The estimation of influencing factors for carbon emissions based on EKC hypothesis and STIRPAT model: Evidence from top 10 countries

Ellen Thio[1] · MeiXuen Tan[1] · Liang Li[1,2] · Muhammad Salman[3] · Xingle Long[4] · Huaping Sun[5] · Bangzhu Zhu[1]

Abstract

Global climate change due to greenhouse gas emissions has observable impacts on environment. Among the GHG emissions, carbon dioxide is the primary source of global climate change. In order to provide appropriate measures to control carbon emissions, it appears that there is an urgent need to address how such factors such as economic growth, exports, imports, and technology innovation affect carbon emissions in world's top carbon emitter countries. We thus employed an extended Environmental Kuznets Curve, Population, Affluence and Technology (STIRPAT) model combined with panel quantile regression to analyze the driving factors of carbon emissions across top 10 countries from 2000 to 2014. We also conducted the panel quantile regression to ascertain the relationship between variables and examine the EKC. The results obtained show that firstly, the main results are that income per capita significantly increases environmental pollution across top 10 carbon emissions countries; this study also supported the EKC hypothesis in the top 10 countries in China, USA, India, Russia, Japan, Germany, South Korea, Canada, Mexico, and South Africain China, USA, India, Russia, Japan, Germany, South Korea, Canada, Mexico, and South Africa. Second, with the top 10 countries, the STIRPAT model is verified using the panel quantile regression approach, and population, energy use, exports, and imports of information communication technology are found to be the key impact factors of higher level of carbon emissions. However, technology innovation is conducive to the carbon emissions reduction. The results obtained show that the EKC hypothesis holds across top 10 carbon emissions countries. The governments of these countries should institute policies for promoting environmental technology innovation and energy efficiency in order to achieve sustainable development of population, resources, and the environment.

Keywords Environmental Kuznets curve · STIRPAT model · Environmental pollution

✉ Liang Li
    llcwllcw@hotmail.com

Extended author information available on the last page of the article

1 Introduction

Policymakers have challenges developing sustainable plans given the inadequacy of resources, rapid population, economics, and environmental pollution (Ji et al., 2017; Zha et al., 2014; Sun et al., 2020a). Carbon dioxide (CO_2) is generally produced from fossil fuel energy such as fuel oil in vehicles and coal power plant. The examples of carbon emissions are CO_2, exhaust gases from burning gasoline, diesel, wood, and other fuels. Carbon emissions also can be generated from residential, commercial, and industrial buildings (Zhou & Zhang, 2020; Kharbach & Chfadi, 2017; Wang et al., 2020a; Li et al., 2018, 2020a, 2020b).

Carbon dioxide accounts for around 75% of greenhouse gas emissions which is one of the leading causes of greenhouse gases that contribute to global warming. The mounting level of CO_2 has not only increased earth's temperature and caused global warming but also endangered human health (Manisalidis et al., 2020; Li et al., 2020c). In addition, CO2 emission was 1.2% during 2016–2017 but increased to 1.9% in 2018, which is considered pretty high (EDGAR, 2019). The U.N. Intergovernmental Panel on Climate Change warns that the global temperature increased by 1.5 °C, which is obviously quite high. Therefore, rapid measures are necessary to reduce CO2 emissions from top emitted countries.

The world's top 10 carbon emitters namely, China, USA, India, Russia, Japan, Germany, South Korea, Canada, Mexico, and South Africa are held responsible for about two-third of the global carbon emissions. The BP Statistical Review of World Energy (2019) reports that the top emitter countries contribute significantly to the global carbon emissions; for example, China (27.8%), USA (15.2%), India (7.3%), Japan (3.4%), South Korea (2.1%), Iran (1.9%), Saudi Arabia (1.7%), Canada (1.6%), Brazil (1.3%), and South Africa (1.2%), which shows that these countries are the key players for reducing the number of emissions in the world. Moreover, these countries together represent around 51% of the world population, 65% of worldwide GDP, 80% of overall global fossil fuel consumption, and 67.5% of total global fossil CO_2 (World Bank, 2020). Therefore, knowing the roles of key impact factors such as economic growth, exports, and imports of ICT in carbon emissions reduction is one of the important issues for policy makers across these countries.

Previous researchers have suggested that Environmental Kuznets Curve (EKC) hypothesis estimates the relationship between carbon emission and economic growth. These studies have shown that economic growth and carbon emissions can be reflected through an inverted U-shaped curve. The EKC demonstrated that in the initial stages of economic growth, economic growth positively affects carbon emissions. However, after a certain income increase level, carbon emission will decrease when there is increasing in economic growth, then environmental quality improves. Numerous researchers have used carbon emission as a typically indicator of environmental degradation in the EKC model for economic growth and sustainable development. The development of EKC hypothesis continues globally, research in various categories with the approach of developed and developing countries, with one country or a panel data approach in multiple countries. For example, Isik et al. (2019) adopted a heterogeneous panel estimation method with cross-sectional dependence for ten US states from 1980 to 2015. They concluded that Florida, Michigan, Illinois, New York, and Ohio show inverted U-shaped, supporting the EKC hypothesis; Khan et al., (2018a, 2018b), Iwata et al. (2010), and Pata (2018) in UK, Ulucak and Bilgili (2018) across high-, middle-, and low-income countries, Leal & Marques (2020) investigated 20 highest carbon emitters countries in the OECD countries. Balado-Naves et al. (2018) tested 173 countries and the results showed that green innovation's efficiency can address climate change. Hasanov et al. (2019) tested for developing countries. In the same

way, the EKC model is validated in Turkey during 1974 and 2013 (Koçak & Şarkgüneşi, 2018), as well in Singapore and Brazil (Zambrano-Monserrate et al., 2016, 2018). Sugiawan and Managi (2016) examined the hypothesis of inverted U-shaped in Indonesia by adopting the autoregressive distributed lag (ARDL) approach and co-integration within the time series of 1971–2010. Leal & Marques (2020) adopted the Driscoll–Kraay estimator from 1990 to 2016 and found the inverted U shaped for the high-globalized group but the opposite result for the low-globalized group. Based on the previous research results, these researchers provide convincing evidence on the presence of EKC implying that the level of carbon emissions has initially increased as income level increase.

