

The impact of the digital economy and institutional quality in promoting low-carbon energy transition

Young Kyu Hwang^{a,*}, Alanda Venter^b

^a Universidad Autónoma de Madrid, Spain

^b University of Pretoria, South Africa

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ABSTRACT

Given the threat of climate change, the renewable energy transition will play a pivotal role in reaching net-zero goals. The digital economy and institutional quality are considered key enablers of the rapid deployment of renewable energy because they can strengthen the reliability and security of energy systems. This study examines the impacts of the digital economy and institutional quality on renewable energy deployment across 85 countries from 2003 to 2021 using a Two-Step System GMM. The selection of a dynamic panel model is motivated by the path-dependent nature of renewable energy deployment. Sub-sample analyses are conducted to account for the diversity of the dataset in terms of energy mixes, levels of economic development, digital infrastructures, and institutional qualities. A dynamic threshold regression analysis is then conducted to determine the non-linearity of fossil fuel dependence on the impact of the digital economy and institutional quality on renewable energy deployment. The estimates reveal that the digital economy promotes renewable energy deployment, whereas institutional quality has an ambiguous effect. Additionally, depending on the degree of fossil fuel dependency, the impacts of both the digital economy and institutional quality vary significantly and exhibit non-linear and asymmetric features.

1. Introduction

Every year, the majority of the world's countries gather together at the United Nations Climate Change Conference (COP) to pledge to reach net zero emissions. This annual gathering at COP showcases the determination of governments to prevent environmental degradation [1].

Given the climate change threat the global economy is facing, the pace of decarbonization must be significantly accelerated in the coming decades to achieve global net-zero goals and carbon neutrality by 2050. Therefore, transitioning the global economy to low-carbon energy sources, particularly renewable energy sources, is imperative to avoid the catastrophic consequences of climate change and global warming. This low-carbon energy transition is driven by various determinants such as affordability, availability, financing, and the different energy mixes of countries with diverse agendas.

In this context, the digital economy emerges as a key enabler in facilitating low-carbon energy transition. The notion of the 'digital economy' was first introduced by Tapscott [2]. It refers to a set of economic activities that make extensive use of Information and Communication Technologies (ICT) and harness digital information and

knowledge, with data being a key production factor along with the traditional production factors of an economy such as labor and capital [3–6]. In the digital economy, advanced internet networks act as important carriers of data, and ICT serves as a primary driving force to foster production efficiency and optimize economic structure [1,5,6].

Specifically, in the context of renewable energy deployment and development, the application and incorporation of digital technologies into energy systems can be particularly useful for the following reasons:

First, the evolution of digital technologies can make energy systems with a high share of renewable energy sources more reliable and secure. Recent advances in big data and Artificial Intelligence (AI) lead to accurate prediction of climatic conditions, which is essential for an energy mix dominated by various renewable sources [7]. Given the high variability and volatile nature of renewable energy, which depends heavily on climatic conditions and geographical locations, more accurate predictions are imperative for effective power generation. In this sense, the integration of digital technologies can provide additional security and flexibility to the power system promoting reliability and resiliency.

Second, the digital economy can significantly foster technological innovation, which in turn might accelerate the shift from a fossil fuel-

* Corresponding author.

E-mail addresses: young.hwang@estudiante.uam.es (Y.K. Hwang), venteralanda@gmail.com (A. Venter).

based energy system towards a low-carbon, renewable energy-based system, given the latter's highly technology- and knowledge-intensive nature compared to the former [8,9]. Renewable energy technologies, accompanied by significant technological innovation prompted by digitalization in the energy sector, can contribute to reducing carbon emissions and enhancing environmental sustainability by increasing energy efficiency and optimizing energy consumption [7].

Third, the incorporation of advanced digital technologies into energy- and pollution-intensive sectors can enhance the visibility and transparency of production processes. This drives more efficient monitoring and tracking of carbon emissions, natural ecosystem status, and energy utilization throughout the supply chain [10]. According to Scharl and Prakrtinjo [11], the Fourth Industrial Revolution or Industry 4.0,¹ led by the digital economy, can significantly facilitate the integration of renewable energy into future smart factories based on advanced digital technologies, thereby substantially improving energy sustainability.

Fourth, given the foreseeable transition to renewable energy in the coming decades, the national power system is expected to become highly decentralized, unlike traditional fossil fuel-based power plants. This decentralization will bring about more complexity to the power system [12]. In this context, digital technologies such as AI, big data, and blockchain technology can facilitate the efficient management of decentralized power plants with advanced information and data processing capabilities and enable peer-to-peer electricity trade within local communities, contributing positively to local economic development [7, 12]. Furthermore, these digital technologies can substantially reduce operational and maintenance costs, optimize the energy system, minimize electricity losses during transmission, and reduce dependence on fossil fuel-based power plants for backup.

Lastly, the digital economy enables the implementation of effective demand-side management. The integration of advanced digital technologies into electrical grids, known as smart grids, allows for more efficient management of energy flows and is more responsive to sudden changes in energy supply [13]. This is particularly relevant in an electricity mix with a high participation of variable renewable energy sources. Furthermore, technologies such as smart meters enable real-time monitoring of energy consumption and provide accurate information on energy use to consumers, thereby contributing to optimal decision-making, reducing energy consumption, and increasing cost savings.

In the process of the low-carbon energy transition, institutional quality is another crucial factor for enabling successful cooperation between energy and digital enterprises, especially at a national government level [1]. Institutions affect economic operations and outcomes directly and indirectly [14]. High institutional quality can effectively implement and incentivize policies affecting the energy transition at the national level. Institutions have the ability to create market environments that enhance economic activity and innovation, improve investment, and more efficient resource allocation [15–18]. However, a lack of sufficient institutional quality is considered a barrier to renewable energy deployment [19]. The barriers are usually present through corruption, lack of rule of law and regulatory quality, low government effectiveness and voice and accountability as well as political stability [19], discussed more directly in the literature review section.

Several empirical studies highlight the critical role of institutional quality in promoting the deployment of specific types of renewable energy. For instance, Alsaleh and Abdul-Rahim [20] examined the effect of worldwide governance factors (a measure of institutional quality) on geothermal energy output in 27 EU countries. Their findings suggest that improving the level of Worldwide Governance Indicators (WGI) can significantly boost geothermal energy generation in the EU by

enhancing the security and sustainability of geothermal energy production. Similarly, Alsaleh et al. [21] explored the impact of WGI on promoting the sustainability of the bioenergy industry in European countries. Their findings indicate that WGI significantly contributes to enhancing the sustainability of bioenergy production in the EU. Moreover, the influence of each sub-indicator of WGI on bioenergy production varied significantly depending on the group of countries examined. Institutional quality has also been found to significantly impact the development of the hydropower industry. Alsaleh and Abdul-Rahim [22] investigated the effect of WGI on hydropower industry growth in 28 European countries. Their study revealed that factors such as political accountability, government stability, effective governance, judicial enforcement, administrative quality, and the control of fraudulent activities were particularly effective in promoting the growth of the hydropower industry.

Institutions can have a significant role in creating more attractive markets for investors. Developing countries need a significant amount of investment for their energy transitions. Furthermore, investment is needed to enhance the research and development of renewable energy technologies as well as the research and development of ICT's which have an important role in renewable energy. Inadequate institutions can create markets that can be perceived as unattractive to investors when they increase the cost of doing business unnecessarily and create uncertainty in the market for investors on their future returns [23]. These weak institutional frameworks have been observed to discourage renewable energy technological innovation [24]. High-quality institutions often support the private sector and its property rights creating favorable investment opportunities [25]. Given the cross-border nature of climate change and a high degree of urgency of net-zero emissions to avoid its catastrophic consequences, governments have a significant role in ensuring mutual agreements between countries. Governments can use their institutions as vital instruments and mediators in the energy-digital economy transition [1] to assist in obtaining net zero goals.

When it comes to the degree of a country's reliance on natural resources, it might be a critical determinant that influences the impacts of both the digital economy and institutional quality on renewable energy deployment, thereby affecting the pace and success of the low-carbon energy transition. Countries whose production capabilities are highly reliant on natural resource extraction and the revenues generated from these activities may encounter significant difficulties in diversifying their economic structures. Moving away from a fossil-fuel-based energy system to a more sophisticated, knowledge- and technology-intensive renewable energy-based system might be significantly hampered due to political and social opposition. Consequently, their green production capabilities are underdeveloped, and their competitive advantages based on low-value-added primary commodity exports might become a stumbling block on the pathway to a low-carbon energy transition [26].

Considering the potential roles that the digital economy and institutional quality might play in the global low-carbon energy transition, their impact on renewable energy deployment was thoroughly analyzed in this study.

The main contributions of this study can be summarized as follows:

Firstly, this study examines the impact of the digital economy and institutional quality on renewable energy deployment across 85 countries, providing valuable insights into whether incorporating advanced digital technologies and adequate institutions will assist in promoting renewable energy sources, thus contributing to accelerating the global low-carbon energy transition and achieving net-zero goals. Unlike previous studies, this research includes a large number of countries at a global level, allowing us to find significant implications of the impact of the digital economy on renewable energy deployment. Because of the unavailability of a standardized indicator encompassing the broad aspects of the digital economy, the multidimensional Digital Economy Index (DEI) is developed at a global level and incorporated into our analysis, which is another part of the important contributions of this study.

¹ The Fourth Industrial Revolution or Industry 4.0 refers to the digital transformation of the business world, which provides huge opportunities for energy sustainability [82].

Secondly, this study specifically focuses on two modern renewable energy sources with high growth rates in the last decade at a global level, namely solar and wind. These sources have a high potential for improving energy efficiency and cost savings thanks to the learning-by-doing process and significant room for technological innovation and advancement in coming decades. The study excludes more mature and traditional renewable energy sources such as hydropower and biomass, which do not necessarily require high technological content and are not expected to have a substantial learning-by-doing effect given their mature status. This makes the study's approach clearly differentiated from previous literature, which includes all sources of renewable energy without specific distinctions between modern and traditional renewable energy sources.

Thirdly, given the significant challenges facing fossil-fuel-dependent countries in transitioning to low-carbon energy, such as oil and gas exporters, this study is performed for the group of two different countries based on their degree of reliance on non-renewable fossil fuels: low-dependent and high-dependent fossil fuel countries. This is because countries that are fossil fuel rich tend to heavily rely on their fossil fuels resources, often leading to high levels of carbon emissions being emitted as well as facing challenges in transitioning their energy sectors to low carbon sectors. Many of these countries are also developing countries of still industrializing and faced with the challenge of balancing sustainability and economic growth. Given the latter the study then, investigates how much the impacts of the digital economy and institutional quality on renewable energy deployment are different from each other in the two groups. This research is the first attempt to investigate the nexus between the digital economy, institutional quality, and renewable energy deployment in relation to fossil fuel dependence. In this regard, this research might significantly broaden the study of the resource curse hypothesis and provide valuable insights and guidelines for policymakers in countries with high fossil fuel reserves facing stranded assets challenges in the coming decades.

Lastly, this study analyzes the impacts of the digital economy and institutional quality on renewable energy deployment using the Method of Moments Quantile Regression (MMQR) and dynamic panel threshold regressions. Given the wide-ranging data sets of countries in the sample, which include countries with heterogeneous levels of economic development, energy mixes, digital infrastructures, advancements in digital technologies, and political and regulatory systems, the impacts of the digital economy and institutional quality are expected to be non-linear and asymmetric. Hence, in the presence of non-linearity and asymmetry, the impacts of the digital economy and institutional quality may not be estimated accurately by conventional linear regression techniques. In this regard, the MMQR and dynamic panel threshold regression methods are used to address these issues and provide robust estimates.

The structure of the paper is organised as follows: Section 2 provides a literature review. Section 3 presents the dataset and methodology used in this study. Section 4 provides empirical findings in this study, followed by discussions of findings in Section 5. Section 6 concludes with policy implications.

2. Literature review

2.1. Digital economy-renewable energy deployment literature

Since the last decade, the potential roles of the digital economy in boosting the renewable energy transition have been drawing much attention from academics and policymakers. Integration of the digital economy and green energy, namely the incorporation of advanced digital technologies into an energy system dominated by clean and renewable energy sources, can lead to a paradigm shift in the actual energy system. Such a paradigm shift can have profound implications in three aspects of the energy trilemma: energy affordability, energy security, energy sustainability, and might bring about significant changes

in current production and consumption patterns of energy.

Despite the growing potential of the digital economy as a driving force to the integration of renewable energy into the energy mix, the question of whether the digital economy will accelerate renewable energy deployment, thereby facilitating the decarbonization of the global economy and the low-carbon energy transition, remains highly uncertain.

Among the proponents of the digital economy, there are numerous studies in which the digital economy advocates for renewable energy deployment. Huang [27] points out that digitalization might play a key role in accelerating decarbonization since it can attract investors and make financial services more affordable to broader segments of the population and stakeholders. This facilitates the financing of green projects and access to financial services for small and medium enterprises (SMEs) and vulnerable households who are willing to adopt renewable energy technologies but often face difficulties due to the high upfront costs of renewable energy deployment.

