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RESEARCH ARTICLE

Economic complexity, ICT, biomass energy consumption, and environmental degradation: evidence from Iran

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Abstract
Economic complexity, biomass energy consumption, and information communication technology (ICT) have diverse impacts on energy consumption and carbon dioxide (CO_2) emissions. Nevertheless, analysis of these variable effects is not addressed in the previous literature; the antiqueness of this article is stuffing this gap. This study assessed the relationship between gross domestic product (GDP) per capita, biomass consumption, economic complexity index (ECI), ICT, and CO_2 emissions in Iran in 1994–2018. The autoregressive distributed lag (ARDL) model and the quantile regression (QR) econometric technique were used to investigate the factors affecting CO_2 emissions in the tails of the conditional distribution. The share of each influential factor was predicted through the variance decomposition analysis (VD) for the next 10 years. The empirical results showed a long-run relationship between the variables. So, the variables of biomass consumption, ECI, and ICT improve the quality of the environment in Iran by reducing CO_2 emissions, and the per capita GDP variable increases CO_2 emissions. Results suggest no evidence indicating the presence of environmental Kuznets curve (EKC); however, QR demonstrated the existence of EKCs in the lower quantiles of the conditional distribution. The ECI will have the most share to change the CO_2 emissions in the future. The income threshold should be determined at the turning point of the EKC to increase economic development. Moreover, investing in increasing biomass consumption is vital. Policymakers also need to consider strict added value for the export of products.

Keywords ARDL approach · Biomass · CO_2 emissions · Economics complexity · Economic growth · Quantile regression

Introduction

Today, climate change is the most critical environmental problem, and the rising greenhouse gas (GHG) emissions are considered its leading cause (Lin & Zhu, 2019). CO_2 emissions, regarded as the most significant components of GHG emissions, have a prominent contribution to climate change (Ahmed et al., 2019). The International Energy Agency (IEA, 2019) statistics revealed that since 2012, the amount of CO_2 emissions related to fossil fuel energy had shown an alarmingly increasing trend by 1.7% in 2018, thus have reached to 33,444 million tons of CO_2 equivalent. Climate change and continuous air pollution will bring potential threats to life and human activities.

Hence, concerns about the effects of increased CO_2 emissions, including climate change, have intensified such that many countries have committed to reducing CO_2 emissions (Apergis & Payne, 2014). Thus, environmentalists have repeatedly called on the international community to take action to reduce CO_2 emissions. Therefore, countries in various international meetings such as the Stockholm Conference, the Montreal and the Kyoto Protocol, and the Paris Agreement have taken steps to deal with climate change and limit GHG emissions (Razmjoo & Davarpanah, 2019).

This study aimed to explore the impacts of ECI, information communication technology (ICT), and biomass energy

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Highlights
- Focus on Iran as one of the largest Co2 emissions in the world.
- The effects of GDP, economic complexity index biomass consumption and internet consumption on air quality are assessed.
- Economic complexity is significantly affecting the reduction of Co2 emissions in the future.
- Our result provides a new strategy for policymakers to move towards sustainable economic development.
- ARDL, QR and VD analysis techniques were applied.

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consumption on CO_2 emissions to disclose some sustainable development options for Iran. In 2019, among the ten countries producing the most CO_2 emission in the world, only Japan, Germany, and Saudi Arabia have had a successful performance in reducing CO_2 emissions while the others have increased their emission level (IEA, 2019). Iran had the eighth place for the emission of CO_2 in the world by 656 million tons of emissions in 2019. Because of the 5.5% growth compared to the previous year, Iran had the second-highest volume of CO_2 emissions after India (WDI, 2020).

At present, about 81% of the world's energy is supplied by fossil fuels such as coal, oil, and natural gas (WDI, 2020). Consumption of this type of energy leads to air pollution and global warming due to the high emission of CO_2 and GHG (Amirnejad et al., 2021). Therefore, in recent decades, the demand for renewable resources has increased as an alternative to fossil fuels. As a result, the world has witnessed an increase in the production of renewable energy to meet the growing energy demand (Al-Mulali et al., 2016; Apergis & Payne, 2012), which can significantly lower CO_2 and GHG emissions and provide sustainable economic development (Balsalobre-Lorente et al., 2018; Belaïd & Zrelli, 2019; Inglesi-Lotz & Dogan, 2018).

Bioenergy is considered one of the primary sources of renewable energy and an alternative to fossil energy as regards it being renewable, abundant, and infinite (Kim et al., 2020). Biomass bioenergy is the fourth renewable energy resource in the world (FAO, 2020). Since biomass can be produced in large quantities anywhere, this energy resource is the most appropriate and economical energy supply solution in developing countries (Balat & Balat, 2009). Biomass consists of non-food materials, including biodegradable components of agricultural products and wastes (i.e., crops and animal wastes), forests, and related industries, as well as industrial and urban wastes (Bilgili & Ozturk, 2015). Unlike crop-based bioenergy, cellulosic biofuel is a biomass-based biofuel produced from primitive sources such as crop residues, wood residues, and municipal waste. In general, biomass is a clean, low-carbon alternative to fossil fuels produced from locally available sources (Long et al., 2013).

The economic complexity index (ECI) introduced by Hidalgo and Hausmann (2009) provides a measure to calculate countries' technology-intensive export structure. Three databases are used to calculate this index: the United Nations COMTRADE system, the International Trade Standard Classification System, and the North American Industry Classification System (Pata, 2021). Since these databases are only based on the export products, the ECI indicator measures the economic development of countries in terms of export (Doğan et al., 2019).

Most developing countries have a low level of product knowledge and only produce less complex export products. As a result, they create lower levels of competition. But developed countries, which have a higher level of product knowledge, use their resources to diversify their export portfolios and increase competitiveness (Tacchella et al., 2012). A country's production structure can affect GHG emissions. Still, the economic complexity level and product diversity can cause environmental pollution, but the knowledge-based production structure has led to creativity and innovation that can stimulate greener products and environmentally friendly technologies. In this respect, ECI uses countries' international trade data, which shows a country's capability to export products with high added value. In this definition, the word "capabilities" includes physical infrastructure such as airplanes and highways, human capital (i.e., knowledge and skills of the labor force), and the quality of institutions (i.e., legal rights, property rights, and legal rules). Therefore, the ECI includes dimensions of technological advancements, technical knowledge, and increasing efficiency, which can effectively reduce or raise CO_2 emissions (Hidalgo et al., 2007).