However, in terms of previous studies included carbon monoxide (CO) and sulfur dioxide (SO_2) are chosen as some environmental indicators in EKC model for the study in Canada during 1974–1997, but this study did not support EKC hypothesis (Day & Grafton, 2003). Similarly, Isik et al. (2019) analyzed the 50 US states and Pata (2018) analyzed for Turkey, and the results showed partial acceptance of the EKC hypothesis. Pata and Aydin (2020) in top six hydropower energy-consuming countries, and Zambrano-Monserrate et al. (2018) in Peru did not verify the presence of EKC hypothesis across these countries. Thus, we can see that EKC hypothesis was conducted in different countries and different regions, and periods. However, there is lack study about studying carbon emission factors across the top 10 carbon emission countries by extending EKC model.

To be more specific, EKC hypothesis has been extended by using additional variables or control variables. Energy consumption is frequently conducted in EKC hypothesis. For instance, energy consumption was conducted in EKC model testing in European countries by Acaravci and Ozturk (2010), while Baek and Kim (2013) tested EKC hypothesis in Korea by testing energy consumption. This study also was conducted electric production included fossil fuel and nuclear energy. Foreign direct investment (FDI) was also shown in the study of EKC in (MIKTA countries) Mexico, Indonesia, South Korea, Turkey, and Australia by Bakirtas and Cetin (2017). Further, trade openness, population, and energy use were conducted for testing EKC hypothesis in 13 Asian countries (Salim et al., 2019). Moreover, there are various of the methodology of testing EKC hypothesis, cross-section analysis, Johansen cointegration, Granger causality, FMOLS approaches, and autoregressive distributed lag (ARDL) bounds testing that have been used in numerous papers (Sun et al., 2020a, 2020b; Hasanov et al., 2018). For instance, Acaravci and Ozturk (2010) studied EKC in European countries between 1960 and 2005 using the ARDL approach. It is shown that EKC is valid in Denmark and Italy, but the rest on other countries did not support EKC. However, France supported the validity of EKC from 1960 through 2000 using VECM method (Ang, 2007). During 1971 and 2007, autoregressive distributed lag (ARDL) bounds testing approach confirmed that EKC hypothesis was validated in Korea (Baek & Kim, 2013). ARDL modeling approach has tested the EKC hypothesis in Turkey (Shahbaz et al., 2013), Pakistan (Shahbaz et al., 2012), and ASEAN (Saboori & Sulaiman, 2013).

In the addition, considering the previous literature on the validity of the environmental Kuznets Curve, renewable energy has been incorporated in the EKC model to mitigate environmental degradation. For example, Murad et al. (2019) argued that reducing energy consumption by adopting technological innovations. Green technology innovation is emerging, focusing on transportation, building, agriculture, water, and renewable energy related resource-saving infrastructure to improve water, energy efficiency, and reduce greenhouse gas emissions. Ozcan and Ulucak (2020) investigated nuclear energy and population on environmental sustainability through EKC framework from 1971 to 2018 by applying the dynamic ARDL approach. Their empirical findings show that

nuclear energy negatively impacts environmental degradation and population stimulates carbon emissions. Gill et al. (2018) evaluated the EKC for the environmental quality in the world and the author states that a country needs to limit energy use by engaging the government to develop policies that contribute to increasing renewable energy and limiting non-renewable energy lines. However, contradictory to Pata, U.K. (2018) found the renewable and alternative energy consumption had not affected carbon emissions.

Moreover, the validity testing of EKC in 17 OECD countries by FMOLS and panel DOLS estimations between 1977 and 2010 shown that EKC is valid and renewable energy consumption that has a significant negative association with carbon emissions (Bilgili et al., 2016). However, Karasoy (2019) studied the EKC hypothesis in Turkey using the nonlinear autoregressive distributed lag (NARDL) approach from 1965 to 2015. This study added non-renewable energy consumption and renewable energy consumption in the EKC model, but the result does not support the EKC hypothesis in this area.

