1	8.516	8.514	8.518
Th-21	8.530	8.519	8.541
Th-22	9.393	9.357	9.395

Table A.48
Double Threshold effect test ($Y_{it} = Ln\ CO2pc_{it}$, ; $R_{it} = Ln\ REShareTFEC_{it}$, $Q_{it} = Ln\ GDPpc_{it}$)

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	1.800	0.006	68.940	0.020	47.942	60.497	73.508
Double	1.611	0.006	33.820	0.260	45.941	54.995	76.751

Table A.49
FEPTR estimation results ($Y_{it} = Ln\ CO2pc_{it}$, ; $R_{it} = Ln\ REShareTFEC_{it}$, $Q_{it} = Ln\ GDPpc_{it}$)

LnCO2pc	Coefficient	Std.err	t	P > t	[95% Confidence interval]	
LnAFFVadd	−0.095	0.039	−2.400	0.017	−0.172	−0.017
LnInflation	0.011	0.012	0.850	0.398	−0.014	0.035
LnFDI	0.021	0.009	2.310	0.022	0.003	0.039
LnGI	−0.229	0.181	−1.270	0.207	−0.585	0.127
LnDEI	−0.008	0.040	−0.200	0.843	−0.087	0.071
_cat#c.LnREShareTFEC						
0	−0.444	0.032	−14.000	0.000	−0.506	−0.381
1	−0.390	0.033	−11.820	0.000	−0.456	−0.325
2	−0.351	0.033	−10.510	0.000	−0.416	−0.285
_cons	2.920	0.748	3.900	0.000	1.446	4.394
sigma_u	0.268					
sigma_e	0.079					
rho	0.921	(Fraction of variance due to u_i)				
R^2 (within)	0.698					
Number of obs.	306					

Note: *, **, and *** denote significance level at 10%, 5%, and 1% respectively and time dummies were included during the estimation.

Table A.50
Threshold effect test (Y_{it} = *Ln CO2pc*$_{it}$, ; R_{it} = *Ln REShareTFEC*$_{it}$, Q_{it} = *Ln GDPpc*$_{it}$)

model	Threshold	Lower	Upper
Th-1	8.516	8.514	8.518
Th-21	8.516	8.514	8.518
Th-22	9.393	9.357	9.395

Table A.51
Double Threshold effect test (Y_{it} = *Ln CO2pc*$_{it}$, ; R_{it} = *Ln REShareTFEC*$_{it}$, Q_{it} = *Ln GDPpc*$_{it}$)

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	1.795	0.006	69.810	0.017	47.893	57.812	78.015
Double	1.608	0.006	33.570	0.177	40.022	46.213	56.286

Table A.52
FEPTR estimation results (Y_{it} = *Ln CO2pc*$_{it}$, ; R_{it} = *Ln REShareTFEC*$_{it}$, Q_{it} = *Ln GDPpc*$_{it}$)

LnCO2pc	Coefficient	Std.err	t	P > t	[95% Confidence interval]	
LnAFFVadd	−0.100	0.039	−2.550	0.011	−0.178	−0.023
LnInflation	0.011	0.012	0.860	0.392	−0.014	0.035
LnFDI	0.022	0.009	2.370	0.019	0.004	0.040
LnGI	−0.239	0.181	−1.320	0.188	−0.594	0.117
LnDEI	−0.021	0.042	−0.490	0.623	−0.103	0.062
LnREShareTFECxLnDEI	0.050	0.061	0.820	0.411	−0.069	0.169
_cat#c.LnREShareTFEC						
0	−0.444	0.032	−14.070	0.000	−0.506	−0.382
1	−0.389	0.033	−11.820	0.000	−0.454	−0.324
2	−0.350	0.033	−10.560	0.000	−0.416	−0.285
_cons	2.960	0.746	3.970	0.000	1.490	4.430
sigma_u	0.265					
sigma_e	0.078					
rho	0.920	(Fraction of variance due to u_i)				
R^2 (within)	0.702					
Number of obs.	306					

Note: *, **, and *** denote significance level at 10%, 5%, and 1% respectively and time dummies were included during the estimation.

- FEPTR with Y_{it} = *Ln CO2pc*$_{it}$, R_{it} = *Ln REShareTFEC*$_{it}$, Q_{it} = *Ln CO2pc*$_{it}$.