Huang and Lin [28] studied the impact of digitalization in the electricity sector for 93 countries using a two-way fixed effects estimator. According to their findings, digitalization significantly reduces the carbon intensity of power generation by optimizing the energy structure and simultaneously promotes renewable energy development. Specifically, the application of digital technologies can enormously facilitate the integration of renewable energy sources into the energy mix by allowing for effective management of grid scheduling and providing additional flexibility to the grid through advanced data collection and processing, forecasting, and information-sharing capacities of digital technologies such as big data, AI, and Internet of Things (IoT) [29].

Yi et al. (2024) investigated the impact of the digital economy on renewable energy innovation for 65 countries from 2002 to 2019 using a dynamic System Generalized Method of Moments (GMM) approach. The authors assessed the impact of the digital economy on both aggregate and disaggregate renewable energy innovation, including solar, wind, biomass, and geothermal energy. The estimates reveal that the digital economy significantly boosts aggregate renewable energy innovation: the positive impact of the digital economy was found in solar, wind, and biomass energy, but no significant impact of the digital economy was found in geothermal energy. Furthermore, from the heterogeneity analysis, authors found that in countries with high economic development, strong institutional quality (high-policy intensity), and a strong manufacturing base, the impact of the digital economy was substantially stronger. The role of human capital, investment in renewable energy, and market potential are three primary channels through which the digital economy positively affects renewable energy innovation.

In a similar vein, Wang et al. [5,6], found a heterogeneous impact of the digital economy on renewable energy generation in Asian countries from 2003 to 2019 using the IV-GMM method. The estimates indicate that the impact of the digital economy on boosting renewable energy generation was substantially stronger in high-income Asian countries. Moreover, significant regional heterogeneities were observed in terms of geographical location: the impact of the digital economy being significant only in East and South Asian countries.

Dian et al. [4] argued that the digital economy positively affects urban green technology innovation within Chinese cities. The authors found that the digital economy effectively contributes to promoting green technology innovation through human capital accumulation, financial development, and government support. This is because the digital economy enforces the need for a high-quality workforce and supports the optimal allocation of production factors and the digital transformation of financial institutions, which, in turn, improves effectiveness in financial markets. Moreover, the effectiveness of government fiscal policy can be significantly enhanced by the digital economy, given that it optimizes the quality of tax services through increasing the efficiency of tax collection and the effective management of fiscal revenues.

Ma and Zhu [30] emphasized that the digital economy is the main

driving force of high-quality green development in China. Based on panel data from 281 cities, the authors concluded that the digital economy significantly promotes high-quality green development through industrial structure adjustment and green technology innovation, which constitute the primary channels through which the digital economy boosts green development in China.

Other studies remain skeptical about the beneficial impacts of the digital economy on renewable energy deployment and keep raising questions about its validity as an effective means to achieve a low-carbon energy transition and environmental sustainability. Babayomi et al. [31] emphasized that there is a significant gap in renewable energy deployment between developing countries and developed and industrialized countries, which might seriously impede the decarbonization of the global economy. This is because developing countries, unlike developed ones, often lack efficient grid infrastructure, as well as a relatively higher qualified workforce, higher innovation capacity, and absorptive capacities necessary to assimilate advanced digital technologies into their energy systems and production structures. Moreover, given the high upfront costs required for renewable energy development, developing countries might face significant challenges in shifting to a low-carbon energy transition due to their limited fiscal capacity and macroeconomic instability.

Lange et al. [32] stated that digitalization can effectively enhance energy efficiency and prompt sectoral transformation from energy-intensive industries towards knowledge- and service-based ones. However, it also brings about a rapid upsurge in the usage of electronics and might generate massive e-waste. Furthermore, the enhancement of labor and energy productivity, which in turn stimulates economic growth, may drive increased energy consumption if the rebound effect, resulting from cheaper energy and improved energy efficiency, is not properly addressed.

Energy security and privacy are also important issues raised by critics regarding the impact of the digital economy on renewable energy deployment. According to IEA [7], the digitalization of the energy sector, such as the IoT, poses significant threats given that more interconnected energy systems and increased information sharing make them more vulnerable to potential cyber-attacks and put consumer privacy at risk.

When it comes to the implications of the digital economy on energy consumption, energy efficiency, and industrial structure, several relevant studies have investigated this issue. Xue et al. [33] found that the development of the digital economy has significant implications for the scale and structure of energy consumption in 30 provinces and 205 cities in China. According to their estimates, the digital economy significantly expands the scale of energy consumption and contributes to increasing participation in clean energy consumption. Moreover, they found that the digital economy primarily affects energy consumption through improvements in energy efficiency and the upgrading of industrial structures. Yang et al. [34] examined the impact of digital infrastructure on industrial eco-efficiency in three Chinese cities (Beijing, Tianjin, and Hebei). The results indicate that digital infrastructure significantly promotes industrial eco-efficiency. Furthermore, when combined with regional collaborative innovation, digital infrastructure significantly boosts industrial eco-efficiency in these three cities. Wang et al. [35] examined the impact of the digital economy on high-quality energy development in China. They found a significant positive impact of the digital economy on high-quality energy development. The authors argued that the application of advanced digital technologies, such as AI and intelligent robots, can significantly improve energy efficiency, reduce energy consumption, and enhance the efficiency of business operations and management. Moreover, digitalization across different industrial sectors contributes to improving data processing, which in turn leads to better decision-making and more effective resource allocation. In a similar vein, Yi et al. (2022) found that the use of advanced digital technologies such as big data, cloud computing, and AI significantly improves energy efficiency. These technologies also help

transform and upgrade traditional energy- and emission-intensive industries, such as the transportation and industrial production sectors, to reduce carbon emissions in China. Hwang [36] argued that the application of digital technologies in power grids with high participation of renewable energy sources, such as smart grids, can deliver substantial energy savings and reduce energy production costs, thanks to more efficient energy management systems and advanced data processing capabilities. Other studies have reached different conclusions regarding the impact of the digital economy on energy efficiency. For instance, Zhang et al. [37] investigated the nexus between the digital economy, energy efficiency, and carbon emissions in 30 Chinese provinces. According to their estimates, improvements in energy efficiency driven by the digital economy do not occur, and the digital economy significantly increases carbon emissions. The authors emphasize the need to reduce e-waste and carbon emissions resulting from the construction of new digital infrastructure, such as data centers and the build-up of network equipment. In this context, harnessing AI and encouraging the adoption of standardized energy use assessments can be helpful for more accurate energy scheduling and reducing carbon emissions related to digital infrastructure construction.

There are several studies concerning the effects of Information and Communication Technologies (ICT) on the deployment of specific types of renewable energy sectors. For instance, Alsaleh and Wang [38] examined the effect of ICT on geothermal energy sustainability in 27 European Union (EU) countries. For this purpose, the 27 EU countries were divided into two groups: 14 developed EU countries and 13 emerging (developing) EU countries. According to their empirical findings, the positive effect of ICT on geothermal energy output was significantly higher in the 14 developed EU countries than in the 13 developing ones. On the contrary, the magnitude of the impact of geothermal energy on reducing CO₂ emissions was significantly higher in the 13 developing EU countries than in the 14 developed ones. The authors conclude by emphasizing that ICT can play a critical role in boosting sustainable development when combined with renewable energy, as it can help meet the growing energy demand through clean energy sources and greatly enhance energy security. In a similar vein, Alsaleh and Abdul-Rahim [20] and Wang et al. [8] investigated the effects of ICT on bioenergy and hydroenergy sustainability in 27 EU countries, respectively. They found significant and positive impacts of ICT on boosting bioenergy and hydro-energy sustainability. Based on the empirical findings and theoretical foundations of previous studies in this section, the following hypothesis can be formulated:

Hypothesis 1. The digital economy significantly promotes renewable energy deployment.

2.2. Institutional quality renewable energy deployment nexus literature

Rahman et al. [39] and Uzer et al. [40] examine how institutional quality impacts renewable energy. Rahman et al. [39] found that enhanced institutional quality-corruption control and government efficiency has a positive impact on renewable energy through higher productivity, export growth, and capital flow while Uzer et al. [40] results indicated that institutional quality in the long run has a positive effect on renewable energy consumption but the opposite effect in the short run. CO₂ emissions were also found to significantly affect renewable energy consumption and are seen as a determinant for policymakers to promote the use of renewable energy usage, hence affecting the renewable energy generation capacity.

Cadoret [41] found similar results concerning corruption control. The author examines the effect of political factors on the deployment of renewable energy. If the corruption perception index and control of corruption index improved, a positive effect on the deployment of renewable energy was found in the results.

Institutions are considered an important instrument for policies that support the use of renewable energies. In acknowledging this Saidi et al.

(2020) examines the relationship between economic growth and renewable energy while accounting for institutions specifically for the MENA countries. Their finding presents that institutions of good quality can significantly cause renewable energy and economic growth. Hence the presence of strong institutions and the adoption of renewable energies can stimulate economic development and possibly improve human development, especially for rural area communities.

Institutions can play a crucial role in decreasing environmental degradation whether it be through policy measures of reducing fossil fuel subsidies and carbon tax mechanisms, creating [42], and implementing policies that promote renewable energy deployment. Opeyemi et al. [43] investigate the relationship between renewable energy usage and trade performance, conditional on institutional quality for the Sub-Saharan African region. Their findings suggest that RE has a negative relationship with trade and manufacturing, however, improvements in the institutions of corruption control could improve this negative effect between RE and trade. Regulatory quality and finance as institutional measures have also been found to complement the relationship between RE and trade.

Amiri et al. [44] examine how institutions can impact natural resources in the tradability and non-tradability sectors and additionally, the effect it has on economic growth using a data set consisting of 28 different resource-rich countries. Their results found that countries with poor institutional quality often experience the natural resource curse. This however was not the case for countries with good institutional quality.

Shahbaz et al. [1] examined the nexus between the digital economy and renewable energy transition and further explored the mediating role of governance in this relationship. They analyzed 72 countries for the period from 2003 to 2019 using a Fixed Effects Panel Model and a System GMM. To represent the energy transition, they used two core explanatory variables – renewable energy consumption and renewable energy generation – as proxies for the renewable energy transition. Their results indicate that the digital economy has a positive effect on the energy transition for both renewable energy consumption and renewable energy generation structure. Furthermore, the digital economy is found to have a positive effect on the energy transition both from the consumption and production side given the improvement of government capabilities. Concerning the middle-income country group the digital economy was found to reduce renewable energy consumption and generation unlike high-income countries, where the digital economy variable was found to have a positive and significant effect on renewable energy consumption and generation. For the middle-income countries, the authors explain that with the development of the digital economy middle-income countries do consume a higher amount of ICT equipment but this is used with lower energy efficiency which leads to increasing usage of fossil fuel energy consumption.

Policy paradigms have a strong role in the energy governance sector given the political and economic importance in this sector. A paradigm can be seen as the set of beliefs, values, ideas, and principles of a particular sector. Given that the paradigm determines the political and organisational framework, the solutions of the sector can strongly be correlated to the beliefs and values of the parties in charge of the paradigm [45], thereby impacting the institutions implementing the policies. These paradigms can sometimes cause a carbon lock-in. A carbon lock-in can occur when existing carbon-based systems prevent low-carbon technologies from entering the market due to the path dependency of technologies and institutions within a country, hindering the ability to reap the gains derived from the increasing returns of adopting new and clean energy technologies [46].

Institutions can both be an instrument that constrains behaviour and the market while also being an instrument enabling behaviour, innovation, new policies, and promoting renewable energy policies. Given the urgency of addressing climate change, it needs to be addressed on global and national scales. Danish et al. [47], Omri et al. [48], and Sarpog et al. [49] have shown that governments can use adequate

institutions to address these issues through control of carbon emissions and encouraging transition to low-carbon energy mixes. One such example is the Chinese government implementing an Emissions Trading Scheme (ETS). There have been several studies indicating the success of such policies in reducing emissions [28,50]. Adequate governance and institutions can contribute to reducing environmental degradation in many ways through policy formulations and laws. For instance, rule of law and regulatory quality are institutions that governments can use to reduce carbon emissions [51]. *“Chinese government and academia have gradually recognized the potential for realizing a “win-win” situation by achieving positive interactions and multiplier effects between efforts to control air pollution and reduce carbon emissions”* [50]. The latter is an example of when governments and their institutions work together effectively in the low-carbon energy transition. The consensus of most of these papers is that institutions have an impact on renewable energy but certain individual institutions may have a more significant impact on renewable energy than others. The impact of institutions is also highly dependent on the different types of countries being used. The following hypothesis can be formulated based on the literature survey of this section:

Hypothesis 2. Institutional quality plays a crucial role in promoting renewable energy deployment.