ICT is an amalgamation of information and other related technologies, particularly communication technology. ICT can provide information processing and communication functions through technologies, such as components, devices, applications, systems, computer hardware, peripherals, connection to the internet, allowing people or groups of organizations to interact in the digital world. ICT has been qualified as a vital role for reducing energy consumption, improving energy efficiency, and contributing to environmental reduction (Melville, 2010). As Khan et al., (2018a, 2018b) tested, the role of ICT and economic growth contributed CO_2 emission, the interaction between ICT and GDP mitigated the level of pollution. Empirical research evidence against the same background tested by Amri et al. (2019), Zhou et al. (2019), Avom et al. (2020), Ngunyen et al. (2020), Zhang and Liu (2015). Amri et al. (2019) have found that ICT does not significantly impact carbon emissions. Zhou et al. (2019) developed an embodied carbon analysis model by integrating input–output approaches to explore the ICT contributions carbon emissions at the sector level. Atom et al. (2020) argued that ICT affects energy use, which impacts carbon emissions. Zhang and Liu (2015) also found the ICT can enhance economic growth and carbon emission. However, there is very little research on exporting and importing ICT commodities and STIRPAT's model for different technology innovation types on carbon emission (Yu & Du, 2019; Nguyen et al., 2020). They argued that introducing innovation negatively impacts environmental degradation. Therefore, based on the divided opinions of scholars, this study explores the effects of ICT exports and imports on carbon emissions under the framework of EKC across top 10 carbon emitted countries.

Against the above background, the motivation of this study is to introduce the differential roles of ICT exports and imports on carbon emissions under the umbrella of EKC while considering population and energy use as important factors by using panel quantile regression. This might help to avoid variable bias. Thus, the research gap identified above poses several important research questions that beg for answers and motivate future research. Firstly, do the top ten carbon emission countries adopt an EKC hypothesis? Second, what is the impact of export and import ICT on environmental degradation in top carbon emission countries? Third, do STIRPAT's model factors play a role in the environmental degradation in the top 10 carbon emission countries?

To address the proposed questions, this research contributes to the existing literature through following objectives: (1) to examine whether the EKC theory holds for top carbon emissions countries; (2) to investigate the impact of ICT exports and imports on carbon emissions among top carbon emissions countries; and (3) to explore the influence of population, affluence, and technology on carbon emissions in order to avoid variable bias.

This current study of contributes are as follows: This study considers the trade openness of ICT and renewable energy use to solve environmental pollution by incorporating EKC and STIRPAT's model across the top ten countries. To be more specific, this present study fills out the research gap of the impacts of trade openness of ICT on carbon emission and provides empirical supports to verify the implications of EKC and STIRPAT's model on carbon emission across the top 10 countries, moreover to reduce the EKC effect uncertainty and to verify the inconsistent about renewable energy contribution and carbon emission.

2 Literature review and research model

This section provides a comprehensive review of previous studies and outline the research model of the study. Section 2.1 briefly describes the formulation of STIRPAT model based on the classical IPAT identity. Section 2.2 summarizes previous papers regarding the impacts of population, renewable energy use, and economic growth on CO2 emissions and formulate a model based on these variables. In Sect. 2.3, extensive literature is reviewed on the influencing roles of import and export of information communication technology and energy use on CO2 emissions and outline the econometric model based on these indicators. In Sect. 2.4, we integrated panel quantile regression into STIRPAT model. Finally, the research gaps are clearly identified.

2.1 Extending IPAT and STIRPAT model

Considering (I) as human impact, (P) as population, (A) as prosperity, and (T) as technology, Ehrlich and Holdren (1971) introduced the IPAT model as an environmental tool to investigate the main variables affecting environmental quality. Since then, IPAT has been widely used framework in the area of environment (York et al., 2003) and can be expressed as follows:

$$I = P.A.T \tag{1}$$

The classic IPAT model shown above mainly describes the impact of three key drivers: population, affluence, and technology on environment (York et al., 2003). Subsequently, Roca (2002) argued that other key factors of environmental degradation need to be further investigated. Even though IPAT is an extensive approach to analyze the influence of the main factors on the environment, it failed to incorporate other key impact factors of environmental degradation in the model in overcoming the limitations of the IPAT model (Tursun et al., 2015). To tackle the shortcomings of IPAT model, Dietz and Rosa (1994) developed the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model and has been widely used by many researchers (Fan et al., 2006; Wei et al., 2011; Lin et al., 2017; Yang et al., 2018). Additionally, STIRPAT model unlike IPAT identity can empirically test the hypotheses model (York et al., 2003) and incorporate other non-proportional variables on the environment (Lin et al., 2009). The STIRPAT in its general form can be modeled in the following manner:

$$I_i = \alpha P_i^b A_i^c T_i^d e_i \tag{2}$$

where α represents the constant term; b, c, d represents the exponents of P, A, and T, respectively; e is the error term, and i indicates that the quantities of observational units of $I - P - A - T - e$. In line with IPAT, the STIRPAT equation preserves the multiplicative logic from $I = P.A.T$. In formula 2, the variables are without logarithmic form and are suitable for theory analysis only. Therefore, researchers use logarithms in order to obtain the empirical investigation of the driving factors added in this model (Wang et al., 2017). Hence, the logarithmic version of STIRPAT model is outlined as follows:

$$\ln I_{it} \ = \ \alpha \ + \ b\,(P_{it}) \ + \ c\,(A_{it}) \ + \ d\,(T_{it}) \ + \ \ln e_i \tag{3}$$

where ln denotes natural logarithms· a as the constant; b, c, d as the exponents, P, A, T as the determinants, respectively; I as environmental impact; subscript i as the observational units; t as the year; e as the error term.