Table A.53
Threshold effect test (Y_{it} = *Ln CO2pc*$_{it}$, ; R_{it} = *Ln RETI*$_{it}$, Q_{it} = *Ln CO2pc*$_{it}$)

model	Threshold	Lower	Upper
Th-1	−0.001	−0.009	0.019
Th-21	−0.001	−0.009	0.019
Th-22	0.518	0.505	0.522

Table A.54
Double Threshold effect test (Y_{it} = *Ln CO2pc*$_{it}$, ; R_{it} = *Ln REShareTFEC*$_{it}$, Q_{it} = *Ln CO2pc*$_{it}$)

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	1.810	0.006	66.990	0.013	44.147	51.234	67.055
Double	1.542	0.005	50.100	0.037	41.414	48.368	67.598

Table A.55
FEPTR estimation results (Y_{it} = *Ln CO2pc*$_{it}$, ; R_{it} = *Ln REShareTFEC*$_{it}$, Q_{it} = *Ln CO2pc*$_{it}$)

LnCO2pc	Coefficient	Std.err	t	P > t	[95% Confidence interval]	
LnAFFVadd	−0.198	0.036	−5.530	0.000	−0.268	−0.127
LnInflation	0.011	0.012	0.890	0.372	−0.013	0.035
LnFDI	0.014	0.009	1.520	0.129	−0.004	0.031
LnGI	−0.070	0.171	−0.410	0.683	−0.406	0.267
LnDEI	0.011	0.039	0.270	0.785	−0.066	0.088

(*continued on next page*)

Table A.55 (*continued*)

LnCO2pc	Coefficient	Std.err	t	P > t	[95% Confidence interval]	
cat#c.LnREShareTFEC						
0	−0.516	0.031	−16.580	0.000	−0.577	−0.455
1	−0.465	0.030	−15.270	0.000	−0.525	−0.405
2	−0.421	0.031	−13.430	0.000	−0.483	−0.360
_cons	2.659	0.710	3.740	0.000	1.261	4.058
sigma_u	0.243					
sigma_e	0.077					
rho	0.910	(Fraction of variance due to u_i)				
R^2 (within)	0.713					
Number of obs.	306					

Note: *, **, and *** denote significance level at 10%, 5%, and 1% respectively and time dummies were included during the estimation.

Table A.56
Threshold effect test ($Y_{it} = Ln\ CO2pc_{it},$; $R_{it} = Ln\ RETI_{it}, Q_{it} = Ln\ CO2pc_{it}$)

model	Threshold	Lower	Upper
Th-1	−0.001	−0.009	0.019
Th-21	−0.083	−0.104	−0.068
Th-22	0.518	0.505	0.522

Table A.57
Double Threshold effect test ($Y_{it} = Ln\ CO2pc_{it},$; $R_{it} = Ln\ REShareTFEC_{it}$, $Q_{it} = Ln\ CO2pc_{it}$)

Threshold	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single	1.804	0.006	67.930	0.020	44.276	51.801	76.854
Double	1.532	0.005	51.360	0.037	41.025	48.744	62.184

Table A.58
FEPTR estimation results ($Y_{it} = Ln\ CO2pc_{it},$; $R_{it} = Ln\ REShareTFEC_{it}$, $Q_{it} = Ln\ CO2pc_{it}$)

LnCO2pc	Coefficient	Std.err	t	P > t	[95% Confidence interval]	
LnAFFVadd	−0.170	0.036	−4.720	0.000	−0.241	−0.099
LnInflation	0.013	0.012	1.100	0.274	−0.011	0.037
LnFDI	0.015	0.009	1.710	0.088	−0.002	0.033
LnGI	−0.048	0.171	−0.280	0.779	−0.385	0.289
LnDEI	−0.006	0.041	−0.140	0.888	−0.087	0.075
LnREShareTFECxLnDEI	−0.084	0.060	−1.390	0.166	−0.203	0.035
cat#c.LnREShareTFEC						
0	−0.532	0.032	−16.870	0.000	−0.594	−0.470
1	−0.465	0.030	−15.270	0.000	−0.524	−0.405
2	−0.420	0.031	−13.400	0.000	−0.482	−0.358
_cons	2.474	0.710	3.480	0.001	1.076	3.872
sigma_u	0.248					
sigma_e	0.076					
rho	0.913	(Fraction of variance due to u_i)				
R^2 (within)	0.715					
Number of obs.	306					

Note: *, **, and *** denote significance level at 10%, 5%, and 1% respectively and time dummies were included during the estimation.