2.3. The nexus digital economy-institutional quality-renewable energy deployment

Natural resources can be part of the capital accumulation of a country as well as its economic growth should the country be endowed with high quantities of resources. However, it was found that after the 20th century, the importance of natural resources in abundance diminished compared to the role of capital and labour. For developing countries with low institutional quality, having an abundance of natural resources can be dangerous. In these countries, the lack of effective government governance, low regulatory capacity, and high levels of corruption, along with the misallocation of revenues from natural resources and lower saving rates, pose significant challenges [52]. Instead of harnessing these natural resource revenues for investment in physical and human capital, they are often used to purchase perishable consumer goods or to maintain the political power of small elites, leading to their squandering. As a result, these countries become excessively dependent on and specialize in low-value-added primary commodity exports, which can cause macroeconomic instability due to the volatile nature of commodity prices in the global market. This dependency results in a lower degree of development in manufacturing capacity, which is fundamental for achieving long-term economic growth, ultimately leading to lower economic growth in natural resource-abundant countries with low institutional quality. This phenomenon is known as the resource curse hypothesis. Previous studies on the natural resource curse hypothesis have shown that countries with high dependence on natural resource rent as a percentage of their GDP can experience lower GDP per capita growth rates [53]. Entele [53] examines the role institutional and ICT services play in the resource curse. The results indicate that countries with a higher rate of institutional quality that have abundant resources can escape the resource curse. Adequate institutions will foster market efficiency, and competitive market conditions and enforce fair regulations while combating corruption, hence fighting resource rents within the markets. The latter leads to enhanced productivity, and innovation thereby attracting Foreign Direct Investment (FDI). Adequate governance and institutions are key to an inclusive and sustainable future that can lead to the more effective usage of economic resources, alleviating the resource curse [53,54].

Zhang et al. [55] emphasized that government policy support plays a critical role in the early stages of renewable energy deployment. They highlighted that green technology innovation and environmental regulation are two mechanisms through which an abundant endowment of natural resources can result in a resource-blessing effect.

Makhdom et al. [56] examine the relationship between institutional factors, financial development, renewable energy, and natural resources to economic growth as well as the environmental footprint in China. The results indicated that long-run relationships exist between institutional quality, natural resources, economic growth, financial expansion, and renewable energy along with the environmental footprint. Higher institutional quality was found to be linked with the protection of the environment and resources. The authors also found a unidirectional causality exists between national resources and economic growth and between institutional quality and environmental footprint within China.

When it comes to fossil fuel dependency, several studies have highlighted its crucial role and significant impact on economic growth, carbon emissions, renewable energy deployment, digital economy development, and institutional quality. Specifically, many relevant studies emphasize the asymmetric and non-linear impact of fossil fuel dependence on these variables. Anser et al. [57] examined the effect of the ICT-led natural resource growth hypothesis in Saudi Arabia and found that ICT contributes to reducing carbon emissions. Furthermore, they found that the impact of natural resource rents (natural resource dependence) on economic growth varies significantly depending on the type of natural resource. Specifically, natural gas rents did not contribute to fostering economic growth, whereas oil and forest rents were found to have a significant positive impact on economic growth in Saudi Arabia. In a similar vein, Hadj [58] analyzed the role of fossil fuel energy and natural resource rents on the ecological footprint in Saudi Arabia, a country heavily reliant on fossil fuel energy resources. The estimated results indicate that, in the short run, fossil fuel energy and natural resource rents contribute to reducing the ecological footprint, as the revenues derived from them provide the necessary funds to finance clean energy projects. However, in the long term, natural resource rents and increased fossil fuel energy consumption lead to environmental degradation, as they contribute to an increased ecological footprint.

The asymmetric effects of fossil fuel dependency are observed not only in developing countries but also in developed economies, such as the United States. Thombs [59] analyzed the impact of fossil fuel dependency on the carbon intensity of well-being (CIWB) at the U.S. state level. They found that an increase in fossil fuel dependency in U.S. states leads to an increase in CIWB, whereas a decrease in dependency has no significant impact on CIWB. The author concludes that the climate and social well-being crises in the U.S. are closely linked to fossil fuel dependency and emphasizes the necessity of a coordinated and orderly energy transition strategy to ensure that the shift to renewable energy is just and equitable. The following hypothesis can be formulated based on the literature survey of this section:

Hypothesis 3. The impacts of both the digital economy and institutional quality on renewable energy deployment are expected to vary significantly in association with the country's fossil fuel dependency.

3. Data and methodology

3.1. Data

3.1.1. Dependent variable: Renewable energy deployment (SEGFR)

In this study, the deployment of renewable energy is proxied by the share of electricity generated from modern renewable sources, specifically solar and wind energy. Focusing on modern renewable sources, rather than including all types of renewable energy, provides a more accurate analysis of the ongoing low-carbon energy transition. This approach acknowledges the significant potential of modern renewable sources to enhance energy affordability, environmental sustainability, energy security, and economic growth, and job creation. Unlike traditional renewable energies such as hydropower and biomass, of which technologies are already matured, modern renewable energy sources can significantly benefit from continuous technological advancement and innovation through the learning-by-doing process.

3.1.2. Main explanatory variable: Digital Economy Index (DEI) and institutional quality

• Digital Economy Index (DEI)

The Digital Economy Index (DEI) is developed in this study to encompass the multidimensional features of the digital economy. Principal Component Factor (PCF) analysis was used to construct the DEI, including a total of 13 indicators grouped into three different dimensions: 1) connectivity, digital infrastructure and Internet penetration among populations, 2) human capital and high-skilled labor, and 3) ICT goods trade and the capacity to produce technologically sophisticated products, as shown in Table 1.

• Institutional quality

In this study, institutional quality is measured by assigning an equally weighted average to six indicators and grouping them into a single multidimensional index: 1) corruption control, 2) rule of law, 3) regulatory quality, 4) government effectiveness, 5) political stability and absence of violence/terrorism, and 6) voice and accountability. Table 2 shows each component of Institutional quality with detailed descriptions.

3.1.3. Control variables: GDP per capita, inflation, CO₂Fuel combustion

The set of control variables used in this study includes Gross Domestic Product per capita (GDPpc) as a proxy for a country's income level, Consumer Price Index (CPI) as a proxy for energy prices, and CO₂ emissions from burning fossil fuels (CO₂FuelComb), which are used as a proxy for a country's emission levels. The inclusion of these control variables is justified for the following reasons: GDPpc is used as a proxy for economic development and growth and included as a control variable since countries with higher GDP per capita are expected to have higher rates of renewable energy consumption (Chen et al., 2021). CPI is often used as a proxy for energy prices due to the limited availability of energy price data. The proxy often provides a larger availability of data and frequency and includes energy as a good within its basket. Literature such as Vatamanu et al. [60], Islam et al. [61], and Chang et al. [62]

Table 1
Digital economy index (DEI).

Dimension	Indicator	Unit	Source
Connectivity, digital infrastructure, and Internet penetration among populations (70 %)	Fixed broadband subscriptions	Per 100 people	World Bank
	Mobile cellular subscriptions	Per 100 people	World Bank
	Individuals using the internet	% of population	World Bank
	Households with a computer	% of population	ITU
	Telecommunication infrastructure index	–	UN
	Online service index	–	UN
Human capital and high-skilled labors (19 %)	Human capital index	–	UN
	Wage and salaried workers (formal jobs)	% of population	World Bank
	Employment in services	% of total employment	World Bank
	Output per worker	(GDP constant 2015 US \$)	ILOSTAT
ICT goods trade and capacity to produce technologically sophisticated products (11 %)	ICT goods exports	% of total goods export	World Bank
	ICT goods imports	% of total goods import	World Bank
	Medium and high-tech manufacturing value added	%	World Bank
	manufacturing value added		

Table 2
Institutional quality (InsQuality).

Variable	Description	Source
Corruption control	This variable is measured as the perception the public has of public power used for its private gain.	World Governance Indicators
Rule of law	This variable is measured as the perception the public has confidence that the country's society will abide by its rules.	World Governance Indicators
Regulatory quality	This variable is measured as the perception the public has of the country's government's ability to formulate and impede given policies and regulations for private sector development.	World Governance Indicators
Government effectiveness	This variable is measured as the perception the public has confidence in the ability of the government to provide quality services in such a manner that these services are performed. A degree of independence from political pressure.	World Governance Indicators
Political stability and absence of violence/ Terrorism	This variable is measured as the perception the public has of the likelihood of political instability violence or terrorism occurrences in the country.	World Governance Indicators
Voice and accountability	This variable is measured as the perception the public has of the freedom that citizens have in expression and association, also accounting for the freedom of the media.	World Governance Indicators

have used the proxy. It is important to include CPI as it will provide economic context specifically concerning inflationary pressures. **CO2FuelComb** is included as a control variable to account for emissions produced during fossil fuel consumption [63]. Table 3 shows the description of the control variables used in this study.

3.2. Methodology

The basic regression model in this study can be formulated as follows:

$$\ln SEGFR = F(\ln DEI, \ln InsQuality, \ln Control) \quad (1)$$

Where $\ln SEGFR$ denotes the share of electricity generation from modern renewable energy sources, $\ln DEI$, $\ln InsQuality$, and $\ln Control$ refer to the digital economy, institutional quality, and control variables, respectively. The control variables used in this study are $\ln GDPpc$, $\ln CPI$, and $\ln CO2FuelComb$, which denote per capita gross domestic product,

Table 3
Control variables.

Variable	Description	Unit	Source
Gross Domestic Product per capita	GDP per capita is the gross domestic product of a country divided by the country's mid-year population.	GDP per capita (constant 2015 US \$)	World Bank
CPI	Consumer price index	Base year (2010 = 100)	Our World in Data & FRED St. Louis
CO2FuelComb	CO ₂ emissions originate from the combustion of fossil fuels	CO ₂ fuel combustion (million tonnes of CO ₂)	OECD

consumer price index (a proxy for energy price), and carbon dioxide (CO₂) emissions from the combustion of fossil fuels, respectively. These control variables are incorporated into our model to minimize omitted variable bias and to control for factors other than the digital economy and institutional quality that might affect the share of electricity generation from modern renewables. It is worth noting that all variables are previously transformed into logarithmic terms to reduce variability, heteroskedasticity, and non-normality in our data, and to facilitate the interpretation of the coefficients in terms of elasticities. Prior to conducting regression analyses, a series of preliminary tests are performed to understand the characteristics of the panel data in this study and to identify the appropriate estimation techniques for achieving research goals. This battery of preliminary tests includes a correlation matrix, multicollinearity test, cross-section dependence (CSD) test, unit root test, Hausman test, Wald test, Wooldridge test for autocorrelation, and modified Wald test for group-wise heteroskedasticity.

3.2.1. Benchmark regression analysis (static panel regressions)

After conducting preliminary tests, the two-way fixed effects estimator is used to investigate the impact of explanatory variables—digital economy and institutional quality—on renewable energy deployment, proxied by the share of electricity generation from modern renewable energy sources, employing a static linear regression approach. The use of two-way fixed effects with Driscoll-Kraay Standard Errors as our benchmark model is motivated by the fact that it is robust in the presence of CSD, heteroskedasticity, and serial correlation as indicated by the preliminary tests. Furthermore, the inclusion of both time and country-fixed effects allow us to control for unobserved heterogeneity, which is particularly relevant when studying a broad set of countries with different characteristics such as in our study. The formulation of the static two-way fixed effects regression model is as follows:

$$\ln SEGFR_{it} = \alpha_0 + \beta_1 \ln DEI_{it} + \beta_2 \ln InsQuality_{it} + \beta_3 \ln GDPpc_{it} + \beta_4 \ln CPI_{it} + \beta_5 \ln CO2FuelComb_{it} + \sigma_i + \tau_t + \varepsilon_{it} \quad (2)$$

Where α_0 represents the constant term, β_1 – β_5 are coefficients or parameters to be estimated, σ_i and τ_t denote the country- and time-fixed effects, respectively, and ε_{it} is an independently, and identically distributed disturbance term. The incorporation of both country- and time-fixed effects into our regression model allows for controlling unobserved heterogeneities that remain constant across countries (country-fixed effect) and over time (time-fixed effect), thereby providing a more accurate estimation compared to conventional Ordinary Least Squares (OLS) when such fixed effects are present in our dataset.

3.2.2. Two-step system GMM (dynamic panel regressions)

Once the static panel regression analysis is completed, the dynamic panel regressions are performed. Unlike static panel regressions, dynamic panel regressions account for the path dependence of the dependent variable by incorporating its lagged term as an explanatory variable in the regression model. Moreover, dynamic panel regressions do not assume strict exogeneity of regressors with the error term, unlike static panel regressions. Instead, they allow for the possibility that variables might be predetermined or endogenous, thereby providing more accurate and robust estimates in the presence of endogeneity, reverse causality, and serial correlation.

Specifically, the two-step System GMM [64,65] is used to analyze the impact of the digital economy and institutional quality on renewable energy deployment in this study. The rationale behind employing the two-step System GMM lies in its several advantages over other types of GMM, such as the difference GMM [66], especially when the time period (T) of the panel data is relatively small compared to the number of cross-sections (N), as is the case in this study. In such scenarios, the two-step System GMM not only provides more accurate estimates, but it is also more efficient than the difference GMM. Furthermore, unlike the

difference GMM, the two-step System GMM uses additional moment conditions in which both lagged levels and lagged differences are used as instruments for the differenced and level equations, respectively [67].

The dynamic panel regressions in this study can be formulated as follows:

$$\ln SEGFR_{it} = \alpha_0 + \beta_1 \ln SEGFR_{it-1} + \beta_2 \ln DEI_{it} + \beta_3 \ln \ln Quality_{it} + \beta_4 \ln GDPpc_{it} + \beta_5 \ln CPI_{it} + \beta_6 \ln CO2FuelComb_{it} + \sigma_i + \tau_t + \varepsilon_{it} \quad (3)$$

Where $\ln SEGFR_{it-1}$ denotes the lagged term of the dependent variable ($\ln SEGFR_{it}$) and it is used as an explanatory variable to capture the path dependence of renewable energy deployment.