2.2 Population, renewable energy use, and economic growth and CO_2 emissions

The effect of population growth on environmental quality is assumed by when population growth occurs, the pressure on resources and consumption levels will increase, and an increase in energy use triggers environmental degradation. For example, population growth increase carbon dioxide emissions through increased human activity, such as consumption and energy use (Sulaiman & Abdul-Rahim, 2018). Moreover, Khan et al. (2021) found that the growth of the population has a unidirectional impact on energy consumption which will ultimately increase carbon emissions. Similarly, Yeh & Liao (2017) investigated the effect of people on carbon emissions in Taiwan from 1990 to 2014 by using the STIRPAT model. The results showed that the population growth significantly increase carbon emissions. Based on the STIRPAT model, Salman et al. (2019) examined the effect of population growth across seven ASEAN member countries over the period 1990–2018. The results of panel quantile regression revealed that population growth is not conducive to carbon emissions abatement. Saleem et al. (2018) examined population growth–carbon emissions interplay across 11 countries using panel regression and found that population growth significantly triggers carbon emissions. Aligned with Shi (2001) argued that as the population grows, human activities will increase, contributing to the generation of carbon emissions and the increase of energy boost. This research stated that a 1.28% increase in carbon emissions results from a 1% increase in population.

The relationship between GDP and carbon emissions can be understood through the Environmental Kuznets Curve (EKC) hypothesis initially introduced by Grossman and Krueger (1991a, 1991b) and subsequently modified by Grossman and Krueger (1995) in the context of environment. Since then, a huge literature has blossomed investigating the existence of EKC considering different countries and estimation approaches. For example, Zhang and Zhang (2018) analyzed the presence of EKC in China over the period from 1982 to 2016. Based on the results of ARDL estimator, they confirmed the validity of EKC. Using generalized method of moments (GMM) method, Chaabouni and Saidi (2017) stated that there is bidirectional causality between GDP per capita and carbon emissions across 51 countries during 1995–2013. On contrary, the studies of Zambrano-Monserrate and Fernandez (2017) for Germany, Koc and Bulus (2020) for Korea, He and Richard (2010) for Canada did not support the EKC hypothesis.

The third strand of literature describes the role of renewable energy use in carbon emissions reduction. It is generally argued that renewable energy technology innovation can

reduce the level of carbon emissions. Hence, numerous studies have been conducted to explore the impact of renewable energy on carbon emissions. Nguyen et al. (2020) stated that countries need to be aware of the understanding and the increasing role of renewable energy innovation in emissions reduction. In addition, Ali et al. (2017) found an insignificant negative relationship between renewable energy innovation and carbon emissions in Singapore. Other stream of studies including Mensah et al. (2018) for OECD countries, Fan and Hossain (2018) for China and India, Ngunyen et al. (2020) for G-20 countries, Ganda (2020) for selected OECD countries, Wang and Zhu (2020) for China, and Erdoğan et al. (2020) for G-20 countries considered renewable technology innovation–carbon emissions nexus for their empirical analysis and claimed that renewable technology innovation is conducive to carbon emissions abatement.

According to the above findings, we have following the EKC theory and STIRPAT model for data analysis formed in Eq. (2) that CO_2 in carbon emissions level represents the environmental impacts (stands for I in STIRPAT equation), POP is population (stands for P in STIRPAT equation), the affluence stands for A in STIRPAT equation represented by GDP, and ANE depicts alternative and renewable energy represents the renewable energy use (stands for T in STIRPAT equation). In line with Zhang and Liu (2015); Yeh & Liao (2017); Pham et al., (2020) and following the STIRPAT model, this study outlines the following model:

$$CO_{2it} = f(POP_{it}, GDP_{it}, TI_{it}) \qquad (4)$$

2.3 Import and export of information communication technology, energy use and CO_2 emissions

Along with the development of technology from time to time, the internet-based digital economic development, import and export of the ICT sector continue to grow. Global market demand for ICT technology innovation has encouraged the import and export of ICT, such as communication equipment, electronic devices, computers and peripherals, and other supporting equipment. In 2009, the export of ICT goods represented 12% of the total world goods trade (UNCTAD, 2011). However, the export of ICT goods has grown by 26% in the last 2 years, with China as the top exporter replacing the USA (OECD, 2013). In 2009, Asian countries contributed 66.3% of the total exports of ICT Goods globally, with one-third of the total coming from China and Hong Kong. As reported from Indexmundi (2019), the highest ICT goods export country is Hong Kong with the value of 51.67% of the total percentage of total goods export.

The use of ICT has an impact on both micro- and macro-economy, as Gordon (2000) stated that there was an increase in productivity and growth with the adoption of ICT in the early 1990s. Knoema (2019) described the goods imported by a country: telecommunications, audio, video, computers, and electronic components. The weights of export and import trade in ICT goods contributed 16.1% in 2000 of total global export and import, then experienced a significant decline due to the economic crisis in 2008 and began to show a rising trend in 2014 with an annual increase of 6% (UNCTAD, 2019). As reported by UNCTAD (2019), the Republic of Korea had the highest growth rate in 2014 with a growth value of 29%. The top 10 countries of ICT exports in 2017 were China, Korea, Taiwan, Singapore, Germany, USA, Malaysia, Mexico, Japan, and the Netherlands, representing 86% of total ICT goods export. The 10 countries with the top imports of ICT goods in 2017 were the USA, China, Hong Kong, Germany, Singapore, Japan, Korea, Taiwan,

Mexico, and the Netherlands with Taiwan having the highest growth rate (18%). The most significant annual growth in importing ICT goods is occupied by transition countries in Southeast Europe (29%) and developed countries (10%).