Given the Industrial Revolution in the late eighteenth century and the application of labor-saving machines in production, most countries have witnessed unprecedented economic development. This mechanization has led to the worldwide emission of significant volumes of CO_2. Since then, nations have sought to reduce CO_2 emissions by increasing the use of ICT (Sadorsky, 2012; Salahuddin & Alam, 2015). ICT is a term that refers to electronic computer equipment and concerned software to convert, store, process, communicate, and retrieve digitized information (Zadek et al., 2010). The role of ICT in countries' economic growth and prosperity is irrefutable, but due to its positive and negative environmental effects, it can be considered a double-edged sword (Ahmed & Le, 2021; Raheem et al., 2020). Positively, the increasing ICT technologies have introduced the trend of e-goods and services, such as e-banking, e-commerce, e-books, online education, and video conferencing (Ahmed & Le, 2021). Thus, replacing the traditional methods, goods, and services with electronic ones causes more efficient economic development with less energy demand. The lower energy consumption reduces the GHG emission finally improves the environmental quality (Sadorsky, 2012).

Negatively, the production and distribution of ICT equipment require the consumption of energy and materials. Therefore, ICT equipment increases the electronic wastes entering the environment because they have a short life cycle (Hargroves & Smith, 2005). Also, the growing trend of ICT strengthens economic activity and accelerates industrialization, which increases energy consumption and CO_2 emissions. Al-Mulali et al. (2015), Ozcan and Apergis (2018), and Toffel and Horvath (2004) stated that ICT penetration reduces CO_2 emissions. However, Salahuddin and Alam (2015) in a study came to the opposite conclusion, but the amount of CO_2 emissions is not significant. Thus, the relationship between ICT and the environment is a complex and multidimensional issue that needs to be studied. It is estimated that 1 to 3% of the global CO_2 emissions are due to the production and application of ICT.

Increasing CO_2 emissions in Iran, a significant producer of fossil fuels, has caused severe concerns for experts. Considering the various biomass supply resources, their environmental benefits, and renewability, the development of biomass application is reasonable and cost-effective in Iran. According to the IEA forecast, Iran's balance of trade will grow positively and be placed within the countries with a growth of 0.9 to 1.6% by doubling the share of renewable energy in global consumption (IEA, 2019). On the one hand, renewable energy consumption (especially biomass) does not necessarily lead to sustainable economic development. Increasing efficiency and technical knowledge have a significant impact on CO_2 emissions due to the high dependence of Iran's economy on oil exports. Therefore, the ECI has been considered a measure of Iran's structural and technological changes.

On the other hand, the advancement of ICT has eliminated the distance between countries. Regarding the growing ICT trend globally, one may ask, "Does the increase in ICT along with the elimination of the digital divide between developing and developed countries affect the emission of CO_2 in developing countries (especially Iran)?".

Literature review

Climate change and global warming and raising awareness of these problems have made understanding environmental degradation and its elements.

Economic growth and environmental degradation

Considering the importance of the environment's quality for the sustainable development of countries, the relationship between environmental variables has been studied by many researchers around the world. Regarding the issue, some studies that have been conducted in the last years are mentioned. Ahmad et al. (2021) explored the symmetric and asymmetric impacts of economic growth and clean energy development investments on CO_2 emissions for Japan. Results showed that economic growth caused higher CO_2 emissions in Japan. Kanat et al. (2022) found similar results found in Russia. He et al. (2021), for the top 10 energy transition countries, examined the impacts of EC, economic growth, renewable energy, and globalization on CO_2 emissions. The results confirmed the co-integration among the variables and also economic growth increase the carbon emission in long-run. Zeraibi et al. (2021) reviewed the EKC hypothesis using China's fiscal, monetary, and environmental policies. Results showed the long-run relationship between CO_2 emissions, economic growth, and other variables. In addition, the empirical results rejected the EKC hypothesis as the relationship between economic growth and CO_2 emissions is confirmed to N-shape portray in China. Hanif et al. (2019), using the autoregressive distributed lag (ARDL) model, explored the economic growth-fossil fuel consumption nexus for selected Asian countries using data between 1990 and 2013. The authors confirmed that economic growth and the usage of fossil fuels contribute to air pollution. Besides, they also authenticated the growth hypothesis by putting forward evidence of unidirectional causality stemming from the utilization of energy resources to economic growth. Other researchers also evaluated the connections between economic growth and CO_2 emissions, such as the studies by Kibria et al. (2019) for 151 global nations, Mensah et al. (2019) for 22 African countries, and Mohamed et al. (2019) for France.

Economic complexity and environmental degradation

Recently, analyzing the impact of economic complexity and environmental quality has gained substantial research interest. In this regard, Martins et al. (2021) examined the relationship between economic complexity and CO_2 emissions for the top 7 economic complexity countries. Their findings revealed that economic complexity increases the CO_2 emissions; also, there was a unidirectional causality from economic complexity to CO_2 emissions. Ahmad et al. (2021) explored the linkage between economic complexity and CO_2 emissions for emerging countries. The study results showed that economic complexity by amplifying the ecological footprint (EPT) increases environmental degradation, and a high level of economic complexity reduces the EPT. Can and Gozgor (2017) initiated a debate on the linkage between economic complexity and environmental degradation by using the dataset of France. Their empirical findings highlight that a higher degree of economic complexity (structural transformation) helps curb France's environmental degradation. Doğan et al. (2019) report that economic complexity deteriorates the environment quality in the lower middle and higher middle-income economies while improves in high-income economies.

Similarly, Neagu and Teodoru (2019) analyzed the linkage between economic complexity, energy consumption structure, and environmental degradation in European Union (EU) economies. Their results unveil that economic complexity deteriorates the environmental quality, but the effect is higher within the subpanel of countries with lower economic complexity. Shahzad et al. (2021) also reported the detrimental impact of economic complexity on the EF in the USA. Pata (2021) and Chu (2021) documented an inverted U-shaped relationship between economic complexity and

CO_2 emissions. Nevertheless, there is no evidence of a significant association between economic complexity and environmental degradation in some of the regions of EU countries (Fatai Adedoyin et al., 2021).