To examine the moderation effect of institutional quality on the digital economy from the perspective of boosting renewable energy deployment, the interaction term between the digital economy and institutional quality is incorporated into the regression model:

$$\ln SEGFR_{it} = \alpha_0 + \beta_1 \ln SEGFR_{it-1} + \beta_2 \ln DEI_{it} + \beta_3 \ln \ln Quality_{it} + \beta_4 \ln DEI_{it} \ln \ln Quality_{it} + \beta_5 \ln GDPpc_{it} + \beta_6 \ln CPI_{it} + \beta_7 \ln CO2FuelComb_{it} + \sigma_i + \tau_t + \varepsilon_{it} \quad (4)$$

Where $\ln DEI_{it} \ln \ln Quality_{it}$ is a term representing the interaction between the digital economy and institutional quality.

3.2.3. Sub-sample analysis in terms of fossil fuel rents

Given the heterogeneous feature of the panel data of this study in the sense that economic development, energy mix, level of technological advancement, institutional quality, and resource endowments differ significantly across countries, the countries are divided into two groups by the median value of the average annual mean of a country's fossil fuel rents as a share of GDP (FFR). Countries with an FFR above the median are classified as having high reliance on fossil fuels, whereas those with an FFR below the median are classified as having low reliance on fossil fuels. After categorizing the countries into two different groups, the impact of both the digital economy and institutional quality on renewable energy deployment is thoroughly analyzed in these two groups to determine whether significant differences exist in terms of FFR.

For those countries with high reliance on fossil fuels, the following equation is used:

$$\ln SEGFR_{it} = \alpha_0 + \beta_1 \ln SEGFR_{it-1} + \beta_2 \ln DEI_{it} + \beta_3 \ln \ln Quality_{it} + \beta_4 \ln GDPpc_{it} + \beta_5 \ln CPI_{it} + \beta_6 \ln CO2FuelComb_{it} + \sigma_i + \tau_t + \varepsilon_{it} \quad (5)$$

where $FFR_i \geq \text{med}(FFR_i)$

Here, FFR_i refers to the annual average value of fossil fuel rents of country i and $\text{med}(FFR_i)$ denotes the median of average annual value of fossil fuel rents of all countries.

Conversely, for those countries with low reliance on fossil fuels, the following equation is used:

$$\ln SEGFR_{it} = \alpha_0 + \beta_1 \ln SEGFR_{it-1} + \beta_2 \ln DEI_{it} + \beta_3 \ln \ln Quality_{it} + \beta_4 \ln GDPpc_{it} + \beta_5 \ln CPI_{it} + \beta_6 \ln CO2FuelComb_{it} + \sigma_i + \tau_t + \varepsilon_{it} \quad (6)$$

where $FFR_i < \text{med}(FFR_i)$

3.2.4. Dynamic panel threshold regression

Given the potential non-linear impacts of fossil fuel dependence on the nexus between the digital economy, institutional quality, and renewable energy deployment, a dynamic panel threshold regression, developed by Seo and Shin [68] is used to analyze such effects. The dynamic panel threshold model by Seo and Shin [68] is based on other first-differenced GMM estimation method, effectively addressing endogeneity issues by allowing both threshold and regressors to be endogenous. Unlike the static panel threshold regression model, the dynamic panel threshold model used in this study does not require the covariates

to be strictly exogenous to obtain consistent estimates. Moreover, the dynamic panel threshold regression produces consistent and asymptotically normal estimates and is particularly suitable when the number of entities (N) is much larger than the number of years (T), as is the case in our study. According to Seo and Shin [68] and Seo et al. [69], the generic dynamic panel can be formulated as follows:

$$Y_{it} = (1, X'_{it})\phi_1 * I\{q_{it} \leq \gamma\} + (1, X'_{it})\phi_2 * I\{q_{it} > \gamma\} + \mu_i + \varepsilon_{it} \quad (7)$$

Where $i = 1, \dots, n$ and $t = 1, \dots, T$

Here, Y_{it} is the dependent variable, X_{it} is $K_i \times 1$ vector of time-varying regressors, $I\{\cdot\}$ is an indicator function, q_{it} is the threshold variable, ϕ_1 and ϕ_2 are the slope coefficients related to different regimes, and γ refers to the critical threshold value.

Adapting this generic form of dynamic panel threshold regression to our specific case:

$$\begin{aligned} \ln SEGFR_{it} = & (\phi_1 \ln SEGFR_{it-1} + \theta_{11} \ln DEI_{it} + \theta_{21} \ln \ln Quality_{it} + \theta_{31} \ln GDPpc_{it} \\ & + \theta_{41} \ln CPI_{it} + \theta_{51} \ln CO2FuelComb_{it}) * I\{FFR_{it} \leq \gamma\} \\ & + (\phi_2 \ln SEGFR_{it-1} + \theta_{12} \ln DEI_{it} + \theta_{22} \ln \ln Quality_{it} \\ & + \theta_{32} \ln GDPpc_{it} + \theta_{42} \ln CPI_{it} + \theta_{52} \ln CO2FuelComb_{it}) * I\{FFR_{it} > \gamma\} \\ & + \mu_i + \varepsilon_{it} \end{aligned} \quad (8)$$

3.2.5. Method of moments quantile regression (MMQR)

To examine the asymmetric impacts of the digital economy and institutional quality on renewable energy deployment, the MMQR is used. Given the heterogeneous and diverse nature of countries included in panel data, the impacts of the digital economy and institutional quality on renewable energy deployment are expected to vary significantly and may not have uniform and homogenous effects across all countries. The MMQR, developed by Machado and Silva [70], is particularly useful in this context because it enables to estimate of the impacts of regressors on the conditional mean of the dependent variable, namely, it allows for the estimation of marginal impacts of each regressor at specific quantile distributions of the dependent variable [70]. Furthermore, the MMQR is robust in the presence of outliers, heteroskedasticity, and non-normal distributions, as it does not rely on specific distributional assumptions during estimation [71]. Additionally, the MMQR is a nonparametric regression method, meaning that it does not assume any particular functional form, which is useful when the relationships between the outcome variable and the independent variables are non-linear. This robustness makes the MMQR particularly useful for achieving the research goal of this study on analyzing the asymmetric impacts of both the digital economy and institutional quality on renewable energy deployment.

The generic MMQR model can be formulated as follows:

$$Q_Y(\tau|X_{it}) = (\alpha_i + \delta_i q(\tau)) + X'_{it}\beta + Z'_{it}\gamma q(\tau) \quad (9)$$

Where $Q_Y(\tau|X_{it})$ refers to the conditional quantile distribution of the dependent variable Y , τ represents quantile, X'_{it} denotes k -vector of covariates, $\alpha, \delta, \beta, \gamma$ represent the parameters of interest to be estimated, the term $(\alpha_i + \delta_i q(\tau))$ indicates the scalar coefficient which refers to the quantile fixed effect for an individual country, and Z_{it} represents a k -vector of known components of X_{it} normalized to satisfy the moment conditions [36,70].

Adapting the generic form of MMQR to our specific case:

$$Q_{\ln SEGFR}(\tau|X_{it}) = (\alpha_i + \delta_i q(\tau)) + X'_{it}\beta + Z'_{it}\gamma q(\tau) \quad (10)$$

Where $Q_{\ln SEGFR}(\tau|X_{it})$ represents the quantile distribution of $\ln SEGFR$ and X_{it} is the vector of explanatory variables composed of $\ln DEI$,

² It may include lagged dependent variable, Y_{it-1} .

lnInsQuality, lnGDPpc, lnCPI, lnCO2FuelComb.

4. Empirical findings

4.1. Preliminary tests

Before conducting the benchmark regression analysis of this study (static panel regressions), a set of preliminary tests were performed.³ Firstly, the correlation matrix revealed significant correlations at the 1 % level between the dependent and independent variables, suggesting a priori that the independent variables chosen for our regression model are pertinent to explaining the deployment of renewable energy (lnSEGFR), which is dependent variable in this study. The correlation matrix also indicated that there was a high positive correlation between lnDEI and lnGDPpc (0.7333 at the 1 % significance level), as well as between lnInsquality and lnGDPpc (0.8365 at the 1 % significance level). Conversely, high negative correlation between lnDEI and lnDEI lnInsQuality (−0.8546 at the 1 % significance level), and between lnInsQuality and lnDEI lnInsQuality (−0.8899 at the 1 % significance level) were found, indicating the necessity of performing a multicollinearity test before proceeding with the regression analysis. The results of the multicollinearity test revealed a mean-variance inflation factor (VIF) of 8.31, which falls below 10. This indicates a moderate correlation among the variables, suggesting that multicollinearity is not a serious concern in this study [72]. After conducting the multicollinearity test, the Pesaran cross-section dependence (CSD) test was performed. The results revealed that all variables have CSD, as the null hypothesis of weak cross-section dependence was rejected at the 1 % significance level for all variables. Subsequently, the second-generation unit root test (CIPS test),⁴ developed by Pesaran [73], was carried out to examine the presence of unit roots in the variables. The CIPS tests showed that most variables (lnSEGFR, lnDEI, lnGDPpc, lnCPI, and lnCO2FuelComb) were not stationary at levels, but became stationary after first differencing, indicating that they are integrated of order 1. After that, Westerlund cointegration tests were applied to examine whether the variables used in this study have jointly stable long-run equilibrium relationships between them. The tests showed that all the variables in this study are strongly cointegrated, as the null hypothesis of no cointegration was rejected at the 1 % significance level. Hausman tests followed Westerlund cointegration tests. According to Hausman tests, all the regression models have fixed effects since the null hypothesis of a non-systematic difference in coefficients was rejected at the 1 % significance level. After that, time-fixed effects tests were performed to examine the existence of unobserved heterogeneities that remain constant over time. The results of the tests indicated that time-fixed effects are present in our model. Lastly, Wooldridge test and modified Wald test results indicated that autocorrelation of order 1 and heteroskedasticity should be considered in our model, given that the null hypotheses of no first-order autocorrelation and absence of groupwise heteroskedasticity were strongly rejected at the 1 % significance level.

4.2. Driscoll-Kraay two-way fixed-effects (static panel regressions)

Based on previous preliminary tests, the Driscoll-Kraay two-way fixed-effects estimator is used to evaluate the impacts of the digital economy and institutional quality on renewable energy deployment in static panel regressions. This is because the Driscoll-Kraay two-way fixed-effects estimator is robust in handling first order autocorrelation and heteroskedasticity present in our regression models [74], as demonstrated in Wooldridge and modified Wald tests previously.

The estimation results in Table 4 indicate that the digital economy

has a strong positive impact on renewable energy deployment and its impact is shown to be robust, as the coefficients of lnDEI are positive and statistically significant at the 1 % level across different model specifications. When it comes to institutional quality, its impact on renewable energy deployment was negative and statistically significant at the 1 % level, except when a time-fixed effect was incorporated into the regression model. In this case, the coefficient of lnInsQuality was negative and statistically significant at the 10 % level.

4.3. Two-step system GMM (dynamic panel regressions)

Since static panel regressions do not take into account the path dependence of renewable energy deployment and the endogeneity issue, dynamic panel regressions, specifically the two-step System GMM, were applied to address them.

As shown in Table 5, the p-values of Arellano-Bond tests for the first-order autocorrelation in all specifications are statistically significant, thus rejecting the null hypothesis of no first-order autocorrelation in the error term. However, the same tests for the second-order autocorrelation indicate that all p-values are greater than 0.10, meaning that there is no second-order autocorrelation in the error term of our regression models. Regarding the Sargan-Hansen tests, the results indicate that the instruments selected in our regression models are valid, as the null hypothesis (the overidentifying restrictions are valid) is not rejected across all specifications.

According to the estimates from the two-step System GMM, the digital economy is found to have a strong positive impact on renewable energy deployment, as the coefficients of lnDEI are positive and statistically significant at the 1 % level, except when the time effect is considered. In this case, the coefficient of lnDEI is positive but not statistically significant anymore. Regarding institutional quality, its impact on renewable energy deployment is positive and statistically significant, except when a time effect is considered. It is worth noting that, unlike in static panel regressions where the impact of institutions on renewable energy deployment is systematically negative, once the path-dependence nature of renewable energy deployment and the endogeneity issue is appropriately addressed, the sign of the coefficient of lnInsQuality becomes positive and statistically significant.

To examine the moderation effect of institutional quality on the digital economy in fostering renewable energy deployment, the interaction term lnDEI lnInsquality is incorporated into our regression models.

As shown in Table 6, the digital economy has a significant positive impact on renewable energy deployment when the interaction term between lnDEI and lnInsQuality is included in the regression model. This finding is consistent with the estimates from the previous regression model without including the interaction term. Regarding institutional quality, it is found to have a positive and statistically significant impact on renewable energy deployment but unlike the digital economy, its impact is not significant in all specifications (see columns 2, 4, and 6 in Table). When it comes to the interaction term between the digital economy and institutional quality, it generally has a positive and significant impact on renewable energy deployment. However, in columns 4 and 5 of the table, the coefficient of lnDEI lnInsQuality is positive but not statistically significant.