Salman (2019) adopted the hypothesis of a pollution haven due to international trade on environmental degradation. Trade across countries encourages exports and imports that impact the environment both positive and negative. Tiba and Belaid (2020) found a two-sided causality between trade and carbon emissions. Xu et al. (2020) stated that manufactured products plays an essential role in avoiding environmental pollution and increasing the value-added ratio of a trade. The application of new and high technology reduces carbon emissions in developed countries but increases in developing countries (Wang et al., 2020a, 2020b). Additionally, Mahmood et al. (2020) claimed that exports have negative effects on carbon emissions for the home country and a positive effects for the host countries. According to Sinha (2018), the ICT exports might affect the environment by increasing the exports of cooling technologies. The extensive use of cooling technologies raise the temperature which will ultimately enhance carbon emissions. Secondly, the higher ICT export may contribute to an increase in energy use thereby, increasing carbon emissions (Zhou et al., 2019). Third, ICT exports have a positive relationship with energy demand, which would intensify carbon emissions as Li et al., (2020c) stated that the energy demand that are finally used and produced by enterprises plays a significant role in producing the total energy CO_2. Lastly, ICT exports could increase economic growth. Previous studies found both positive and negative effects of trade openness on carbon emissions such as positive effect (Osobajo et al., 2020) and negative effect (Acheampong, 2018).

Regarding ICT imports–carbon emissions nexus, there is a little evidence in the existing literature. Therefore, we will review previous studies that actively analyzed ICT-carbon emissions interplay. For example, Godil et al. (2020) examined the impact of ICT on carbon emissions in Pakistan in 1995–2018 period by using ARDL. The findings shown that ICT has a negative correlation with carbon emissions, which means the higher presence of ICT will reduce the release of CO_2 in the environment. In line with Godil et al. (2020), Ozcan & Apergis (2018), and Zhang and Liu (2015) investigated the impact of ICT industry in China using STIRPAT model, and they have found that the ICT industry is effective in overcoming environmental pollution problems. Ozcan & Apergis (2018) use internet usage to represent the ICT, the empirical results disclosed that internet usage lowers carbon emissions.

Zhang et al. (2019) stated that ICT actively mitigated carbon emissions in Belt and Road countries, mitigated the environmental problem such as climate change. Faisal et al. (2020) examine the effect of ICT and other exogenous variables on carbon emissions in the fast-emerging countries from 1993 to 2014. The results indicate there is a unidirectional causality between ICT and CO_2, the other finding shown that ICT has an inverted U shape with carbon emissions, which means after reach at a threshold point in using ICT, the impact on environmental pollution will decline. Moreover, Filos (2010) stated ICT plays an important role for promoting environmental sustainability.

However, many scholars, such as Khan et al., (2018a, 2018b), Raheem et al. (2020), Asongu (2017), Malmodin & Lunden (2018a), Salahuddin et al. (2016) found that ICT has a positive effect on carbon emissions, impling that ICT stimulates the level of carbon emissions. In addition, in line with the thought of Godil et al. (2020), operating on the further development of ICT will use higher energy to increase carbon emissions. Majeed (2018) claimed that ICT yields mixed effects on carbon emissions reduction across developed and developing countries. According to the research findings, ICT

plays an unprecedented role in reducing carbon emissions in developed countries, while the argument is opposite in case of developing countries.

In relation to energy use–carbon emissions nexus, numerous studies have examined the causality among energy use and carbon emissions. Previous studies found that energy use causes an increase in economic growth (Esen & Bayrak, 2017; Ali et al., 2016); Ketenci (2018) stated that the impact of energy consumption on carbon emissions is stronger than income, underlined by the findings that an increase in per capita carbon emissions of more than 100% when there is an increase of every 1% per capita energy consumption, but an increase in real income per capita of 1% has an effect on an increase in carbon emissions by 1%. In Pakistan, Khan et al. (2021) by using annual time series 1965–2015 and ARDL approach found that energy consumption has a positive relationship with carbon emissions, which energy consumption tends to increase carbon emissions both in the short and long run. Wu et al. (2020) uses GMM method and found that energy consumption plays a crucial role in enhancing carbon emissions. Liu et al. (2020) applied a nonlinear ARDL lag model in China with time series 1971–2014. The findings show a relationship among energy consumption and carbon emissions either in the short run or long run. Farabi et al. (2019) examined the causality in Indonesia and Malaysia through a series of econometric techniques. The results indicate the causality between energy use and carbon emissions exist in short run and long run. Similarly, Waheed et al. (2019) found that high energy consumption levels are associated with increased carbon emissions in developed and developing countries.

York et al. (2003) stated that the additional factors in Eq. (3) can be incorporated only and if they are conceptually consistent with the multiplicative logic of the model. Therefore, based on the above literature, this study extended the STIRPAT model by adding Export ICT (EXPICT), Import ICT (IMPICT), and Energy Use (EU). Therefore, this study developed the model as follows:

$$CO_{2it} = f(POP_{it}, GDP_{it}, TI_{it}, EXPICT_{it}, IMPICT_{it}, EU_{it}) \tag{5}$$

Each variable is then transformed in the natural logarithm (ln) form to determine the parameter's value. Natural logarithms (Ln) in this study are intended to reduce excess data fluctuations and overcome heteroskedastic problems. Thus, Eq. 5 is expressed as follow:

$$\ln CO_{2it} = \alpha_{it} + \alpha_1(\ln POP_{it}) + \alpha_2(\ln GDP_{it}) + \alpha_3(\ln TI_{it}) + \alpha_4(\ln EXPICT_{it}) + \alpha_5(\ln IMPICT_{it})$$
$$+ \alpha_6(\ln EU_{it}) + \varepsilon_{it}$$
$$\tag{6}$$