Conversely, Ahmed et al. (2021a) investigated the effect of economic complexity (EC) and other variables on EFP in G7 countries. Their outcomes indicated that in the long run, EC reduces the EFP. Doğan et al. (2021) found the mitigating effect of economic complexity on the environmental deterioration in the case of 28 (OECD) countries. In a recent study, Romero and Gramkow (2021) argue that economic complexity contributes to reducing greenhouse gas emissions. Boleti et al. (2021) confirm that economic complexity helps to improve environmental quality by curtailing CO_2 emissions in 88 developed and developing countries.

ICT and environmental degradation

Carbon emission is considered the major factor of climate change and environmental degradation. In the literature, various determinants of CO_2 emissions are discussed. With the ICT revolution in the 1990s, numerous studies explored the positive and negative impacts of ICT on CO_2 emissions. Concerning the positive nexus, Salahuddin et al. (2016) revealed that ICT enhances emissions in OECD countries; However, their empirical analysis does not reveal causality between emissions and ICT. The Danish et al. (2018) study partially confirmed the claim that ICT stimulates emission. Empirical results of their study established that ICT significantly affects CO_2; however, the interaction between ICT and gross domestic product (GDP) reduces pollution levels. Raheem et al. (2020) showed that ICT has a positive long-run impact on emissions in G7 countries. Avom et al. (2020) investigated the effect and transmission channels of ICT on CO_2 emissions in 21 sub-Saharan African countries. Their results confirmed that ICT proxies, i.e., internet penetration and mobile phone significantly, increase the CO_2 emissions. For the BRICS countries, some studies indicated ICT and its proxies boost CO_2 emissions (Balsalobre-Lorente et al., 2019; Haseeb et al., 2019). Similar results were found by studies in the Asia region (Lee & Brahmasrene, 2014; Lu, 2018).

Conversely with the previous studies, several papers found that ICT improves environmental quality. For instance, Ahmed and Le (2021) examined the effect of ICT and globalization index on CO_2 emissions in ASEAN-6 countries. Results showed that ICT by reducing emissions contributes to high environmental quality. In a study for Latin American and Caribbean countries, Ahmed et al. (2021a) probed the impacts of the ICT index and various variables on environmental sustainability. Their results unfold that ICT contributes to reducing CO_2 emissions. Dehghan Shabani and Shahnazi (2019) analyzed the sectoral impacts of ICT on CO_2 emissions in the Iranian economy. The results found the negative effect of ICT on CO_2 in the industrial sector and the negative effect in the service and transportation sector. N'dri et al. (2021) studied the association between ICT and CO_2 emissions in 85 developing nations. This study disclosed that for low-income developing countries, ICT mitigates emissions. For China, Zhang and Liu (2015) reported that ICT helps in improving environmental sustainability. However, they also disclosed some regional disparities in the effect of ICT on emissions. Similarly, using the quantile regression method, Chen et al. (2019) suggested that ICT reduces emissions in different provinces of China; however, they also illustrated some regional differences in results.

Biomass energy consumption and environmental degradation

With the rapid growth in renewable energy, mainly due to global economic and environmental aspects, biomass energy has been gaining popularity due to its potential to reduce GHGs significantly. Regarding the relationship between CO_2 emissions and biomass consumption, Bilgili (2012) employs co-integration analyses with one and two possible regime changes to investigate the possible existence of a long-run relationship between CO_2 emissions and biomass consumption in the USA from 1990 to 2011. Considering possible structural breaks, the author finds that biomass consumption has a negative impact on CO_2 emissions, implying biomass consumption results in reduced CO_2 emissions. Kim et al. (2020) assessed the causal connection between biomass energy consumption, CO_2 emissions, and GDP in the USA. The results implied that biomass energy reduces GHG and also improves environmental quality. For the world economy, Majeed et al. (2022) explored the impacts of biomass energy consumption on environmental quality among heterogeneous income groups. The potential of biomass energy consumption on emission reduction in the high-income group was confirmed, while the upper-middle-income, lower-middle-income, and low-income groups reported a wrecking role on environment. Other studies investigated the causal relationship between biomass energy consumption and CO_2 emission and found strong evidence of causal relationships in many different countries (Adewuyi & Awodumi, 2017; Sinha et al., 2017; Sulaiman et al., 2020).

By considering the past studies, this study is expected to contribute to the literature review in the following ways:

First, this study focuses on Iran as one of the largest emitters of CO_2 in the world, which supplies about 98% of its energy from fossil fuels. The results of this study could reveal a new perspective for Iran and other developing countries, which derive most of their energy from fossil fuels. Second, we have not found a study that examines the effect of the three variables of biomass energy consumption, ICT, and ECI besides the GDP per capita in a single study on CO_2 emissions. Because in the near future, these variables will have a great impact on the economies of countries in achieving sustainable development.

Methodology

Econometric methodology

The estimation process used in this study includes six key phases of econometrics. The first phase was to perform a unit root test to examine the stationarity of the variables. In the second phase, the bounds test is carried out to explore long-term relationships between variables. In the third phase, short-term and long-term coefficients of the ARDL model and adjustment speed were estimated in the ECM model. The fourth phase addressed diagnostic and sustainability tests. So, some relevant tests are used to detect variance heterogeneity, serial correlation, determine the functional form of the model, measure the normal distribution of error terms, and evaluate the stability of the estimation coefficients. Finally, in the fifth and sixth phases, quantile regression (QR) and variance decomposition (VD) analysis were used to investigate the effect of independent variables on the dependent variable at points outside the mean area and to predict the share of each variable on CO_2 emissions.

ARDL model

Various econometric methods are used in literature to estimate the short-run and long-run relationship between variables. The results of techniques such as Engle-Granger in studies dealing with small samples are not valid because they do not consider the short-run dynamic reactions between variables. Besides, the resulting estimates are subjected to bias; thus, testing hypotheses using standard t test statistics does not provide reliable results. In this respect, models considering short-run dynamics are applied to result in the more accurate coefficient of the model (Pesaran et al. 2001; Pesaran & Smith, 1995; Sertoglu & Dogan 2016). Accordingly, the econometric method of ARDL has been used in this study. The ARDL econometric method was first proposed by Pesaran and Shin (1999) to investigate the long-run co-integration relationship between variables.