MMQR

Table A.59
Test for slope homogeneity for the MMQR

Statistics	MMQR 1		MMQR 2	
	Delta (Hac)	Delta $(Hac)_{adj}$	Delta (Hac)	Delta $(Hac)_{adj}$
	−3.522***	−4.840***	−4.176***	−6.088***
Statistics	**MMQR 3**		**MMQR 4**	
	Delta (Hac)	Delta $(Hac)_{adj}$	Delta (Hac)	Delta $(Hac)_{adj}$
	−2.924***	−4.018***	−3.704***	−5.400***

Note: ***, **, * denote statistical significance level at 1%,5%, and 10% respectively; MMQR 1- MMQR 4 correspond to equation 12–15 respectively in section 4.6; the option 'Hac' which refers to heteroskedasticity and autocorrelation consistent was included in the test; H_0: slope coefficients are homogenous.

Table A.60
Shapiro–Wilk W test for normal data for the MMQR

Variable	Obs	W	V	z	Prob > z
LnGDPpc	306	0.9658	7.405	4.704***	0.000
LnCO2pc	306	0.9631	8.000	4.886***	0.000

Note: ***, **, * denote statistical significance level at 1%,5%, and 10% respectively; H_0: normality of the data.

Table A.61
Skewness-Kurtosis test for the MMQR

Variable	Obs	Pr (skewness)	Pr (kurtosis)	Joint test	
				Adj chi2 (2)	Prob > chi2
LnGDPpc	306	0.0735	0.0000	26.04	0.000
LnCO2pc	306	0.5198	0.0000	39.04	0.000

Note: ***, **, * denote statistical significance level at 1%,5%, and 10% respectively; H_0: normality of the data.

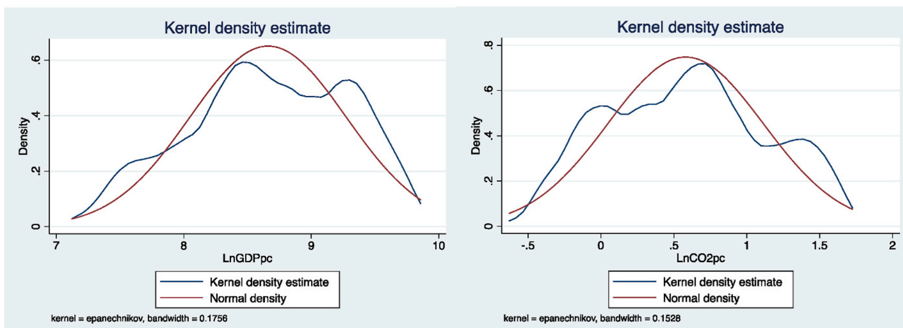

Fig. A1. Kernel and normal density for LnGDPpc and LnCO2pc

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2023.138146.