In Eq. 6, $lnCO_{2it}$ is the natural logarithm form of CO_2, $lnPOP_{it}$ represents the natural logarithm of population, $lnGDP_{it}$ represents the natural logarithmic form of affluence, $lnTI_{it}$ denotes the natural logarithm of Technology Innovation, $lnEXPICT_{it}$ and $lnIMPICT_{it}$ represent the natural logarithmic forms of export ICT and import ICT, and $lnEU_{it}$ represents the natural logarithm form of energy use. ε_{it} represents the error term. The elasticity of CO_2 emissions concerning population, GDP, technology innovation, export ICT, import ICT, and energy use is indicated by the respective coefficients of α_1, $\alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6$, while α_{it} represents the constant parameter. Furthermore, this study also verifies the presence of the EKC (Grossman & Krueger, 1991a, 1991b) in the selected countries by adding the square root of GDP per capita. Hence, Eq. 6 is transformed into EKC framework in the following manner:

$$\ln CO_{2it} = \alpha_{it} + \alpha_1(\ln POP_{it}) + \alpha_2(\ln GDP_{it}) + \alpha_3(\ln GDP_{it})^2 + \alpha_4(\ln TI_{it}) + \alpha_5(\ln EXPICT_{it})$$
$$+ \alpha_6(\ln IMPICT_{it}) + \alpha_7(\ln EU_{it}) + \varepsilon_{it}$$

$$(7)$$

2.4 Panel quantile regression for testing STIRPAT model

Quantile regression introduced by Koenker and Bassett (1978) is an effective estimation approach by dividing data into certain quantiles. This approach is often used to overcome the limitations in the OLS approach (Salman et al., 2019). Quantile regression can overcome the limitations of linear regression that fails to solve the problem of heteroscedasticity. Moreover, Bera et al. (2016) stated that quantile regression estimation overcomes the limitation of non-robust findings in asymmetric distribution of data. In dealing with undistributed normal data, quantile regression can also overcome the limits as this method does not contemplate distribution assumptions. In addition, this approach minimizes the weighted absolute error that is not symmetrical and estimate the conditional quantile function on data distribution. Estimation of quantile regression parameters does not require parametric assumptions. The panel quantile regression's standard form formula can be written as below:

$$Q_\theta(Y_{it}) = X_{it}\beta(\theta) + \varepsilon_{it}$$

$$(8)$$

where Y represents the dependent variable, X denotes the independent variable, ϵ indicates the error term. $\beta(\theta)$ indicates the θth dependent quantile regression coefficient at $(0 < \theta < 1)$.

Based on Environmental Kuznets Curve (EKC), the signs of GDP per capital and the square root of GDP per capital coefficients are expected to be positive and negative, respectively. According to the above discussion, the STIRPAT model integrated with panel quantile regression in this study can be outlined as follows:

$$Q_\tau(LNCO_{2it}) = \alpha_\tau + \beta_{1\tau}LNPOP_{it} + \beta_{2\tau}LNGDP_{it} + \beta_{3\tau}(LNGDP_{it})^2 + \beta_{4\tau}LNTI_{it} + \beta_{5\tau}LNEXPICT_{it}$$
$$+ \beta_{6\tau}LNIMPICT_{it} + \beta_{7\tau}LNEU_{it} + \varepsilon_{it}$$

$$(9)$$

Q_T indicates the parameters of the regression at τth quantile coefficient point, τ denotes the quantile distribution point for exogenous variables.

After scrutinizing related literature, we found that scholars have indeed analyzed the driving factors of carbon emissions with respect to different countries and estimation techniques. However, the current study identifies several research gaps that need to be addressed as follows. Unlike previous studies that considered the effect of trade openness as a whole (exports and imports) or only exports or import, this study considers the disaggregated impacts of trade openness (exports and imports) of ICT innovation on carbon emissions across top ten emitter countries under a single multivariate framework. This will provide useful insights to the policy makers designing suitable policies regarding the influence mechanisms of ICT exports and imports. Second, this study verifies the implications of EKC and STIRPAT model on carbon emission across top 10 carbon emitter countries while considering the role of renewable energy technology innovation. The third significant contribution consist in the estimation techniques by applying panel quantile regression that addresses various panel data issues and overcome the shortcomings of ordinary least square method.

3 Methodology and data

3.1 Descriptive statistics

This study considers a panel of top 10 carbon emitter countries namely: China, USA, India, Russia, Japan, Germany, South Korea, Canada, Mexico, and South Africa over the period from 2000 to 2014. The data on carbon emissions, export of ICT, import of ICT, population, GDP, energy use, renewable energy use are extracted from World Bank Indicator (WDI). The unit and descriptive statistics of each variable are reported in Tables 1 and 2. Consistent with Salman (2019), Hasanov et al. (2018), Menyah and Rufael (2010), Ozcan and Ulucak (2020), this study uses renewable energy to represent technological innovation.