4.4. Sub-sample analysis

After analyzing the aggregated sample, a sub-sample analysis is conducted. Given the large number of countries in the panel data of this study, the countries are divided into two groups in terms of fossil fuel resource rents as a share of GDP (FFR), which are used as a proxy for fossil fuel dependency in this study. The rationale for dividing countries based on fossil fuel rents to conduct a sub-sample analysis can be justified as follows:

From the perspective of the digital economy, countries with

³ See Appendix for complete results of preliminary tests.

⁴ Unlike first-generation panel unit root tests, the second-generation panel unit root tests are robust in the presence of cross-sectional dependence.

Table 4

Driscoll-Kraay Two-way Fixed effects.

Dependent variable: lnSEGFR						
	(1)	(2)	(3)	(4)	(5)	(6)
lnDEI	3.794*** (0.285)	3.878*** (0.279)	3.566*** (0.406)	3.592*** (0.411)	3.772*** (0.431)	1.937*** (0.652)
lnInsQuality		−0.930*** (0.163)	−1.091*** (0.185)	−1.101*** (0.186)	−0.881*** (0.206)	−0.377* (0.208)
lnGDPpc			0.632* (0.339)	0.655* (0.339)	1.291*** (0.318)	0.644* (0.363)
lnCPI				−0.034 (0.040)	−0.014 (0.043)	−0.046 (0.038)
lnCO2FuelComb					−1.326*** (0.132)	−0.861*** (0.137)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	Yes
Constant	−0.910*** (0.287)	−1.547*** (0.331)	−7.691** (3.468)	−7.732** (3.476)	1.215 (3.917)	0.351 (4.261)
Observations	1615	1615	1615	1615	1615	1615
Countries	85	85	85	85	85	85
Within R ²	0.369	0.372	0.374	0.374	0.394	0.426

Note: () indicates Driscoll-Kraay robust standard errors. ***, **, * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 5

Two-step System GMM for aggregate sample (without interaction term).

Dependent variable: lnSEGFR						
	(1)	(2)	(3)	(4)	(5)	(6)
L1.lnSEGFR	0.938*** (0.027)	0.935*** (0.024)	0.940*** (0.035)	0.919*** (0.034)	0.904*** (0.033)	0.947 (0.034)
lnDEI	0.297** (0.128)	0.245** (0.117)	1.025*** (0.235)	0.992*** (0.229)	1.163*** (0.284)	1.644 (0.509)
lnInsQuality		0.829** (0.473)	1.577* (0.897)	1.255** (0.589)	2.060** (0.944)	1.574 (1.007)
lnGDPpc			−1.580*** (0.532)	−1.092*** (0.412)	−1.233** (0.502)	−0.580 (0.496)
lnCPI				−0.069 (0.063)	−0.030 (0.064)	−0.049 (0.068)
lnCO2FuelComb					−0.358 (0.247)	−0.806 (0.400)
Constant	0.147*** (0.052)	0.720** (0.361)	16.380*** (5.429)	11.908*** (4.012)	17.580*** (5.039)	16.926 (6.118)
Time effect	No	No	No	No	No	Yes
Arellano-Bond test for autocorrelation of the first-differenced residuals						
H0: no autocorrelation of order 1	−2.270**	−2.263**	−2.290**	−2.280**	−2.271**	−2.263**
H0: no autocorrelation of order 2	0.384	0.392	0.392	0.430	0.417	0.423
Sargan-Hansen test of the overidentifying restrictions						
2-step moment function, 2-step weighting matrix	2.473	7.040	15.171	17.802	21.265	15.288
2-step moment functions, 3-step weighting matrix	2.476	6.932	13.461	18.515	22.635	36.741

Note: () indicates cluster error. ***, **, * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

relatively high reliance on fossil fuels typically base their economies on commodity exports. These nations are characterized by low levels of economic diversification and complexity. Moreover, they often lack high-skilled labor and high-quality digital infrastructure. Such deficiencies hinder their ability to leverage the digital economy to enhance renewable energy deployment. This limitation is primarily due to their restricted capacity to absorb advanced technologies and the low quality of their existing infrastructure.

From the perspective of institutional quality, countries with a relatively high reliance on fossil fuels may face significant challenges in transitioning to low-carbon energy, compared to countries with lower reliance on these fuels. This is because of the lock-in of carbon-intensive fossil fuel technologies within their economies, and the vested interests and strong political lobbying power of fossil fuel companies in the government decision-making process.

To divide countries into two different groups in terms of fossil fuel rents (FFR),⁵ firstly, the average annual FFR for each country is calculated. And then, the median value of these averages for all countries in the panel data is computed, which is 0.3645. The sub-sample analysis is conducted using a two-step System GMM.

The results presented in Table 7 reveal that in countries with relatively high dependence on fossil fuels, the impacts of both the digital economy and institutional quality on renewable energy deployment are not statistically significant.

When it comes to countries with relatively low dependence on fossil fuels, the impacts of the digital economy and institutional quality on

⁵ The complete list of countries with average annual fossil fuel rents (FFR) below and above the median value is included in the appendix.

Table 6

Two-step System GMM for aggregate sample (with interaction term).

Dependent variable: lnSEGFR							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L1.lnSEGFR	0.939*** (0.029)	0.938*** (0.025)	0.901*** (0.038)	0.940*** (0.033)	0.911*** (0.042)	0.898*** (0.052)	0.906*** (0.047)
lnDEI	0.294** (0.143)	0.229* (0.119)	1.866*** (0.683)	0.940** (0.469)	1.432** (0.602)	1.963** (0.885)	3.464*** (1.029)
lnInsQuality		0.709 (0.438)	4.823*** (1.693)	1.947 (1.352)	2.733* (1.549)	3.948 (1.950)	5.213** (2.111)
lnDEI_lnInsQuality			1.702** (0.689)	0.419 (0.397)	0.634 (0.620)	1.181** (0.977)	1.787** (0.847)
lnGDPpc				−0.743* (0.421)	−0.976*** (0.358)	−1.090 (0.551)	−0.726 (0.624)
lnCPI					−0.052 (0.068)	−0.040 (0.065)	−0.030 (0.049)
lnCO2FuelComb						0.083 (0.298)	−0.505 (0.548)
Constant	0.145*** (0.054)	0.624* (0.333)	3.706*** (1.281)	8.651* (4.487)	11.736*** (3.677)	12.786** (5.507)	17.768*** (6.044)
Time effect	No	No	No	No	No	No	Yes
Arellano-Bond test for autocorrelation of the first-differenced residuals							
H0: no autocorrelation of order 1	−2.269**	−2.267**	−2.239**	−2.274**	−2.247**	−2.237**	−2.266**
H0: no autocorrelation of order 2	0.383	0.391	0.425	0.690	0.433	0.438	0.438
Sargan-Hansen test of the overidentifying restrictions							
2-step moment function, 2-step weighting matrix	5.678	8.884	12.708	24.023	31.083	34.804	19.608
2-step moment functions, 3-step weighting matrix	5.709	8.944	12.345	26.877	35.712	41.953	46.413

Note: () indicates robust error. ***, **, * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 7

Sub-sample analysis of countries with relatively high reliance on fossil fuel rents (FFR>0.3645).

Dependent variable: lnSEGFR					
	(1)	(2)	(3)	(4)	(5)
L1.lnSEGFR	0.998*** (0.041)	0.943*** (0.045)	0.971*** (0.042)	0.953*** (0.053)	0.927*** (0.051)
lnDEI	0.076 (0.157)	0.148 (0.194)	−0.001 (0.301)	0.343 (0.391)	0.398 (0.325)
lnInsQuality		1.058 (0.744)	0.500 (0.455)	0.750 (0.610)	0.617 (0.582)
lnGDPpc			0.258 (0.391)	−0.326 (0.620)	−0.050 (0.643)
lnCPI				0.011 (0.027)	0.010 (0.027)
lnCO2FuelComb					−0.336 (0.621)
Constant	0.213** (0.096)	0.919 (0.597)	−1.884 (3.853)	3.764 (6.125)	5.074 (5.516)
Arellano-Bond test for autocorrelation of the first-differenced residuals					
H0: no autocorrelation of order 1	−1.737*	−1.727*	−1.735*	−1.730*	−1.716**
H0: no autocorrelation of order 2	0.692	0.700	0.697	0.693	0.691
Sargan-Hansen test of the overidentifying restrictions					
2-step moment function, 2-step weighting matrix	2.091	7.054	11.740	18.428	21.200
2-step moment functions, 3-step weighting matrix	2.064	7.057	12.321	20.282*	22.05

Note: () indicates robust error. ***, **, * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

renewable energy deployment are positive and statistically significant (except in columns 1 and 2 for the digital economy and institutional quality). The results shown in Table 8 clearly contrast with those obtained for countries with a relatively high dependence on fossil fuels, where both the digital economy and institutional quality are found to have no meaningful impact on renewable energy deployment.

4.5. Panel threshold regression analysis

After confirming the heterogeneous impacts of the digital economy and institutional quality on renewable energy deployment in association with fossil fuel dependence, the potential non-linear impacts of the digital economy and institutional quality on renewable energy deployment are examined using panel threshold regressions. Specifically, the dynamic panel threshold model developed by Seo and Shin [68] is applied for this purpose, as it addresses the endogeneity issue by incorporating the lagged term of the dependent variable (lnSEGFR(-1)) in the threshold regression.

Table 9 shows that, depending on whether a country's fossil fuel dependence is above or below the threshold value, the impacts of the digital economy and institutional quality on renewable energy deployment differ significantly and exhibit non-linear and asymmetric impacts. Specifically, for countries with fossil fuel rents below the threshold (countries with relatively low dependence on fossil fuels), both the digital economy and institutional quality have positive and significant impacts at the 1 % level on renewable energy deployment. Conversely, for countries with fossil fuel rents above the threshold (countries with relatively high dependence on fossil fuels), only the digital economy is found to have a positive and significant impact on renewable energy deployment, at the 5 % level.

4.6. Method of moments quantile regression (MMQR)

Before proceeding with MMQR, the Shapiro-Wilk test and Skewness/Kurtosis test are carried out to examine the normality of the residuals of renewable energy deployment (lnSEGFR). According to the Shapiro-Wilk test and Skewness/Kurtosis test, the null hypothesis of normality

Table 8

Sub-sample analysis of countries with relatively low reliance on fossil fuel rents (FFR ≤ 0.3645).

Dependent variable: lnSEGFR					
	(1)	(2)	(3)	(4)	(5)
L1.lnSEGFR	0.900*** (0.032)	0.874*** (0.047)	0.885*** (0.052)	0.900*** (0.049)	0.886*** (0.053)
lnDEI	0.268 (0.200)	0.531* (0.281)	1.300*** (0.431)	1.312*** (0.402)	1.398*** (0.486)
lnInsQuality		2.615 (1.647)	2.131*** (0.602)	1.733* (0.966)	3.056** (1391)
lnGDPpc			−1.550** (0.680)	−1.305 (0.867)	−1.086 (0.967)
lnCPI				−0.173 (0.178)	−0.177 (0.163)
lnCO2FuelComb					−0.384 (0.263)
Constant	0.015 (0.075)	1.827 (1.181)	16.475** (6.613)	14.842* (8.278)	17.660* (9.002)
Arellano-Bond test for autocorrelation of the first-differenced residuals					
H0: no autocorrelation of order 1	−1.892*	−1.867*	−1.915*	−1.932*	−1.948*
H0: no autocorrelation of order 2	−1.048	−1.074	−1.064	−1.381	−1.391
Sargan-Hansen test of the overidentifying restrictions					
2-step moment function, 2-step weighting matrix	6.330	3.743	9.493	13.306	11.223
2-step moment functions, 3-step weighting matrix	6.771	4.109	9.840	15.674	14.390

Note: () indicates robust error. ***, **, * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

is strongly rejected at the 1 % significance level, justifying the use of MMQR to analyze the impact of the digital economy and institutional quality on renewable energy deployment, given the non-normal distribution of the dependent variable and potential asymmetric impacts the digital economy and institutional quality might have on renewable energy deployment [74].

Table 10 shows that the impact of the digital economy on renewable energy deployment is positive and statistically significant at the 1 % level across all quantile distributions, suggesting that regardless of a

country's share of renewable energy in the electricity mix, the digital economy significantly boosts renewable energy deployment in this study. Conversely, the impact of institutional quality on renewable energy deployment is significant only at the 60th and 70th quantiles. Furthermore, the coefficient sign of lnInsQuality is negative, indicating no evidence of institutional quality fostering renewable energy deployment and its influence on significantly affecting the share of renewable energy in the electricity mix remains ambiguous in MMQR.

4.7. Robustness tests

For the static model, the Instrumental Variable-Two-Stage Least Squares (IV-2SLS) method is performed to examine the robustness of our estimates, which effectively addresses the endogeneity issue by using an instrumental variable. As shown in Table 11, the coefficients for the digital economy (lnDEI) are positive and statistically significant at the 1 % level, confirming the robustness of our estimates. Regarding institutional quality, the robustness test reveals no statistically significant impact on renewable energy deployment, although the coefficients for lnInsQuality are negative, as in previous estimates.