Iran is a developing country that has a significant share in CO_2 emissions. Therefore, this study discussed the relationship between the factors affecting CO_2 emissions through the ARDL model. Accordingly, the framework of the experimental model was used (Eq. 1) in this study:

$$\begin{aligned} Ln(CO_2)_t = a_0 + \beta_1 Ln(GDP)_t + \beta_2 (Ln(GDP)_t)^2 + \beta_3 Ln(BIOMASS)_t \\ + \beta_4 Ln(ECI)_t + \beta_5 Ln(ICT)_t + \varepsilon_t \end{aligned} \tag{1}$$

In Eq. (1), t denotes the time interval (1994–2018). Also, CO_2, GDP, BIOMASS, ECI, and ICT stand for CO_2 emission per capita, gross domestic production per capita, biomass consumption, the economic complexity index, and information communication technology index, respectively.

The dynamic form of Eq. (1) is used as Eq. (2):

$$\begin{aligned} \Delta Ln(CO_2)_t = a_0 + \sum_{i=1}^{p} \beta_{1i} \Delta Ln\left(CO_2\right)_{t-i} + \sum_{i=0}^{q} \beta_{2i} \Delta Ln(GDP)_{t-i} \\ + \sum_{i=0}^{q} \beta_{4i} \Delta Ln(BIOMASS)_{t-i} + \sum_{i=0}^{q} \beta_{5i} \Delta Ln(ECI)_{t-i} + \sum_{i=0}^{q} \beta_{6i} \Delta Ln(INT)_{t-i} \\ + \beta_7 Ln(CO_2)_{t-1} + \beta_8 Ln(GDP)_{t-1} + \beta_9 (Ln(GDP)_{t-1})^2 + \beta_{10} Ln(BIOMASS)_{t-1} \\ + \beta_{11} Ln(ECI)_{t-1} + \beta_{12} Ln(ICT)_{t-1} + \varepsilon_t \end{aligned} \tag{2}$$

where $\beta_1 - \beta_6$ and $\beta_7 - \beta_{12}$ are respectively short-term and long-term coefficients of the model.

Error correction model (ECM)

In the case of co-integration of variables, the short-run fluctuations can be related to long-term values of variables through the ECM. The ECM of ARDL is expressed by Eq. (3):

$$\begin{aligned} \Delta Ln(CO_2)_t = a_0 + \sum_{i=1}^{p} \beta_{1i} \Delta Ln\left(CO_2\right)_{t-i} + \sum_{i=0}^{q} \beta_{2i} \Delta Ln(GDP)_{t-i} \\ + \sum_{i=0}^{q} \beta_{3i} \Delta (Ln(GDP)_{t-i})^2 + \sum_{i=0}^{q} \beta_{4i} \Delta Ln(BIOMASS)_{t-i} + \sum_{i=0}^{q} \beta_{5i} \Delta Ln(ECI)_{t-i} \\ + \sum_{i=0}^{q} \beta_{6i} \Delta Ln(ICT)_{t-i} + \eta ECM_{t-1} + v_t \end{aligned} \tag{3}$$

where η shows the speed of adjustment in each interval until approaching the long-run equilibrium.

Quantile regression (QR)

Typical regression analysis based on mean responses is vulnerable to outlier observations. Therefore, finding alternative regression methods for mean regression has always been of interest to researchers. In this regard, Koenker and Bassett (1978) introduced a generalized median regression model (i.e., QR) to model the area of concentration and change in the form of the distribution. QRs are analytical tools by which different potential effects of an explanatory variable are estimated on different quantiles of the conditional distribution. QR, unlike common regression, estimates the model parameters by minimizing the sum of the absolute value of the residuals, which is called the least absolute deviation (LAD) method (Koenker & Bassett, 1978).

In this study, QR was used to investigate the effect of independent variables in different quantiles on the dependent variable through Eq. (4):

$$Q_\tau(\beta_\tau) = min_\beta \sum_{t=1}^{n} \left[\left| Ln(CO_2)_t - \beta_\tau X_t \right| \right] = min_\beta \left[\sum_{t:Ln(CO_2)_t \geq X_t'\beta}^{n} \tau \left| Ln(CO_2)_t - X_t'\beta \right| + \sum_{t:Ln(CO_2)_t \leq X_t'\beta}^{n} (1-\tau) \left| Ln(CO_2)_t - X_t'\beta \right| \right] \quad (4)$$

where X_t is an explanatory variable of the model.

Data

According to the study objectives, information on CO_2 emissions per capita (metric tons per capita), GDP per capita (constant 2010 US$), biomass consumption (tons), ECI, and the ICT for Iran was used between 1994 and 2018. CO2 emissions, GDP per capita, and ICT data were retrieved from the World Bank. Furthermore, biomass consumption and ECI information were obtained from www.worldbioenergy.org and comtrade.un.org, respectively. Model estimation and tests were performed through Eviews 9 and Microfit 5 software.

Due to data unavailability on some ICT proxies for the period under analysis, three ICT indicators (individual internet user, mobile cellular subscriptions, and fixed telephone subscriptions) were used to create an ICT index. All these proxies are measured in terms of per 100 people. Thus, we have used principal component analysis (PCA) to create an ICT index. So, the three variables mentioned above are composed into a merged index using the PCA instead of using them separately. PCA transforms the data from one feature space to another feature space of low dimension. The transformed feature space should explain most of the variance of the original data set by making a variable reduction. It is a beneficial method to understand the total impact of ICT on CO_2 emissions in Iran.

Table 1 shows various steps of PCA, the first section of the table depicts eigenvalues, and the first component has a high eigenvalue. As it can be seen, the first component includes the highest proportion variation with almost 98.44%, which indicates that it has about 98% of the information out of the total information that ICT indicators carry. In the second section of the table, PC1 has high eigenvector values while other components have negative values. Finally, the last section implies a high correlation between the ICT proxies. To the PCA outcomes, we concluded to use the first principal component that contains the most information on the ICT data.

Results

Econometric techniques are used based on assuming the stationarity of variables. Therefore, it is necessary to check the stationarity of the variables before the model estimation phase. Since there is a non-stationary variable in the model, the critical values of *F* and *t* statistics are not applicable and they cause spurious regression (Baltagi, 2008). Accordingly, in this study, two standard tests of augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) were used (Cong & Shen, 2014). The null hypothesis of these two tests indicates the existence of a unit root and non-stationary variables.