References

Alola, A.A., Bekun, F.V., Sarkodie, S.A., 2019. Dynamic impact of trade policy, economic growth, fertility rate, renewable and non-renewable energy consumption on ecological footprint in Europe. Sci. Total Environ. 685, 702–709.
Alvarado, R., Tillaguango, B., Dagar, V., Ahmad, M., Işık, C., Méndez, P., Toledo, E., 2021. Ecological footprint, economic complexity, and natural resources rents in Latin America: empirical evidence using quantile regressions. J. Clean. Prod. 318, 128585.
Apergis, N., Payne, J.E., 2010. Renewable energy consumption and economic growth: evidence from a panel of OECD countries. Energy Pol. 38 (1), 656–660. https://doi.org/10.1016/j.enpol.2009.09.002.
Asif, M., 2020. Role of energy conservation and management in the 4D sustainable energy transition. Sustainability 12 (23), 10006.
Bárcena Ibarra, A., Samaniego, J., Peres, W., Alatorre, J.E., 2020. The Climate Emergency in Latin America and the Caribbean: the Path Ahead–Resignation or Action. ECLAC.
Ben Jebli, M., Ben Youssef, S., Apergis, N., 2019. The dynamic linkage between renewable energy, tourism, CO2 emissions, economic growth, foreign direct investment, and trade. Latin American Economic Review 28 (1), 1–19.
Bhattacharya, M., Paramati, S.R., Ozturk, I., Bhattacharya, S., 2016. The effect of renewable energy consumption on economic growth: evidence from top 38 countries. Appl. Energy 162, 733–741. https://doi.org/10.1016/j.apenergy.2015.10.104.
CEPAL, N., 2022 a. Latin American Economic Outlook 2022: towards a Green and Just Transition. ECLAC.
CEPAL, N., 2022 b. A Digital Path for Sustainable Development in Latin America and the Caribbean.
Charfeddine, L., Kahia, M., 2019. Impact of renewable energy consumption and financial development on CO2 emissions and economic growth in the MENA region: a panel vector autoregressive (PVAR) analysis. Renew. Energy 139, 198–213. https://doi.org/10.1016/j.renene.2019.01.010.
D'agostino, R.B., Belanger, A., D'Agostino Jr., R.B., 1990. A suggestion for using powerful and informative tests of normality. Am. Statistician 44 (4), 316–321.
Destek, M.A., Sinha, A., 2020. Renewable, non-renewable energy consumption, economic growth, trade openness and ecological footprint: evidence from organisation for economic Co-operation and development countries. J. Clean. Prod. 242, 118537 https://doi.org/10.1016/j.jclepro.2019.118537.
Dong, F., Li, Y., Gao, Y., Zhu, J., Qin, C., Zhang, X., 2022 a. Energy transition and carbon neutrality: exploring the non-linear impact of renewable energy development on carbon emission efficiency in developed countries. Resour. Conserv. Recycl. 177, 106002 https://doi.org/10.1016/j.resconrec.2021.106002.
Dong, F., Li, Y., Qin, C., Zhang, X., Chen, Y., Zhao, X., Wang, C., 2022 b. Information infrastructure and greenhouse gas emission performance in urban China: a difference-in-differences analysis. J. Environ. Manag. 316, 115252 https://doi.org/10.1016/j.jenvman.2022.115252.
Dong, K., Hochman, G., Zhang, Y., Sun, R., Li, H., Liao, H., 2018. CO2 emissions, economic and population growth, and renewable energy: empirical evidence across regions. Energy Econ. 75, 180–192. https://doi.org/10.1016/j.eneco.2018.08.017.
Doytch, N., Narayan, S., 2016. Does FDI influence renewable energy consumption? An analysis of sectoral FDI impact on renewable and non-renewable industrial energy consumption. Energy Econ. 54, 291–301.
Doytch, N., Narayan, S., 2021. Does transitioning towards renewable energy accelerate economic growth? An analysis of sectoral growth for a dynamic panel of countries. Energy 235, 121290. https://doi.org/10.1016/j.energy.2021.121290.
ECLAC, 2022. A Digital Path for Sustainable Development in Latin America and the Caribbean.
Fankhauser, S., Jotzo, F., 2018. Economic growth and development with low-carbon energy. Wiley Interdisciplinary Reviews. Climate Change 9 (1). https://doi.org/10.1002/wcc.495 n/a.
Fattouh, B., Poudineh, R., West, R.R., 2019. The Rise of Renewables and Energy Transition: what Adaptation Strategy Exists for Oil Companies and Oil-Exporting Countries. Springer Science and Business Media LLC. https://doi.org/10.1007/s41825-019-00013-x.
Fuinhas, J.A., Marques, A.C. (Eds.), 2019. The Extended Energy–Growth Nexus: Theory and Empirical Applications. Academic Press.
Fuinhas, J.A., Koengkan, M., Santiago, R., 2021. Physical Capital Development and Energy Transition in Latin America and the Caribbean. Elsevier.
Grossman, G.M., Krueger, A.B., 1995. Economic growth and the environment. Q. J. Econ. 110 (2), 353–377.
Grottera, C., 2022. Reducing Emissions from the Energy Sector for a More Resilient and Low-Carbon Post-pandemic Recovery in Latin America and the Caribbean.