For the dynamic model, Continuously Updated Two-Step System GMM [75] is used to check the robustness of estimates. The Continuously Updated Two-Step System GMM is particularly useful in cases of finite samples, where the estimation of the optimal weighting matrix might be sensitive to the arbitrary selection of the initial weighting matrix [76]. This method addresses this issue by allowing for the direct obtention of an optimal weighting matrix through a part of the minimization process [76]. As shown in Table 12, both the digital economy and institutional quality have positive impacts on renewable energy deployment across all specifications, except when time effects are included. In such cases, the coefficient of the digital economy is positive but not statistically significant. The results from the Continuously Updated Two-Step System GMM indicate that our previous estimates using the Two-Step System GMM are both robust and consistent.

As for the moderation effect of the digital economy and institutional quality on renewable energy deployment, the Continuously Updated Two-Step System GMM confirms the robustness of our estimates. The signs and significance levels of the coefficients for the variables of interest, namely lnDEI, lnInsQuality, and the interaction term lnDEI_lnInsQuality, are consistent with previous estimates from the Two-Step System GMM. In general, the digital economy, institutional quality, and their synergy (interaction term) significantly promote renewable energy deployment. However, the impact of institutional quality was not significant in columns 2, 4, and 6 of Table 13, while in columns 4 and 5, the interaction term was not statistically significant, although the

Table 9

Dynamic panel threshold regression.

lnSEGFR	Coefficient	Std. err.	z	P-value	[95 % conf. interval]	
Below the threshold						
llnSEGER(-1)	0.847***	0.011	78.5	0.000	0.826	0.868
lnInsQuality	0.989***	0.155	6.36	0.000	0.685	1.294
lnGDPpc	0.372***	0.076	4.92	0.000	0.224	0.521
lnCPI	−0.079***	0.005	−14.85	0.000	−0.09	−0.069
lnCO2FuelComb	−0.223***	0.076	−2.95	0.003	−0.371	−0.075
lnDEI	0.563***	0.085	6.6	0.000	0.396	0.73
Above the threshold						
cons	−4.428***	1.351	−3.28	0.001	−7.075	−1.78
llnSEGER(-1)	−0.277***	0.017	−15.85	0.000	−0.311	−0.243
lnInsQuality	−0.031	0.233	−0.13	0.895	−0.488	0.427
lnGDPpc	−0.820***	0.11	−7.47	0.000	−1.036	−0.605
lnCPI	0.043***	0.009	4.52	0.000	0.024	0.061
lnCO2FuelComb	0.882***	0.027	33.06	0.000	0.829	0.934
lnDEI	0.465**	0.188	2.47	0.013	0.096	0.833
Threshold (r)	2.281***	0.701	3.25	0.001	0.907	3.654

Note: lnDEI is specified as the endogenous variable in this regression. ***, **, * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 10
Method of moments quantile regression.

Dependent Variable: lnSEGFR		Location								
	Scale	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
lnDEI	0.082 (0.347)	3.651*** (0.837)	3.683*** (0.714)	3.710*** (0.609)	3.736*** (0.518)	3.770*** (0.405)	3.806*** (0.320)	3.835*** (0.293)	3.860*** (0.309)	3.894*** (0.380)
lnInsQuality	0.227 (0.463)	-1.215 (1.118)	-1.128 (0.954)	-1.052 (0.814)	-0.982 (0.692)	-0.886 (0.542)	-0.787* (0.428)	-0.708* (0.391)	-0.637 (0.413)	-0.544 (0.508)
lnGDPpc	0.412 (0.736)	1.898 (1.775)	1.740 (1.514)	1.602 (1.293)	1.474 (1.100)	1.299 (0.861)	1.119 (0.679)	0.976 (0.622)	0.847 (0.657)	0.677 (0.807)
lnCPI	-0.062 (0.071)	0.077 (0.171)	0.053 (0.146)	0.033 (0.125)	0.014 (0.106)	-0.013 (0.083)	-0.040 (0.065)	-0.061 (0.060)	-0.081 (0.063)	-0.106 (0.078)
lnCO2FuelComb	0.023 (0.323)	-1.361** (0.675)	-1.352** (0.576)	-1.344*** (0.492)	-1.337*** (0.418)	-1.327*** (0.327)	-1.317*** (0.258)	-1.309*** (0.236)	-1.301*** (0.250)	-1.292*** (0.307)
Constant	4.807 (7.395)	-5.861 (17.828)	-4.019 (15.21)	-2.404 (12.988)	-0.919 (11.045)	1.122 (8.648)	3.223 (6.827)	4.888 (6.249)	6.401 (6.599)	8.377 (8.106)

Note: 0 indicates standard error. ***, **, * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 11

Robustness test for static model (IV-2SLS).

Dependent Variable: lnSEGFR					
lnDEI	4.542*** (0.457)	4.633*** (0.458)	4.936*** (0.560)	4.972*** (0.565)	5.233*** (0.589)
lnInsQuality		-1.011 (0.691)	-0.855 (0.661)	-0.872 (0.665)	-0.571 (0.682)
lnGDPpc			-0.663 (1.249)	-0.637 (1.253)	0.204 (1.269)
lnCPI				-0.045 (0.038)	-0.024 (0.035)
lnCO2FuelComb					-1.679*** (0.455)
Constant	-0.347 (0.343)	-1.041* (0.589)	5.384 (11.829)	5.370 (11.849)	16.422 (12.212)
Observations	1360	1360	1360	1360	1360

Note: Cluster errors in parentheses. lnDEI is considered as the endogenous variable, and two-lagged terms (l2.lnDEI) and three-lagged terms (l3.lnDEI) are employed as instrumental variables in this regression. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

coefficients were positive.

When it comes to the robustness of sub-sample analysis, the Continuously Updated Two-Step System GMM reveals that previous estimates from the Two-Step System GMM are robust and consistent with the results of the robustness tests.

As shown in Table 14, for countries with high reliance on fossil fuels, the impacts of both the digital economy and institutional quality on renewable energy deployment are far from clear. In the former case, we found its significant and positive impact only in column 5. As for institutional quality, the positive and statistically significant impact was observed only in columns 2 and 5.

As shown in Table 15, for countries with low reliance on fossil fuels, the impacts of the digital economy and institutional quality on promoting renewable energy deployment are found to be positive and statistically significant, aligning with previous estimates from the Two-Step System GMM analysis. This contrasts sharply with countries highly reliant on fossil fuels, where the impacts of both the digital economy and institutional quality on renewable energy deployment are ambiguous.

To examine the robustness of dynamic panel threshold regression, panel threshold regression with kink specification is performed. According to Seo and Shin [68], kink specification is particularly useful when the function is continuous but might have a discontinuity at a threshold point. The robustness test in Table 16 indicates that the sign and significance level of the coefficients of lnDEI and lnInsQuality do not change significantly (remaining positive and statistically significant at the 1 % level), thereby confirming the robustness of our previous findings in the dynamic panel threshold regression.

Lastly, to examine the robustness of Method of Moments Quantile Regression (MMQR) obtained previously, Generalized Quantile Regression [77] is performed. The Generalized Quantile Regression effectively accounts for the endogeneity issue and allows for estimating unconditional quantile treatment effects, even in the presence of endogenous and additional control variables [77]. Table 17 shows that the impact of the digital economy on renewable energy deployment is positive and statistically significant across all quantile groups, in line with previous estimates from MMQR. Regarding institutional quality, its impact on renewable energy deployment is positive and statistically significant at Q10, Q20, Q30, and Q50, while at Q40 and Q80, its impact is negative and statistically significant. At the remaining quantiles, Q60, Q70, and Q90, its impact is not significant. These results are in line with previous estimates from MMQR, as we could not verify a robust and significant impact of institutional quality on renewable energy deployment across the quantile distribution.

Table 12
Robustness test for Dynamic model (Continuously Updated Two-Step System GMM).

Dependent Variable: lnSEGFR						
	(1)	(2)	(3)	(4)	(5)	(6)
L1.lnSEGFR	0.939*** (0.025)	0.943*** (0.022)	0.959*** (0.025)	0.944*** (0.024)	0.914*** (0.023)	1.065*** (0.016)
lnDEI	0.295** (0.125)	0.217* (0.115)	1.075*** (0.262)	1.140*** (0.248)	0.897*** (0.215)	0.276 (0.179)
lnInsQuality		1.340** (0.606)	2.135*** (0.701)	2.312*** (0.580)	2.709*** (0.617)	4.675*** (0.509)
lnGDPpc			−1.857*** (0.544)	−1.749*** (0.443)	−0.894*** (0.370)	−0.292 (0.271)
lnCPI				−0.000 (0.021)	0.014 (0.015)	−0.034** (0.014)
lnCO2FuelComb					−0.376** (0.151)	−0.376*** (0.126)
Constant	0.149*** (0.049)	1.114** (0.454)	19.409*** (5.395)	18.557*** (4.287)	14.783*** (4.443)	10.810*** (2.693)
Time effect	No	No	No	No	No	Yes
Underidentification test (Kleibergen-Paap rk LM statistic):	36.881***	19.342*	33.817***	36.707***	42.050***	64.597***
Weak identification test (Cragg-Donald Wald F statistic):	14.015	0.564	0.045	0.037	0.035	0.056
Hansen J statistic (overidentification test of all instruments):	2.472	6.675	12.316	15.570	17.863	38.707

Note: () indicates robust error. ***, **, * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 13
Robustness test for Dynamic model with interaction term (Continuously Updated Two-Step System GMM).

Dependent Variable: lnSEGFR							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
L1.lnSEGFR	0.939*** (0.025)	0.941*** (0.020)	0.906*** (0.041)	0.951*** (0.036)	0.869*** (0.023)	0.901*** (0.016)	0.878*** (0.013)
lnDEI	0.297** (0.125)	0.217** (0.101)	2.299*** (0.601)	1.868*** (0.560)	2.369*** (0.336)	1.700*** (0.255)	2.247*** (0.177)
lnInsQuality		0.776** (0.382)	6.773*** (1.984)	7.540*** (1.591)	4.341*** (0.647)	2.486*** (0.589)	5.059*** (0.478)
lnDEI_lnInsQuality			2.274*** (0.604)	1.788*** (0.455)	1.538*** (0.260)	0.453 (0.279)	1.981*** (0.190)
lnGDPpc				−0.837*** (0.549)	−1.149*** (0.345)	−0.921*** (0.287)	−0.754*** (0.154)
lnCPI					0.005 (0.012)	−0.478*** (0.091)	−0.008 (0.006)
lnCO2FuelComb						0.106 (0.126)	0.268** (0.110)
Constant	0.147*** (0.049)	0.678** (0.285)	5.139*** (1.473)	13.520** (5.731)	14.215*** (3.403)	12.133*** (2.723)	7.693*** (1.570)
Time effect	No	No	No	No	No	No	Yes
Underidentification test (Kleibergen-Paap rk LM statistic):	37.027***	21.222*	21.256	46.707***	49.212***	50.401**	71.799**
Weak identification test (Cragg-Donald Wald F statistic):	11.354	0.472	0.030	0.022	0.019	0.014	0.028
Hansen J statistic (overidentification test of all instruments):	5.704	8.915	11.494	20.993	32.324	36.244	56.584

Note: () indicates robust error. ***, **, * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

5. Discussion of findings

Based on the empirical results of this study, several key findings can be highlighted as follows:

In all models, the lagged term of renewable energy deployment had a positive and significant effect on renewable energy deployment. This indicates that renewable energy deployment has a path-dependent nature, and its past evolution affects importantly current and future status of renewable energy deployment.

The digital economy was found to have a positive and significant effect on renewable energy deployment in the aggregate models, confirming the validity of [Hypothesis 1](#) of this study. However, it is worth noting that in the sub-sample analysis, the digital economy had no meaningful impact on renewable energy deployment in countries with a relatively high dependence on fossil fuels, whereas in countries with relatively lower reliance on fossil fuels, the digital economy had a

positive and significant effect on renewable energy deployment. The estimated results for the aggregate model and the group with less reliance on fossil fuels are similar to those of Wang et al. [5,6], who found that the digital economy positively impacts renewable energy generation in Asian countries. Furthermore, the authors also found that the effect of the digital economy on fostering renewable energy generation significantly differs in terms of a country's economic development levels and geographical location. Specifically, in high-income countries with relatively well-established digital infrastructure (East and South Asian economies), the impact of the digital economy on boosting renewable energy generation was much stronger than the others. Shahbaz et al. [1] argue that digital development can lead to improvements in the energy transition to a low-carbon economy. Therefore, it is important to consider the digital economy as an effective instrument for governments to use within the energy transition.

Advancements in renewable energy deployment are accompanied by

Table 14

Robustness test for Sub-sample analysis for countries with high reliance on fossil fuels (Continuously Updated Two-Step System GMM).

	(1)	(2)	(3)	(4)	(5)
L1.lnSEGFR	0.999*** (0.040)	1.055*** (0.065)	0.958*** (0.027)	0.994*** (0.060)	0.916*** (0.023)
lnDEI	0.077 (0.159)	−0.407 (0.409)	0.097 (0.205)	−0.352 (0.585)	0.314* (0.161)
lnInsQuality		5.984** (2.422)	0.421 (0.280)	6.164 (2.049)	0.737*** (0.339)
lnGDPpc			0.173 (0.298)	−1.105 (0.853)	0.122 (0.229)
lnCPI				1.111*** (0.282)	0.006 (0.004)
lnCO2FuelComb					−0.230 (0.199)
Constant	0.219** (0.093)	4.881** (1.934)	−1.157 (2.853)	9.674 (8.253)	2.992 (2.923)
Time effect	No	No	No	No	No
Underidentification test (Kleibergen-Paap rk LM statistic):	20.192***	12.016	22.137**	22.011*	24.147
Weak identification test (Cragg-Donald Wald F statistic):	7.601	0.622	0.034	0.032	0.031
Hansen J statistic (overidentification test of all instruments):	2.058	5.546	12.127	16.381	21.100

Note: () indicates robust error. ***, **, * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 15

Robustness test for Sub-sample analysis for countries with low reliance on fossil fuels (Continuously Updated Two-Step System GMM).