Table 1 Principal component analysis (PCA)

Eigenvalues: (sum = 3, average = 1)					
Number	Value	Difference	Portion	Cumulative value	Cumulative portion
1	2.95339	2.91930	0.9844	2.95339	0.9844
2	0.03419	0.02179	0.0113	2.98758	0.9959
3	0.01240	-	0.0041	3.0000	1.0000
Eigenvectors (loadings)					
Variables	PC1	PC2	PC3		
LnMOB	0.57906	−0.25505	0.77435		
LnTEL	0.57760	−0.54196	−0.61044		
LnINT	0.57537	0.80076	−0.16651		
Correlation					
	LnMOB	LnTEL	LnINT		
LnMOB	1				
LnTEL	0.98669	1			
LnINT	0.97543	0.96794	1		

Table 2 Unit root test results

Variables	ADF		PP		Order of integration
	t-Statistic	Prob	t-Statistic	Prob	
lnCO2	−0.8830	0.7780	−0.9516	0.7555	I(1)
Δ(ln CO2)	−5.4119***	0.0002	−5.5452***	0.0001	
lnGDP	−0.5005	0.8764	−0.5120	0.8740	I(1)
Δln(GDP)	−5.0511***	0.0004	−5.0505***	0.0004	
ln(GDP)2	−2.7144*	0.0851	−1.9442	0.3082	I(1)
Δ(ln(GDP)2)	−4.1218***	0.0038	−4.0357***	0.0047	
lnBIOMASS	−2.2844	0.1838	−2.2798	0.1852	I(1)
Δ(ln BIOMASS)	−5.5523***	0.0001	−5.5523***	0.0001	
lnECI	−0.6887	0.8333	−0.7256	0.8236	I(1)
Δ(ln ECI)	−5.1911***	0.0003	−5.1914***	0.0003	
lnICT	−3.5620***	0.0010	−6.6088***	0.0000	I(0)
Δ(ln ICT)	−20.3961***	0.0000	−20.2158***	0.0000	

The asterisks *, **, and *** refer to significance levels of 10%, 5%, and 1%

The ARDL method can be used only when the variables are stationary with a degree of I (0) or I(1). Therefore, from the results of Table 2, ARDL co-integration analysis can be used in this study.

However, these unit root tests do not provide any possible structural break in the data series. Shahbaz et al. (2014) argue that the results of traditional unit root tests are not reliable in the presence of structural breaks. Therefore, we used the Zivot-Andrews unit root test with a structural break (Zivot & Andrews, 2002). This test is a generalization of the Perron test, which is used to find the endogenous date of structural change. In this test, the null hypothesis indicates the existence of a unit root (Perron, 1989).

The results of the structural break unit root test are reported in Table 3. As it can be seen, all variables are stationary in the first difference with a structural break. Per capita CO_2 emission is stationary with one structural break in 1999. This structural break resulted from a 36% increase in fossil fuel consumption in 1998 to achieve high economic growth by the Iranian government, accompanied by a rise in CO_2 emission. The variables of per capita GDP and the ECI are stationary, with one structural break in 2012. In 2011, the start of international sanctions reduced foreign investment, increased the exchange rate, and reduced economic growth in Iran, resulting in the loss of international markets for exports of the commodity. Because the Iranian government started investing in renewable energy in 2007, the biomass consumption variable is stationary with one structural break in 2008. Finally, the variable of ICT in 2000 is stationary with one structural break. This break could be due to the widespread use of the Internet, the prevalence utilized of fixed telephone and mobile cellphone in Iran in 1999.

Table 3 Zivot and Andrews unit root tests with structural breaks

Variables	Structural break year	t-Statistic	Prob	Order of integration
$lnCO_2$	2005	−3.7696	0.7125	**I(1)**
Δ(ln CO_2)	1999	−8.8181***	0.0000	
lnGDP	2016	−2.7662	0.8030	**I(1)**
Δln(GDP)	2012	−5.3755***	0.0001	
$ln(GDP)^2$	2016	−3.0798	0.6399	**I(1)**
$\Delta(ln(GDP)^2)$	2012	−5.3982***	0.0005	
lnBIOMASS	2007	−2.4458	0.9159	**I(1)**
Δ(ln BIOMASS)	2008	−8.1419***	0.0000	
lnECI	2015	−2.6283	0.8577	**I(1)**
Δ(ln ECI)	2012	−8.8520***	0.0001	
lnICT	2005	−2.5593	0.8937	**I(1)**
Δ(ln ICT)	2000	−9.8642***	0.0000	

To estimate the dynamic model, the optimal lag length should be determined based on one of the Akaike (AIC), Schwarz-Bayesian (SBC), or Hannan Quinn (HQ) criteria. According to the low number of observations, the Schwarz-Bayesian criterion (SBC) was used to determine the optimal lags of the model. This criterion is known as a saving criterion because it chooses the shortest possible lag length and, as a result, has a greater degree of freedom (Pesaran et al., 2001). So the optimal dynamic model was obtained as ARDL (1, 1, 0, 0, 1, 1).

The bound test was used to examine the co-integration of variables through entering the optimal lags obtained by the SBC. The existence of the long-run equilibrium relationship is confirmed if the F-statistics generated by the bound test is greater than the upper critical bound (UCB) of Pesaran et al. (2001). Conversely, if the lower critical bounds (LCB) exceed the F-statistics, it implies no co-integration. Lastly, if the *F*-statistic value lies between the UCB and LCB, the decision is made based on the error correction term. In this study, we compared the computed F-statistics with the critical bounds of Pesaran et al. (2001), which are generally preferred in the case of a small sample.

As can be seen from Table 4, the value of the *F*-statistic is above the critical limit at the level of 1%. Thus, the null hypothesis stating that there is no long-term relationship between the model variables was rejected. Consequently, there is co-integration between the variables of CO_2 emission, economic growth, biomass consumption, ECI, and ICT.

According to the co-integration, the results of the short-run dynamic model, error correction model (ECM), and the long-run model coefficients (Eq. 2) are shown in Table 5.