Guimarães, L.N. (Ed.), 2020. The Regulation and Policy of Latin American Energy Transitions. Elsevier.
Hafner, M., Luciani, G., 2022. The Palgrave Handbook of International Energy Economics. Springer Nature, p. 770.
Hampl, N., 2022. Equitable Energy Transition in Latin America and the Caribbean: Reducing Inequity by Building Capacity. Elsevier BV. https://doi.org/10.1016/j.rset.2022.100035.
Hao, X., Li, Y., Ren, S., Wu, H., Hao, Y., 2023. The role of digitalization on green economic growth: does industrial structure optimization and green innovation matter? J. Environ. Manag. 325, 116504 https://doi.org/10.1016/j.jenvman.2022.116504.
Henderson, J., Sen, A., 2021. *The Energy Transition: Key Challenges for Incumbent and New Players in the Global Energy* System (No. 01). OIES Paper: ET.
Hübner, K. (Ed.), 2018. National Pathways to Low Carbon Emission Economies: Innovation Policies for Decarbonizing and Unlocking. Routledge.
IEA, 2017. Digitalization & Energy.
Inglesi-Lotz, R., 2016. The impact of renewable energy consumption to economic growth: a panel data application. Energy Econ. 53, 58–63. https://doi.org/10.1016/j.eneco.2015.01.003.
IPCC, 2022. *Climate Change 2022: Impacts, Adaptation, and Vulnerability.* Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press. Cambridge University Press, Cambridge, UK and New York, NY, USA, p. 3056. https://doi.org/10.1017/9781009325844.
Ivanovski, K., Hailemariam, A., Smyth, R., 2021. The effect of renewable and non-renewable energy consumption on economic growth: non-parametric evidence. J. Clean. Prod. 286, 124956 https://doi.org/10.1016/j.jclepro.2020.124956.
Jimenez, V.M.M., Gonzalez, E.P., 2022. The role of artificial intelligence in Latin americas energy transition. IEEE Latin America Transactions 20 (11), 2404–2412.
Kaya, Y., 1990. Impact of Carbon Dioxide Emission Control on GNP Growth: Interpretation of Proposed Scenarios. Paper presented to the IPCC Energy and Industry Subgroup, Response Strategies Working Group, Paris. Mimeo.
Koengkan, M., Fuinhas, J.A., 2022. Globalisation and Energy Transition in Latin America and the Caribbean. Springer Books.
Kuc-Czarnecka, M.E., Olczyk, M., Zinecker, M., 2021. Improvements and spatial dependencies in energy transition measures. Energies 14 (13), 3802. https://doi.org/10.3390/en14133802.
Labra, R., Torrecillas, C., 2014. Guía CERO para datos de panel. Un enfoque práctico. UAM-Accenture Working Papers 16 (1), 57.
Lange, S., Pohl, J., Santarius, T., 2020. Digitalization and energy consumption. Does ICT reduce energy demand? Ecol. Econ. 176, 106760 https://doi.org/10.1016/j.ecolecon.2020.106760.
Li, J., Chen, L., Chen, Y., He, J., 2022 a. Digital economy, technological innovation, and green economic efficiency—empirical evidence from 277 cities in China. Manag. Decis. Econ. 43 (3), 616–629. https://doi.org/10.1002/mde.3406.
Li, R., Wang, X., Wang, Q., 2022 b. Does renewable energy reduce ecological footprint at the expense of economic growth? An empirical analysis of 120 countries. J. Clean. Prod. 346, 131207 https://doi.org/10.1016/j.jclepro.2022.131207.
Lin, B., Huang, C., 2023. Promoting variable renewable energy integration: the moderating effect of digitalization. Appl. Energy 337, 120891.
Liu, Y., Yang, Y., Li, H., Zhong, K., 2022. Digital economy development, industrial structure upgrading and green total factor productivity: empirical evidence from China's cities. Int. J. Environ. Res. Publ. Health 19 (4), 2414. https://doi.org/10.3390/ijerph19042414.
Luo, S., Yimamu, N., Li, Y., Wu, H., Irfan, M.M., Hao, Y., 2022. Digitalization and Sustainable Development: How Could Digital Economy Development Improve Green Innovation in China? Wiley, pp. 8–23. https://doi.org/10.1002/bse.3223.
Ma, Q., Tariq, M., Mahmood, H., Khan, Z., 2022. The nexus between digital economy and carbon dioxide emissions in China: the moderating role of investments in research and development. Technol. Soc. 68, 101910 https://doi.org/10.1016/j.techsoc.2022.101910.