3.2 Unit root test

Stationarity testing is an essential step in analyzing panel data to see whether or not the unit root panel is contained between variables. In this study, three steps of stationary tests were carried out, first is the individual unit root test from each country using the ADF Unit Root Test and for the Panel Unit Root Test using the Breitung and Lm and Pesaran–Shin tests. The Dickey–Fuller stationarity test was first developed by Dickey and Fuller (1979) and states the null hypothesis of the presence of unit root in the data against the alternative of no unit root in the data and can be expressed in its general format as follows:

$$Y_{it} = \alpha + \rho Y_{i(t-1)} + \beta t + \varepsilon_{it} \tag{10}$$

where "i" means individual cross-section; "t" indicates the time series; $Y_{i(t-1)}$ indicates the lagged of the variable Y_{it}; β denotes the coefficient of t-trend; ε means error term/ residual. Unit root exists if $\rho = 1$, and the time series regression model experiences a non-stationary case. The simple regression model above can be rewritten as follows:

$$\Delta Y_{it} = \alpha + \delta Y_{i(t-1)} + \beta t + \varepsilon_{it} \tag{11}$$

where Δ is the first difference. This model can be estimated and tested for the unit root equivalent of the test $\delta = 0$ where $\delta = \rho - 1$. Since the test is carried out over the residual period of raw data, it is not possible to use the standard t distribution to determine the critical value. Therefore, this t-statistic has a specific distribution known as the Dickey–Fuller. The hypothesis can be assumed as below: Null hypothesis (H_0) as data has unit root/is not stationary; Research hypothesis (H_1): the data does not have a unit/stationary root.

The null hypothesis is accepted when the probability value of the test result is more than the critical values (1, 5, or 10%) and vice versa. However, each method's sample size and strength have statistical limitations in analyzing the panel unit root test (Kasman & Duman, 2015). To address the shortcomings of previous unit root, this study applies two more panel unit root tests, Breitung (2001) which can enhance the estimation power. The Breitung unit root test does not require a bias correction factor (Wagner & Hlouskova, 2005). However, Breitung test has a weakness that the coefficient of autoregressive is limited to resemble among countries and does not consider heterogeneity (Narayan & Narayan, 2010). According to Lm et al. (2003), the heterogeneity of parameters and overall deviations in equilibrium for each country moving at the same speed should be taken into account.

Table 1 Descriptive statistics of the data

Variable	Definition	Unit	n	Min	Max	Std.dev	Mean
CO_2	Carbon emissions	Metric tons/capita	150	.9642754	20.17875	5.057634	9.552908
POP	Population	Person	150	30,685,730	1,364,270,000	463,540,535.9	339,141,294.9
GDP	GDP per Capita	Current US ($)	150	443.3142	55,064.74	17,714.97	20,922.38
EXPICT	Export ICT	% of total goods exports	150	.1674785	34.49626	10.0896	11.20343
IMPICT	Import ICT	% of total goods imports	150	3.677394	26.06887	5.009891	12.18602
EU	Energy Use	kg of oil equivalent per capita	150	416.0144	8455.547	2372.031	3906.693
REU	Technology Innovation	Alternative and nuclear energy (% of total energy use)	150	1.987975	19.91242	6.189571	9.096454

All the variables are from world development index and all the variables without logarithms form

Table 2 Descriptive statistics of the data

Variable	n	Mean	Std. dev	Min	Max	Range
$LNCO_2$	150	2.043	0.766	−0.036	3.005	3.041
LNPOP	150	18.830	1.219	17.240	21.030	3.795
LNGDP	150	9.330	1.341	6.094	10.92	4.822
LNIMPICT	150	2.418	0.411	1.302	3.261	1.959
LNEXPICT	150	1.705	1.462	−1.787	3.541	5.328
LNANE	150	1.906	0.831	0.687	2.991	2.304
LNEU	150	8.014	0.814	6.031	9.043	3.012

All the variables with logarithms form

3.3 Integration degree test

The degree of integration test is carried out if the data is not stationary at the level. This test is intended to check to what degree the data will be stationary. If the data is not stationary, Granger & Newbold (1974) argue that regressions using this data usually have a relatively high R^2 value and low Durbin–Watson statistics. This occurs because the time series economy is dominated by a prolonged trend, where a trend is a long-term change in the average level thereby indicating that the results are biased. In general, if the data requires differentiation up to d to be stationary, it can be expressed as I (d).

3.4 Normality test

Normality test is a test carried out to assess the distribution of data. Based on the empirical experience of several statisticians, the data of which more than 30 digits ($n > 30$) can be assumed to be normally distributed. However, to provide certainty, whether the data is symmetrical or not, it is necessary to implement the normality tests such as, Shapiro–Wilk and Shapiro–Francia Normality Test (Fig. 1).