The estimates of the ARDL model in the short-run period showed that the coefficients of all variables have a significant relationship with CO_2 emissions except the lag and square of GDP per capita, and the lag of ICT and ECI variables in Iran. In the long run, a 0.88% increase will be seen in CO_2 emissions by increasing 1% the economic development. Also, a 1% increase in biomass energy, the ECI, and ICT will cause a 0.04%, 0.68%, and 0.078% decrease in CO_2 emissions, respectively. In this model, the square of the GDP variable is statistically non-significant, suggesting that the EKC is not approved in Iran. The findings are in line with the studies of Dogan and Ozturk (2017) for UAS, Azlina et al. (2014) for Malaysia, and Ben Jebli and Ben Youssef (2015) for Tunisia, also contradicting the results of Bekhet and Othman (2018) and Ali et al. (2017). These researchers endorsed the EKC path in the target countries and concluded that increasing per capita GDP levels would reduce emissions.

The error correction coefficient was obtained − 0.24. This coefficient shows the speed of shocks adjustment on the path from the short-run to the long-run relationship. In this study, the coefficient mentioned above indicates that 24% entered shocks adjusted in each period.

Comparison of short-run and long-run dynamic model coefficients showed that the effect of all variables on CO_2 emissions is more severe in the long run. The coefficient of GDP per capita variable in the long-term period has a greater impact on CO_2 emissions (0.7451 compared to 0.8801); this result confirms the findings of Hdom (2019) and Sinha and Shahbaz (2018) studies and also is contrary to Ridzuan et al. (2020) and Ali et al. (2017). They concluded that in the short run, increasing GDP would increase CO_2 emissions. But in the long run, it reduces CO_2 emissions.

While variable of biomass consumption reduces CO_2 emissions more severely in the long run (− 0.0094 compared to − 0.0396). This result is consistent with the results of Can and Gozgor (2017), Dong et al. (2018), and Yii and Geetha (2017), where a high coefficient in the long run indicates a positive impact on the environment in the long run.

The critical conclusion about ECI and ICT is that their coefficients are positive and significant in the short run; at the same time, they have a negative and significant effect in the long term. In the short term, the production, transportation, and use of hardware such as computers, network cables, and equipment are associated with consuming resources and energy, which has a negative impact and increases emissions. Meanwhile, in the long term, ICT can be a suitable tool to achieve simultaneously economic development and protection and sustainable development of the environment. This

Table 4 Bound test results to investigate the long-term co-integration relationship

Significance	Lower critical bound	Upper critical bound
10%	2.45	3.52
5%	2.86	4.01
2.5%	3.25	4.49
1%	3.74	5.06
F-statistic	6.2790	

Table 5 Results of the dynamic model, error correction model, and the long-term model coefficients

Variables	Coefficient	Std. error	t-Statistic	Prob
Short-run equation				
C	− 8.4203*	4.2430	− 1.9845	0.0505
$LnCO_2(-1)$	0.7631***	0.1509	5.0569	0.0000
LnGDP	0.7451***	0.0670	11.1208	0.0000
LnGDP(− 1)	− 0.5366	0.3626	− 1.4798	0.1455
$(LnGDP)^2$	3.3137 −	3.2065	− 1.0334	0.3067
LnBIOMASS	− 0.0094**	0.0043	− 2.1860	0.0338
LnECI	0.0278**	0.0137	2.8659	0.0481
LnECI(− 1)	− 0.1903	0.1507	− 1.2627	0.2129
LnICT	0.0228*	0.0123	1.8536	0.0700
LnICT(− 1)	− 0.0415	0.1096	− 0.3786	0.7066
ECM(− 1)	− 0.2439***	0.0731	− 3.3365	0.0016
Adjusted *R*-squared	0.9905			
F-statistic	167.4021			
Schwarz criterion	− 4.8293			
Durbin-Watson stat	2.4450			
Long-run equation				
C	− 35.5437***	9.4726	− 3.7522	0.0004
LnGDP	0.8801***	0.0615	14.3105	0.0000
$(LnGDP)^2$	13.9878 −	14.5159	− 0.9636	0.3401
LnBIOMASS	− 0.0396**	0.0165	− 2.4000	0.0204
ECI	− 0.6859***	0.2023	− 3.3905	0.0014
LnICT	− 0.0789**	0.0302	− 2.6125	0.0120

The asterisks *, **, and *** refer to significance levels of 10%, 5%, and 1%

result can attribute to the change in the economic structure, its transition from the energy and materials use to non-physical and informational inputs (such as Emails), changes in design, production, distribution, and products, and increasing the efficiency of the workforce. This finding confirms the results of a study conducted by Salahuddin et al. (2016). In the short run, ECI has increased environmental degradation; on the contrary, in the long run improved environmental quality in Iran. It can be concluded that the high level of structural changes and innovations in Iran would alleviate the environmental degradation challenges by increased energy efficiency.

To provide the validity of the ARDL model, the maximum likelihood, normal distribution of error terms, variance heterogeneity, and Ramsey tests were performed. Table 6 shows the results of the analysis of diagnostic tests. Tests of maximum likelihood, normality of error terms distribution, heteroscedastic variance, and Ramsey were conducted to validate the ARDL model. According to the results, it is observed that the ARDL model has not got any problems of auto co-integration, heteroscedastic variance, and misspecification error; besides, the error terms of the model are normally distributed.

CUSUM and CUSUMSQ tests were performed to show the stability of the model's estimated coefficients. As shown in Figs. 1 and 2, the null hypothesis cannot be rejected because the statistics of these two tests are placed between the two lines. Accordingly, the estimated coefficients will be stable at a significance level of 5%.

Table 7 shows the results of QR estimation. The QR approach provides a more accurate analysis of the whole conditional distribution than the mean regression, which focuses on only one part of the conditional distribution. This section investigates the effect of variables of economic growth, biomass consumption, ICT, and the ECI in different quantiles on CO_2 emissions, since dependent variables may have different impacts on CO_2 emissions outside the mean area.