Machado, J.A., Silva, J.S., 2019. Quantiles via moments. J. Econom. 213 (1), 145–173.
Maddala, G.S., Wu, S., 1999. A comparative study of unit root tests with panel data and a new simple test. Oxf. Bull. Econ. Stat. 61, 631–652.
Messina, D., 2020. Contribuciones determinadas a nivel nacional del sector eléctrico en América Latina y el Caribe: análisis de la transición hacia el uso sostenible de las fuentes energéticas.
Mohsin, M., Kamran, H.W., Atif Nawaz, M., Sajjad Hussain, M., Dahri, A.S., 2021. Assessing the impact of transition from nonrenewable to renewable energy consumption on economic growth-environmental nexus from developing Asian economies. J. Environ. Manag. 284, 111999 https://doi.org/10.1016/j.jenvman.2021.111999.
Murshed, M., Apergis, N., Alam, M.S., Khan, U., Mahmud, S., 2022. The impacts of renewable energy, financial inclusivity, globalization, economic growth, and urbanization on carbon productivity: evidence from net moderation and mediation effects of energy efficiency gains. Renew. Energy 196, 824–838.
Nagasawa, T., Pillay, C., Beier, G., Fritzsche, K., Pougel, F., Takama, T., Bobashev, I., 2017. Accelerating Clean Energy through Industry 4.0 Manufacturing the Next Revolution. A Report of the United Nations Industrial Development Organization.
Nwaiwu, F., 2021. Digitalisation and sustainable energy transitions in Africa: assessing the impact of policy and regulatory environments on the energy sector in Nigeria and South Africa. Energy, Sustainability and Society 11 (1), 1–16.
Ocal, O., Aslan, A., 2013. Renewable energy consumption–economic growth nexus in Turkey. Renewable Sustainable Energy Rev. 28, 494–499. https://doi.org/10.1016/j.rser.2013.08.036.
OECD, 2020. Latin American Economic Outlook 2020: Digital Transformation for Building Back Better. OECD Publishing, Paris. https://doi.org/10.1787/e6e864fb-en.
OLADE, 2020. Panorama energético de América Latina y el Caribe.
Pablo-Romero, M.P., Sánchez-Braza, A., Romero, M.G.P., 2022. Renewable energy in Latin America. AIMS Energy 10 (4), 695–717.
Pesaran, M.H., Ullah, A., Yamagata, T., 2006. A Bias-Adjusted Test of Error Cross Section Dependence.
Pesaran, M.H., 2007. A simple panel unit root test in the presence of cross-section dependence. J. Appl. Econom. 22 (2), 265–312.
Pesaran, M.H., Yamagata, T., 2008. Testing slope homogeneity in large panels. J. Econom. 142 (1), 50–93.
Ramzan, M., Raza, S.A., Usman, M., Sharma, G.D., Iqbal, H.A., 2022. Environmental cost of non-renewable energy and economic progress: do ICT and financial development mitigate some burden? J. Clean. Prod. 333, 130066.
Ren, S., Hao, Y., Xu, L., Wu, H., Ba, N., 2021. Digitalization and energy: how does Internet development affect China's energy consumption? Energy Econ. 98, 105220 https://doi.org/10.1016/j.eneco.2021.105220.
Royston, J.P., 1983. A Simple method for evaluating the shapiro–francia W′ test of non-normality. J. Roy. Stat. Soc.: Series D (The Statistician) 32 (3), 297–300.
Royston, P., 1992. Comment on sg3. 4 and an improved D'Agostino test. Stata Technical Bulletin 1 (3).
Santarius, T., Pohl, J., Lange, S., 2020. Digitalization and the decoupling debate: can ICT help to reduce environmental impacts while the economy keeps growing? Sustainability 12 (18), 7496. https://doi.org/10.3390/su12187496.
Santiago, R., Fuinhas, J.A., Marques, A.C., 2020. The impact of globalization and economic freedom on economic growth: the case of the Latin America and Caribbean countries. Econ. Change Restruct. 53, 61–85.
Sebri, M., Ben-Salha, O., 2014. On the causal dynamics between economic growth, renewable energy consumption, CO2 emissions and trade openness: fresh evidence from BRICS countries. Renewable Sustainable Energy Rev. 39, 14–23. https://doi.org/10.1016/j.rser.2014.07.033.