	(1)	(2)	(3)	(4)	(5)
L1.lnSEGFR	0.910*** (0.018)	0.890*** (0.041)	0.892*** (0.035)	0.898*** (0.028)	0.900*** (0.038)
lnDEI	0.181** (0.077)	0.545** (0.229)	1.468*** (0.405)	1.338*** (0.206)	1.238*** (0.289)
lnInsQuality		3.562*** (1.119)	2.409*** (0.583)	2.395*** (0.411)	4.514*** (0.529)
lnGDPpc			−2.041** (0.794)	−0.758 (0.508)	−0.609 (0.609)
lnCPI				−0.375*** (0.099)	−0.212*** (0.072)
lnCO2FuelComb					−0.521*** (0.136)
Constant	−0.015 (0.053)	2.461*** (0.756)	21.294*** (7.614)	11.147** (4.559)	15.710*** (5.008)
Time effect	No	No	No	No	No
Underidentification test (Kleibergen-Paap rk LM statistic):	22.544***	11.314	15.682	16.998	15.593
Weak identification test (Cragg-Donald Wald F statistic):	13.540	0.151	0.020	0.017	0.014
Hansen J statistic (overidentification test of all instruments):	5.908	3.527	9.455	13.550	12.574

Note: () indicates robust error. ***, **, * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

Table 16

Robustness test for dynamic panel threshold regression (kink Specification).

lnSEGFR	Coefficient	Std. err.	z	P-value	[95 % conf. interval]	
Below the threshold						
llnSEGER(-1)	0.628 ^a	0.003	242.550	0.000	0.623	0.634
lnDEI	1.950 ^a	0.027	71.730	0.000	1.897	2.004
lnInsQuality	1.616 ^a	0.064	25.080	0.000	1.490	1.743
lnGDPpc	−1.075 ^a	0.045	−23.670	0.000	−1.164	−0.986
lnCPI	−0.059 ^a	0.002	−32.670	0.000	−0.062	−0.055
lnCO2FuelComb	0.450 ^a	0.044	10.210	0.000	0.364	0.537
Kink slope	−0.076 ^a	0.001	−58.720	0.000	−0.079	−0.074
Threshold	2.619 ^a	0.182	14.400	0.000	2.263	2.976

Note: N = 85, T = 19. Number of moment conditions is equal to 255. * $p < 0.10$, ** $p < 0.05$.^a $p < 0.01$.

policy challenges impeding a transition to a low-carbon economy. Such policies are typically exemplified by a lack of subsidies toward renewable energy deployment, the fossil fuel industries being significantly subsidized and a lack of proper regulatory quality frameworks.

Institutions may be used by governments to act in correcting market failures. However, the energy market is perceived to be heavily influenced by the political domain which exerts positive or negative influences on the energy mix of a country given the political elite's stance

Table 17

Robustness test for quantile regression -Powell's Generalized quantile regression.

Dependent variable: lnSEGFR									
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
lnDEI	1.995 ^b (0.187)	3.834 ^b (0.083)	5.279 ^b (0.214)	6.315 ^b (0.191)	3.219 ^b (0.054)	4.261 ^b (0.598)	2.606 ^b (0.030)	2.494 ^b (0.521)	1.793 ^a (0.969)
lnInsQuality	3.725 ^b (0.270)	1.976 ^b (0.117)	0.925 ^b (0.249)	-1.170 ^b (0.362)	0.299 ^b (0.093)	1.270 (1.650)	-0.039 (0.049)	-2.131 ^b (0.408)	-2.925 (3.370)
Constant	-2.954 ^b (0.145)	-1.179 ^b (0.080)	-0.037 (0.043)	0.069 (0.270)	-0.735 ^b (0.016)	1.073 (1.336)	-0.566 ^b (0.028)	-1.255 ^b (0.187)	-1.016 (1.128)
Observations	1615	1615	1615	1615	1615	1615	1615	1615	1615

Note: lnDEI is considered as the endogenous variable, and two-lagged terms (12.lnDEI) and three-lagged terms (13.lnDEI) are employed as instrumental variables in this regression. ** $p < 0.05$.

^a $p < 0.10$.

^b $p < 0.01$.

on renewable energy. The policies are inherently implemented by institutional aspects such as rule of law [78].

Institutional quality was found to have a positive and significant effect on renewable energy deployment within the aggregate model as well as with the subsample model of countries with low reliance on fossil, thus confirming the validity of [Hypothesis 2](#) of this study. Governments and their institutions are responsible for implementing policies and incentives for renewable energy deployment.

Mahmood et al. [78] found that regulatory quality attributed to an improved private sector's renewable energy deployment by appropriate government policies. Adequate institutional aspects play an important role in promoting a country's renewable energy deployment by creating government policies that incentivize sustainable energy practices. Mahmood et al. [78] found that certain institutional aspects do have the ability to increase renewable energy usage and deployment, and they matched the results of this study. This, however, was not the case for countries with a high reliance on fossil fuels, where the results in this study showed that institutions had an insignificant impact on renewable energy deployment. Developing countries usually belong to fossil fuel-intensive countries that often face carbon lock-in given their unique challenges. Coal and other emission-intensive industries are usually found to have a significant role in developing countries' economies, accounting for a significant share of their GDP and employment, thereby decarbonizing these economies becomes complex. Given the carbon lock-in challenges, these countries may rather stick to old mechanisms for longer while using fossil fuels. Institutions tend to be sticky and can take some time to influence public sectors might be challenging, the latter explains the insignificant effect of the institutional index above furthermore, institutional bottlenecks can lead to challenges in implementing legal and regulatory frameworks that are used to incentivize renewable energy development. Hence, inherent flaws and loopholes can also lead to weakening the impact of institutions on renewable energy development and deployment [1].

The government is responsible and can formulate policies and regulations that incentivize renewable energy deployment [1,79]. Using the digital economy to its advantage governments can improve investment and financial support for renewable energy deployment [1,55]. The digital economy further can support governments in the R&D of renewable energy [80]. This leads literature such as Shahbaz et al. [1] and Zheng et al. [81] to find similar results to this study where the interaction term brings about a positive and significant effect on renewable energy deployment.

According to the estimation results of this study, both the digital economy and government intervention through institutions play a significant role in renewable energy deployment. Moreover, their impacts on renewable energy deployment vary significantly depending on fossil fuel dependence. To explore how fossil fuel dependence influences the effects of the digital economy and institutional quality on renewable energy deployment, countries were divided into two groups: fossil fuel-reliant and non-fossil fuel-reliant nations (see Appendix).

In light of the empirical findings in this study, most fossil fuel-reliant countries are developing nations in their industrial phases, characterized by higher CO₂ emissions as they begin incorporating renewable energy sources into their energy mix. This group includes resource-rich countries like Saudi Arabia, with its vast oil reserves, and South Africa, rich in coal.

On the other hand, non-fossil fuel-reliant countries are primarily upper-middle-income or developed nations that are already transitioning towards low-carbon economies. This group also includes developing countries like Uganda, which faces energy poverty due to limited access to energy. Uganda is classified in this group because the majority of its energy mix consists of renewable sources, such as hydropower.

Based on the empirical results, [Hypothesis 3](#) of this study is confirmed.

6. Conclusion and policy implications

6.1. Conclusions

Countries all over the world are attempting to transition their economies to net zero economies with some of the strategies incorporating renewable energy deployment. Two key facilitators play a role in the deployment of renewable energy especially through the different developmental stages of countries: the digital economy and institutional quality.

This study examines the effect of the digital economy and institutional quality on renewable energy deployment. The analysis of the 85 countries used in the study provided valuable insights into whether digital technologies and institutions can assist in the promotion of renewable energy deployment.

For our empirical analysis, dynamic panel regression, specifically the two-step GMM, was used to evaluate the impacts of the digital economy and institutional quality on renewable energy deployment. Given the heterogeneous nature of our sample, a sub-sample analysis was conducted by dividing countries into two groups based on their fossil fuel dependence. Additionally, the method of moments quantile regression and dynamic panel threshold regression were performed to address potential asymmetric and non-linear impacts of the digital economy and institutional quality on renewable energy deployment.

In conclusion, the results of the study are highlighted in the statement as follows:

Firstly, the digital economy was found to have a significant positive impact on renewable energy deployment, indicating that the digital economy is an important driving force promoting renewable energy sources. The estimated results are robust and consistent across different model specifications and econometric techniques used in this study, except for the sub-sample analysis of countries with a high reliance on fossil fuel rents, where the impact was not significant. This suggests that countries with high dependence on fossil fuels would face substantial challenges to incorporate digital technologies to fuel clean and

sustainable renewable energy and to reap gains from the synergistic effect of the digital economy and renewable energy deployment. The lack of meaningful impact of the digital economy on renewable energy deployment in this sub-sample group can be explained by the fact that their economic activities, production structure, and energy mix have heavily relied on fossil fuel energy, which acts as a stumbling block to harnessing digital technologies to promote renewable energy deployment. Another possible reason is that countries with high dependence on fossil fuels often have low levels of economic diversification and are specialized in low-value-added raw materials and primary commodity exports. These nations often lack the highly qualified workers, technological innovation capacity, expertise, and specialized knowledge required to assimilate advanced digital technologies and harness them to boost renewable energy deployment.

Secondly, regarding the impact of institutional quality, the results indicate that institutions have a positive and significant effect on renewable energy deployment for the aggregate country group. In the subsample analysis, the following results were found: for countries with a low reliance on fossil fuels, institutional quality had a positive and significant effect on renewable energy deployment; however, this effect was not found for countries with a high reliance on fossil fuel usage. The positive effect of institutions on renewable energy deployment can be explained by the implementation of policies and the creation of incentives for sustainable energy practices such as renewable energy deployment. For the highly fossil-fuel-reliant country group, the results were not robust. The study by Shahbaz et al. [1], indicates that this result can be attributed to inherent flaws and loopholes that lead to an insignificant impact of institutions on renewable energy development and deployment. Carbon lock-ins within institutions, governments, and technologies also contribute to this insignificant result.

Thirdly, in the aggregate sample, the synergistic effect between the digital economy and institutional quality, specifically the interaction term between DEI and InsQuality, was found to have a positive and significant impact on renewable energy deployment. This confirms that both the digital economy and institutional quality are mutually beneficial and can reinforce each other on the pathway toward renewable energy transition.

Lastly, according to the dynamic panel threshold regression and the MMQR, the impacts of both the digital economy and institutional quality show non-linear and asymmetric features concerning fossil fuel dependence. Specifically, in the dynamic panel threshold regression, the impact of the digital economy on renewable energy deployment was higher when the value of fossil fuel dependence was below the threshold compared to above it (0.563 versus 0.465). In contrast, institutional quality was found to have a significant positive impact only when the value of fossil fuel dependence was below the threshold. The estimates in the dynamic panel threshold regression are consistent with our previous findings in the sub-sample analysis, indicating that the meaningful impacts of both the digital economy and institutional quality on renewable energy deployment were apparent only in countries with lower reliance on fossil fuels.

Concerning the MMQR, the impact of the digital economy was positive and significant across all quantile groups, showing a stronger effect at higher quantiles. This indicates that in countries with higher levels of renewable energy deployment, the impact of the digital economy on promoting renewable energy was significantly strong. The estimated results align with previous studies, which suggest a path-dependence of renewable energy technology, indicating that countries with already high renewable energy installations are likely to benefit more from the process of digitalization in the energy sector. As for institutional quality, its impact on renewable energy deployment was observed only at the 60th and 70th quantiles, and the sign was negative. This means that, unlike the digital economy, the impact of institutional quality on renewable energy deployment was not robust when considering asymmetric features.

6.2. Policy recommendations

In the era of Industry 4.0, digitalization is rapidly reshaping the global economy and the integration of advanced digital technologies is expected to increase dramatically in the coming decades. Specifically, in the energy sector, the digital economy can be a driving force not only in promoting cleaner and cheaper renewable energy sources in a global energy mix currently dominated by fossil fuels but also in increasing energy efficiency and energy savings through the application of advanced digital technologies. Renewable energy deployment, fueled by digitalization, might be helpful to address the energy trilemma the global economy is currently facing, in its three aspects: energy sustainability, energy affordability, and energy security.

In this regard, the roles and responsibilities of governments and their institutions are recognized as critically important to drive and implement policies accelerating the process of digitalization and achieving net-zero goals. Digital infrastructure has the capability to improve the efficiency of governments, their institutions, and policy implementation. Thus, governments should invest in improving the institutional quality and digital infrastructure of their institutions. In conjunction with digital economy infrastructure, adequate institutions should implement policies and regulations that are conducive to promoting renewable energy deployment through means of subsidies, decreasing dividend taxes of renewable energy deployment and digital infrastructure deployment, and incentivizing R&D through tax breaks.