Experimental analysis shows that most of the estimated coefficients of QR are significant, especially for the variables of GDP, ECI, and the ICT while there are differences in coefficients over the quantiles for the variables of the square of GDP and biomass consumption. Moreover, the results of QR clearly show that the coefficients of all variables are homogeneous in the conditional distributions of CO_2 emissions. The coefficient of the GDP variable is positive and has the highest value in the quantile (0.9274). This means that an increase in GDP has a positive effect on CO_2 emission, which is greater in the lower quantile of the conditional distribution. The coefficient of the square of GDP per capita variable has a significant negative effect on CO_2 emissions only in quantile $\tau=0.1$. The positive coefficient of GDP and the negative coefficient of the square of GDP in $\tau=0.1$; the EKC is confirmed in the lower quantiles of the conditional distribution as an inverse U. In other words, a sudden and severe shock to the GDP per capita variable does not improve the quality of the environment. Accordingly, this process must proceed so that people realize the effect of the environment quality as their income enhances. The coefficient of biomass consumption variable is significant only in the quantiles $\tau=0.1$ and $\tau=0.25$, while it is non-significant in the middle and upper quantiles. Hence, it is concluded that a big shock in increasing the use of biomass as renewable energy does not reduce CO_2 emissions because this variable underperforms at high values and practically loses its efficiency compared to the CO_2 emissions. The ECI has the highest value in the quantile $\tau = 0.9$ (−0.7159). The ICT coefficients show that this variable has a significant negative effect on CO_2 emissions in all quantiles; however, it has a weaker potential to reduce CO_2 emissions than ECI.

Finally, the variance decomposition approach was applied to predict the share of each of the variables of GDP, GDP per capita, biomass consumption, ECI, and the ICT on CO_2 emissions beyond the statistical period of the research (1994–2018). The results are reported in Table 8.

In this study, a 10-year forecast period was considered. Analysis of the findings highlights that about 38.3% of CO_2 emissions are caused by shocks from independent variables in the tenth year. Share of GDP per capita, the square of GDP per capita, biomass consumption, ECI, and ICT variables were 9.82%, 2.31%, 3.43%, 22.51%, and 0.25%, respectively.

The values of prediction show that in developing countries, especially Iran, an increase in efficiency, technological advancement, technical knowledge of the labor force besides, higher added values are the most important factors affecting the reduction of CO_2 emissions in the future. Furthermore, the economic development of Iran should be increased by improving the ECI. Considering the high consumption of fossil fuels in Iran, using renewable energy (biomass) instead of fossil fuel can reduce CO_2 emissions by 2030. The variable of ICT has the least effect on the reduction of CO_2 emissions in the coming years; nevertheless, it can be used to advance aims considering its benefits in improving technology and efficiency.

Table 6 Results of diagnostic tests for dynamic ARDL

Tests	Statistics	F-statistics	Prob
Serial correlation LM test	χ^2_{LM}	1.2553	0.2962
Normality test	χ^2_{NORM}	-	0.3314
Heteroscedasticity test	χ^2_{HET}	0.0393	0.8437
Ramsey RESET test	χ^2_{RESET}	0.3648	0.5493

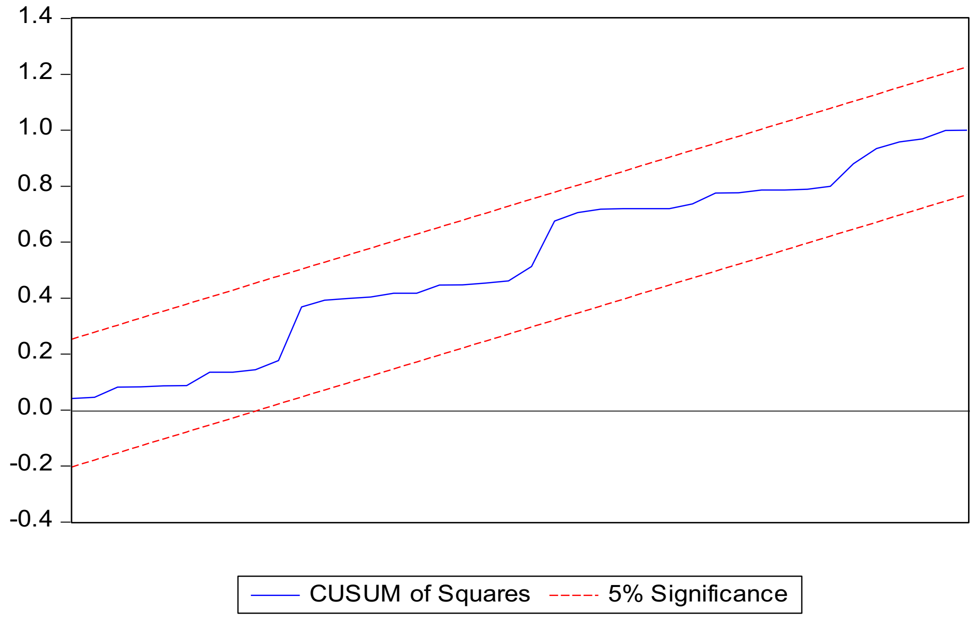

Fig. 1 Cumulative sum of squared residuals (CUSUMSQ)

Conclusion and policy implications

Regarding Iran's economy's dependence on oil and overusing fossil fuels, this study provides new evidence of the impacts of GDP per capita, biomass consumption, ECI, and the ICT variables on CO_2 emissions in Iran. According to the results, during both short-term and long-term periods, the GDP variable had a significant positive effect on CO_2 emissions; however, it had a greater impact during the long term than the short term. To validate the EKC hypothesis, the results showed that the U-shaped curve is not confirmed for Iran during the long run. However, QR analysis showed that this curve could be confirmed as inverse U in the lower quantiles of the conditional distribution.

Results also revealed that renewable energy (biomass) could reduce CO_2 emissions. According to this study, the Iranian government can achieve its aims by 2030 to reduce CO_2 emissions by reducing fossil fuels but using renewable energy. Besides, the long-run and short-run coefficients of biomass consumption are – 0.0094 and – 0.0396,