Shahbaz, M., Wang, J., Dong, K., Zhao, J., 2022. The impact of digital economy on energy transition across the globe: the mediating role of government governance. Renewable Sustainable Energy Rev. 166, 112620 https://doi.org/10.1016/j.rser.2022.112620.
Sharma, G.D., Shah, M.I., Shahzad, U., Jain, M., Chopra, R., 2021 a. Exploring the nexus between agriculture and greenhouse gas emissions in BIMSTEC region: the role of renewable energy and human capital as moderators. J. Environ. Manag. 297, 113316.
Sharma, G.D., Tiwari, A.K., Erkut, B., Mundi, H.S., 2021 b. Exploring the nexus between non-renewable and renewable energy consumptions and economic development: evidence from panel estimations. Renew. Sustain. Energy Rev. 146, 111152.
Singh, H.V., Bocca, R., Gomez, P., Dahlke, S., Bazilian, M., 2019. The energy transitions index: an analytic framework for understanding the evolving global energy system. Energy Strategy Rev. 26, 100382.
Smil, V., 2020. Energy transitions: fundamentals in six points. Papeles de Energia 8, 11–20.
Trinh, H.H., Sharma, G.D., Tiwari, A.K., Vo, D.T.H., 2022. Examining the heterogeneity of financial development in the energy-environment nexus in the era of climate change: novel evidence around the world. Energy Econ. 116, 106415.
Tugcu, C.T., Ozturk, I., Aslan, A., 2012. Renewable and non-renewable energy consumption and economic growth relationship revisited: evidence from G7 countries. Energy Econ. 34 (6), 1942–1950. https://doi.org/10.1016/j.eneco.2012.08.021.
Urban, F., 2014. Low Carbon Transitions for Developing Countries. Routledge.
Vanegas Cantarero, M.M., 2020. Of renewable energy, energy democracy, and sustainable development: a roadmap to accelerate the energy transition in developing countries. Energy Res. Social Sci. 70, 101716 https://doi.org/10.1016/j.erss.2020.101716.
Višković, A., Franki, V., Bašić-Šiško, A., 2022. City-level transition to low-carbon economy. Energies 15 (5), 1737. https://doi.org/10.3390/en15051737.
Wang, B., Wang, J., Dong, K., Dong, X., 2023. Is the digital economy conducive to the development of renewable energy in Asia? Energy Pol. 173, 113381 https://doi.org/10.1016/j.enpol.2022.113381.
Wang, J., Dong, K., Dong, X., Taghizadeh-Hesary, F., 2022a. Assessing the digital economy and its carbon-mitigation effects: the case of China. Energy Econ. 113 https://doi.org/10.1016/j.eneco.2022.106198.
Wang, J., Wang, K., Dong, K., Shahbaz, M., 2022b. How Does the Digital Economy Accelerate Global Energy Justice? Mechanism Discussion and Empirical Test. Elsevier BV. https://doi.org/10.1016/j.eneco.2022.106315.
Wang, Q., Wang, L., 2020. Renewable Energy Consumption and Economic Growth in OECD Countries: A Nonlinear Panel Data Analysis, vol. 207. Energy, Oxford), 118200. https://doi.org/10.1016/j.energy.2020.118200.
Wang, Q., Wang, L., Li, R., 2022c. Renewable energy and economic growth revisited: the dual roles of resource dependence and anticorruption regulation. J. Clean. Prod. 337, 130514 https://doi.org/10.1016/j.jclepro.2022.130514.
Wirawan, H., Gultom, Y.M., 2021. The effects of renewable energy-based village grid electrification on poverty reduction in remote areas: the case of Indonesia. Energy for Sustainable Development 62, 186–194.
World Bank, 2022. Consolidating the Recovery: Seizing Green Growth Opportunities. The World Bank.

Xu, Q., Zhong, M., Li, X., 2022. How does digitalization affect energy? International evidence. Energy Econ. 107, 105879 https://doi.org/10.1016/j.eneco.2022.105879.
Zhang, H., 2023. Pathways to carbon neutrality in major exporting countries: the threshold effect of digital transition. Environ. Sci. Pollut. Res. Int. 1 https://doi.org/10.1007/s11356-022-22592-x.
Zhang, W., Liu, X., Wang, D., Zhou, J., 2022. Digital economy and carbon emission performance: evidence at China's city level. Energy Pol. 165, 112927 https://doi.org/10.1016/j.enpol.2022.112927.