The recommendation follows that countries have clear long-term renewable energy targets that are ambitious but reasonable in aligning with the country's commitments to international agreements while gradually phasing out fossil fuels and incentives for using fossil fuels such as subsidies. Institutions should be used to create stable and innovative environments for their markets to attract the investment needed to deploy renewable energy. Institutions should minimize the uncertainties within the market as well as minimize the cost of doing business. Create the necessary incentives in the market to attract private sector investments such as with subsidies and tax rebates. Through improving institutional quality barriers should be removed for the rise of renewable energy deployment, for example lifting tariffs on renewable energy technologies, and building the necessary grid infrastructure to adopt renewable energy through capacity building. When the necessary investment is acquired, invest in research and development of renewable energy and make use of green financing and investment mechanisms.

In summary, this study recommends that countries review their policy frameworks concerning renewable energy deployment, development, and consumption that can enhance policies targeting renewable energy deployment. Within this framework, governments can remove trade barriers concerning renewable energy technologies that would encourage developing countries and fossil fuels-reliant countries to improve and import new renewable energy technologies.

6.3. Future research directions

In this study, the impacts of the digital economy and institutional quality on renewable energy deployment were thoroughly analyzed for 85 countries. However, the authors acknowledged that both regional and individual country studies are required for a better understanding and identification of the specific challenges and opportunities arising from the synergistic effects, on which the digital economy and institutional quality might have for promoting renewable energy development. Furthermore, for future studies, it would be interesting to compare the impact of the digital economy on traditional renewable energy sources such as biomass and hydropower with non-conventional renewables such as solar and wind, particularly regarding the integration of digital technologies in each source of renewable energy, in terms of the three aspects of the energy trilemma: energy affordability, energy security, and energy sustainability. Additionally, specific analysis of the impact of

each component of institutional quality on renewable energy deployment, performed in a disaggregate manner, can provide more concrete guidelines and valuable insights to policymakers. This analysis can help determine which specific aspects of institutional quality governments would improve to accelerate the renewable energy transition in the face of the climate crisis.

CRediT authorship contribution statement

Young Kyu Hwang: Writing – review & editing, Writing – original

draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alanda Venter:** Writing – review & editing, Writing – original draft, Visualization, Investigation, Formal analysis, Data curation, Conceptualization.

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.

Appendix

A.0

Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
lnSEGFR	1615	$\hat{\alpha}$ 4.014	2.688	$\hat{\alpha}$ 9.21	3.875
lnDEI	1615	$\hat{\alpha}$ 0.818	0.334	$\hat{\alpha}$ 1.771	$\hat{\alpha}$ 0.139
lnInsQuality	1615	$\hat{\alpha}$ 0.759	0.458	$\hat{\alpha}$ 2.481	$\hat{\alpha}$ 0.049
lnDEI lnInsQuality	1615	0.713	0.607	0.027	3.432
lnGDPpc	1615	9.131	1.224	5.542	11.414
lnCPI	1615	4.709	0.632	3.675	12.408
lnCO2FuelComb	1615	10.96	1.765	7.264	16.181

A.1

Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) lnSEGFR	1						
(2) lnDEI	0.394*** 0.000	1					
(3) lnInsQuality	0.376*** 0.000	0.606*** 0.000	1				
(4) lnDEI lnInsQua $\hat{\alpha}$ $\hat{\alpha}$ ^{1/4} y	$\hat{\alpha}$ 0.406*** 0.000	$\hat{\alpha}$ 0.855*** 0.000	$\hat{\alpha}$ 0.890*** 0.000	1			
(5) lnGDPpc	0.224*** 0.000	0.733*** 0.000	0.836*** 0.000	$\hat{\alpha}$ 0.833*** 0.000	1		
(6) lnCPI	0.133*** 0.000	0.220*** 0.000	$\hat{\alpha}$ 0.087*** 0.000	$\hat{\alpha}$ 0.086*** $\hat{\alpha}$ 0.001	$\hat{\alpha}$ 0.046* $\hat{\alpha}$ 0.064	1	
(7) lnCO2FuelComb	0.222*** 0.000	0.341*** 0.000	0.178*** 0.000	$\hat{\alpha}$ 0.274*** 0.000	0.362*** 0.000	0.007 $\hat{\alpha}$ 0.781	1

A.3

Multicollinearity test

Variance inflation factor		
Variables	VIF	1/VIF
lnDEI lnInsQuality	20.905	0.048
lnInsQuality	12.885	0.078
lnDEI	8.236	0.121
lnGDPpc	5.367	0.186
lnCO2FuelComb	1.252	0.799
lnCPI	1.188	0.842
Mean VIF	8.305	.

A.4

Panel unit root tests

Maddala and Wu (1999) Panel Unit Root Test			
	Specification	without	trend
Variable	lags	chi_sq	p-value
lnSEGFR	0.000	312.335	0.000
lnDEI	0.000	871.704	0.000
lnInsQuality	0.000	191.353	0.125
lnDEI lnInsQuality	0.000	500.760	0.000
lnGDPpc	0.000	356.508	0.000
lnCPI	0.000	410.870	0.000
lnCO2FuelComb	0.000	223.180	0.004
Pesaran [57] Panel Unit Root Test			
	Specification	without	trend
Variable	lags	Zt-bar	p-value
lnSEGFR	0.000	$\hat{\alpha}$ 0.588	0.278
lnDEI	0.000	$\hat{\alpha}$ 4.329	0.000
lnInsQuality	0.000	$\hat{\alpha}$ 1.992	0.023
lnDEI lnInsQuality	0.000	$\hat{\alpha}$ 6.555	0.000
lnGDPpc	0.000	4.180	1.000
lnCPI	0.000	1.430	0.924
lnCO2FuelComb	0.000	$\hat{\alpha}$ 0.720	0.236
	Specification	with	trend
Variable	lags	chi_sq	p-value
lnSEGFR	0.000	251.881	0.000
lnDEI	0.000	282.625	0.000
lnInsQuality	0.000	230.180	0.001
lnDEI lnInsQuality	0.000	271.056	0.000
lnGDPpc	0.000	181.135	0.265
lnCPI	0.000	156.728	0.759
lnCO2FuelComb	0.000	247.677	0.000
	Specification	with	trend
Variable	lags	Zt-bar	p-value
lnSEGFR	0.000	4.256	1.000
lnDEI	0.000	$\hat{\alpha}$ 1.242	0.107
lnInsQuality	0.000	$\hat{\alpha}$ 1.936	0.026
lnDEI lnInsQuality	0.000	$\hat{\alpha}$ 5.032	0.000
lnGDPpc	0.000	7.898	1.000
lnCPI	0.000	6.106	1.000
lnCO2FuelComb	0.000	1.404	0.920

A.5

Cointegration tests

Without interaction term		
Kao test for cointegration	Statistic	P-value
Modified Dickey-Fuller t	0.5148	0.3033
Dickey-Fuller t	$\hat{\alpha}$ 2.0455**	0.0204
Augmented Dickey-Fuller t	0.4169	0.3384
Unadjusted modified Dickey-Fuller t	$\hat{\alpha}$ 6.8404***	0.0000
Unadjusted Dickey-Fuller t	$\hat{\alpha}$ 6.8147***	0.0000
Pedroni test for cointegration	Statistic	P-value
Modified Phillips $\hat{\alpha}$ -Perron t	9.6812***	0.0000
Phillips $\hat{\alpha}$ -Perron t	$\hat{\alpha}$ 7.6462***	0.0000
Augmented Dickey-Fuller t	$\hat{\alpha}$ 9.8981***	0.0000
Westerlund test for cointegration	Statistic	P-value
Variance ratio	$\hat{\alpha}$ 3.422***	0.0003
With interaction term		
Kao test for cointegration	Statistic	P-value
Modified Dickey-Fuller t	0.5439	0.2932
Dickey-Fuller t	$\hat{\alpha}$ 1.9118**	0.0279
Augmented Dickey-Fuller t	0.6037	0.2730
Unadjusted modified Dickey-Fuller t	$\hat{\alpha}$ 6.8028***	0.0000
Unadjusted Dickey-Fuller t	$\hat{\alpha}$ 6.685***	0.0000

(continued on next page)

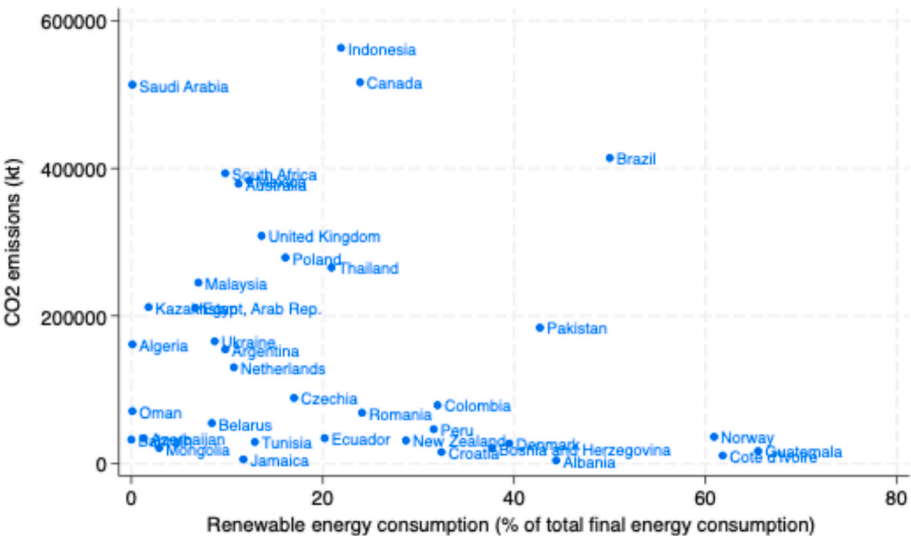
A.5 (continued)

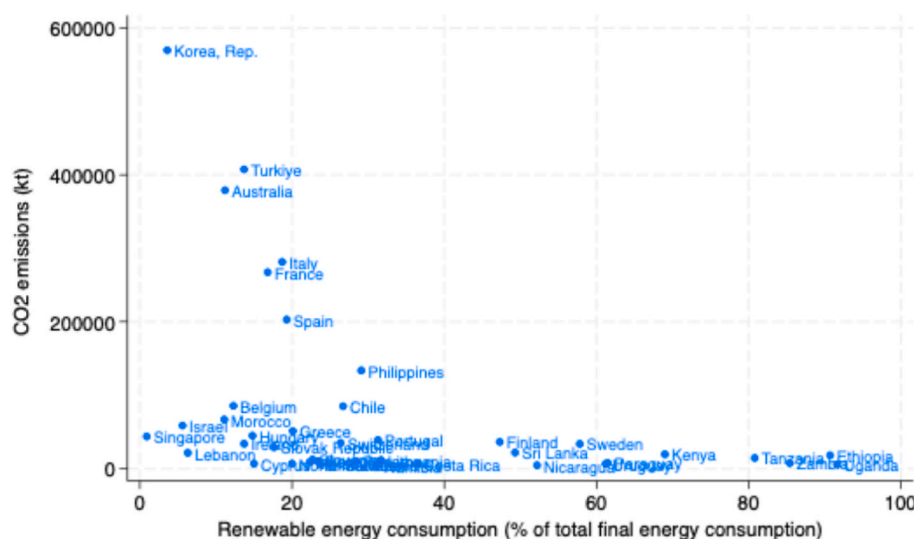
Pedroni test for cointegration	Statistic	P-value
Pedroni test for cointegration	Statistic	P-value
Modified Phillipsâ€“Perron t	10.9536***	0.0000
Phillipsâ€“Perron t	âˆ’9.4082***	0.0000
Augmented Dickey-Fuller t	âˆ’12.1165***	0.0000
Westerlund test for cointegration	Statistic	P-value
Variance ratio	âˆ’2.8787***	0.0020

A.6

List of countries classified according to the fossil fuel reliance

Non-Fossil Fuel reliant countries		Fossil Fuel reliant countries	
Austria	Moldova	Albania	Kazakhstan
Belgium	Morocco	Algeria	Malaysia
Chile	Namibia	Argentina	Mexico
Costa Rica	Nicaragua	Australia	Mongolia
Cyprus	North Macedonia	Azerbaijan	Netherlands
El Salvador	Panama	Bahrain	New Zealand
Ethiopia	Paraguay	Belarus	Nigeria
Finland	Philippines	Bosnia and Herzegovina	Norway
France	Portugal	Brazil	Oman
Georgia	Singapore	Canada	Pakistan
Germany	Slovakia	China	Peru
Greece	Slovenia	Colombia	Poland
Hungary	Spain	Cote d'Ivoire	Romania
Ireland	Sri Lanka	Croatia	Russian Federation
Israel	Sweden	Czechia	Saudi Arabia
Italy	Switzerland	Denmark	South Africa
Japan	Tanzania	Ecuador	Thailand
Kenya	TÃ¼rkiye	Egypt	Tunisia
Korea.Republic	Uganda	Guatemala	Ukraine
Lebanon	Uruguay	India	United Kingdom
Lithuania	Zambia	Indonesia	United States of America
		Jamaica	





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