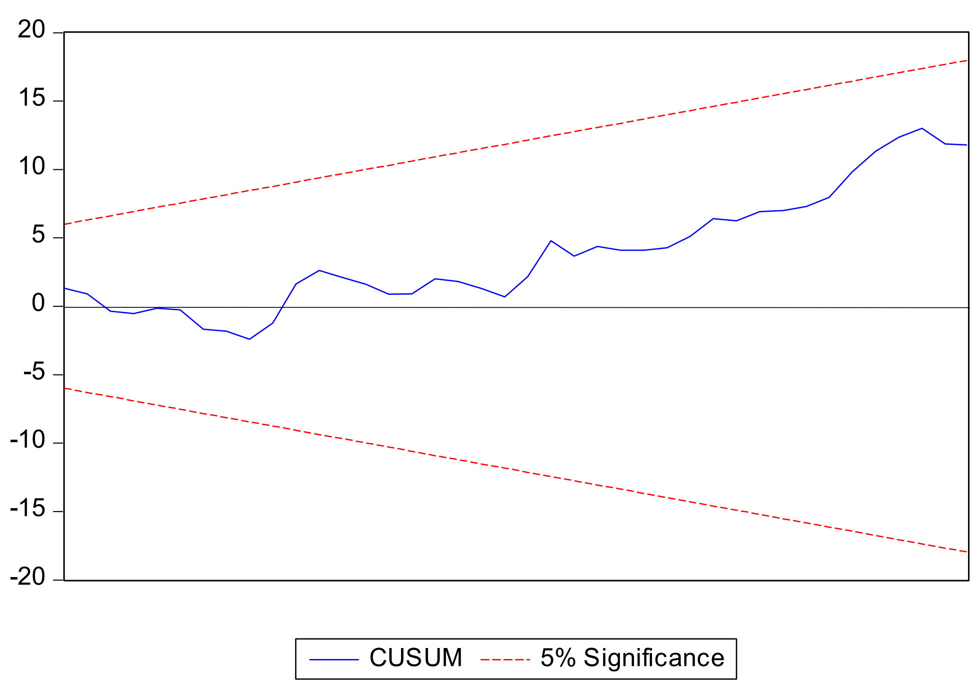

Fig. 2 Cumulative sum of residuals (CUSUM)

Table 7 Results of QR estimation on conditional distributions of CO_2 emissions

Variables	Quantile regression				
	$\tau = 0.1$	$\tau = 0.25$	$\tau = 0.5$	$\tau = 0.75$	$\tau = 0.9$
C	-31.6792^{**} (0.0140)	-33.5941^{***} (0.0036)	-41.7521^{***} (0.0003)	-39.1186^{***} (0.0003)	-35.7074 (0.2796)
LnGDP	0.9278^{***} (0.0000)	0.8721^{***} (0.0000)	0.8932^{***} (0.0000)	0.9105^{***} (0.0000)	0.8173^{***} (0.0000)
$(\text{LnGDP})^2$	-12.4367^{**} (0.0243)	-13.7552 (0.1289)	-17.8642 (0.2467)	-16.7596 (0.2201)	6.3354 (0.7086)
LnBIOMASS	-0.0742^{***} (0.0020)	-0.0699^{*} (0.0624)	-0.0443 (0.2901)	-0.0087 (0.8495)	-0.0218 (0.6001)
LnECI	-0.6485^{***} (0.0000)	-0.6824^{***} (0.0000)	-0.6536^{***} (0.0000)	-0.6378^{***} (0.0000)	-0.7159^{***} (0.0002)
LnICT	-0.0723^{*} (0.0501)	-0.0746^{*} (0.0618)	-0.0762^{**} (0.0344)	-0.0753^{**} (0.0350)	-0.0780** (0.0264)

The asterisks *, **, and *** refer to significance levels of 10%, 5%, and 1%

respectively. This result shows that renewable energy is an efficient tool for sustainable development. A comparison between GDP per capita and renewable energy consumption variables indicates that during the long-run period, 1% growth in GDP per capita and biomass consumption increases and decreases CO_2 emissions by a rate of 0.88% and 0.039%, respectively. This result states that the negative impact of achieving higher economic development on the environment is greater than the ecological benefits of renewable energy consumption in Iran. Thus, the ecological benefits of renewable energy consumption should be considered. Furthermore, the income threshold should be determined to reach the turning point of the EKC.

This study also found a negative and significant relationship between the ECI and CO_2 emissions. Here, the ECI was considered a measure of capabilities and efficiencies for exporting high value-added products. Hence, a diverse and knowledge-based economy can help improve the quality of the environment. Moreover, based on the 10-year forecast, CO_2 emissions are most affected by shocks from the ECI. Therefore, policymakers must consider the role of economic complexity for sustainable economic development.

Eventually, in this study, there was a significant positive relationship between ICT and CO_2 emissions during the short-run period (0.0228), while in the long run it was negative and significant (− 0.0789). During the short-run period, the production of new equipment for ICT and energy consumption increases CO_2 emissions. However, in the long run, due to changes in the economic structure, the prosperity of online business, and growing online sales, the use of E-books instead of paper books will increase the quality of the environment and reduce CO_2 emissions. This study has certain constraints; for instance, it uses three ICT indicators (individual internet users, mobile cellular subscriptions, and fixed telephone subscriptions) to build an ICT index because of data limitations. As well, the renewable energy index (which includes biomass, solar energy, wind, hydropower, and geothermal energies) should have been used instead of biomass. So, future studies can use renewable consumption index and more ICT indicators.

Table 8 Variance decomposition analysis

Response variable	Period	Impulse response						
LnCO2		S.E	LN(CO2)	LnGDP	Ln(GDP)2	LnBIOMASS	LnECI	LnICT
	1	0.034861	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
	2	0.051797	93.07616	4.713425	0.746751	1.139976	0.290225	0.033463
	3	0.064401	85.78564	6.431943	0.816586	1.205987	5.689347	0.070497
	4	0.076101	78.54719	6.762647	0.956993	1.393618	12.26657	0.072982
	5	0.084997	72.23225	7.202401	1.026250	1.426670	18.03650	0.075929
	6	0.093011	68.22904	7.814327	1.385498	2.064881	20.42448	0.081774
	7	0.098995	66.40015	8.249998	1.552817	2.545110	21.16549	0.086435
	8	0.103723	64.74498	8.662112	1.723954	2.895001	21.87713	0.096823
	9	0.107821	62.66823	9.579483	1.989010	3.239991	22.39009	0.133196
	10	0.110641	61.64881	9.828043	2.315713	3.429871	22.52110	0.256463

Author contribution The authors confirm contribution to the paper as follows: study conception and design: AM, SSY; data collection: MHEN and HG; analysis and interpretation of results: AM, SSY; draft manuscript preparation: SSY. All authors reviewed the results and approved the final version of the manuscript.

Data availability The data that support the findings of this study are available from the corresponding author, [second author], upon reasonable request.

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Conflict of interest The authors declare no competing interests.

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