4 Empirical results

4.1 Augmented Dicky–Fuller unit root test

Table 3 reveals the results of Fisher ADF unit root test for individual country. At level, the results show that almost all the variables are not stationary, thereby accepting the null hypothesis. We then took the first difference of the variables and found that some variables such as LNCO2, LNPOP, and LNGDP in case of USA, LNPOP in India, LNPOP, LNGDP, and LNEXPICT in case of Russia, LNPOP, LNGDP, LNEXPICT, LNMPICT, and LNTI in Germany, LNIMPICT in South Korea, LNCO2 and LNPOP in Canada and LNPOP in Mexico are still non-stationary, thus indicating the presence of unit root, for first difference data, and it showed that each country's variables are partly stationary and significant. However, after taking the second difference data, the output shown that almost all variables are stationary which is shown by the statistic
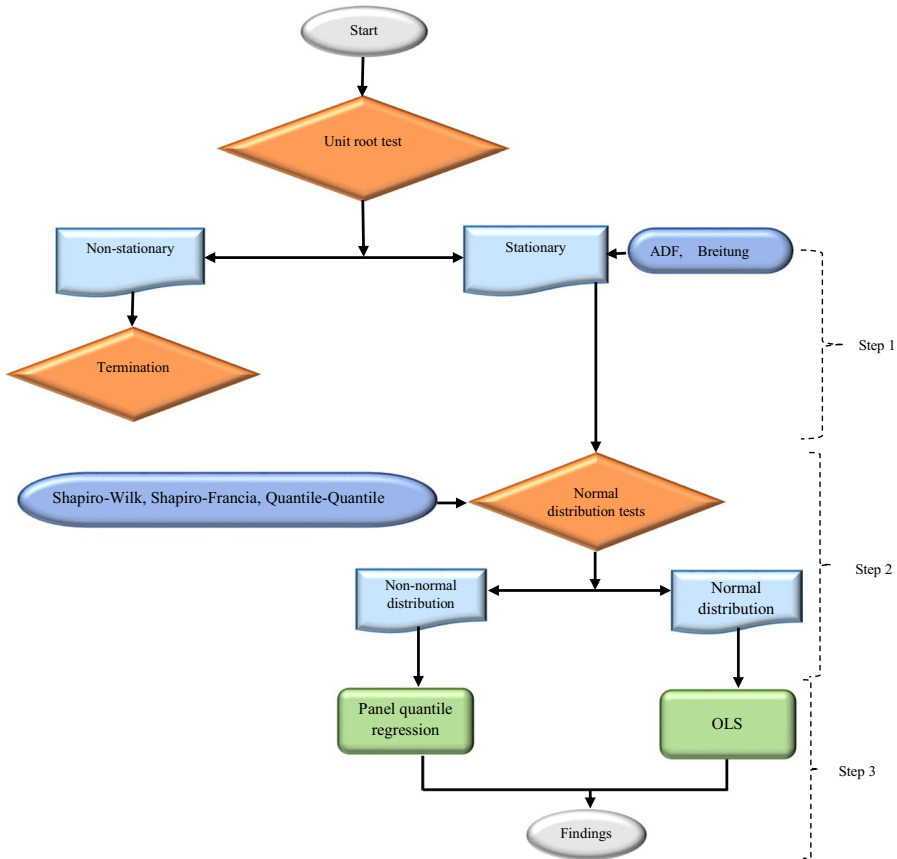
Fig. 1 Flowchart of the estimation process of this study

significance level, respectively, 1%, 5%, and 10%. Thus, as a whole it is concluded that the data rejects the null hypothesis and shown stationary at the second difference level.

4.2 Breitung (2001) and lm, Pesaran and Shin (2003) unit root results

Table 4 presents the results of panel unit root tests obtained through Breitung (2001) and lm et al. (2003) and Guo (2018). The results of both tests accept the null hypothesis implying that the variables are not stationary at level. However, after conducting the first and second difference, all variables are stationary at second difference at the significance level of 1% (except LNPOP for 5%) and reject null hypothesis. For IPS analysis, the results indicate that only LNPOP and LNEXPICT are stationer at the level at level the variables are minor stationary. After first difference and second difference are taken, it is shown that all variables are stationary at the second difference level and reject null hypothesis at the significance level of 1%. Overall, we noticed that the variables have no issue of unit root thus, allowing us to move toward next step of the empirical investigation.

Table 3 The Results of ADF unit root test for the individual country

Variables	China	USA	India	Russia	Japan	Germany	South Korea	Canada	Mexico	South Africa
At level										
LNCO2	−1.62 (0.448)	−0.40 (0.884)	0.86 (0.991)	−1.56 (0.475)	−2.12 (0.241)	−1.14 (0.665)	−0.60 (0.841)	−2.22 (0.209)	−1.56 (0.477)	−1.78 (0.375)
LNPOP	2.59 (1.000)	−6.66*** (0.000)	−1.63 (0.438)	−3.10* (0.056)	−1.37 (0.562)	−0.73 (0.807)	0.13 (0.956)	0.82 (0.990)	−3.11* (0.056)	0.42 (0.973)
LNGDP	0.06 (0.949)	−0.86 (0.770)	−0.80 (0.788)	−1.78 (0.372)	−2.30 (0.186)	−4.12*** (0.010)	−0.86 (0.771)	−1.28 (0.608)	−1.04 (0.708)	−1.31 (0.593)
LNEXPICT	−2.71 (0.103)	−1.28 (0.604)	−2.36 (0.168)	0.85 (0.989)	−0.43 (0.879)	−0.56 (0.851)	−1.01 (0.719)	−0.31 (0.899)	−0.10 (0.723)	−1.73 (0.398)
LNIMPICT	−2.55 (0.131)	−3.40** (0.029)	−3.10** (0.050)	−3.56** (0.022)	−1.68 (0.419)	0.26 (0.963)	−1.73 (0.396)	−3.16** (0.045)	−3.19** (0.044)	−0.60 (0.837)
LNTI	0.28 (0.967)	0.28 (0.967)	−1.03 (0.710)	−2.23 (0.204)	2.68 (1.000)	2.68 (1.000)	−2.31 (0.185)	−1.17 (0.655)	−1.62 (0.440)	−1.99 (0.288)
LNEU	−1.96 (0.297)	−0.78 (0.795)	1.25 (0.997)	−1.40 (0.553)	−0.45 (0.875)	−0.55 (0.850)	−0.44 (0.877)	−1.36 (0.569)	−2.08 (0.253)	−1.84 (0.346)
At first difference										
LNCO2	−2.87* (0.076)	−1.14 (0.657)	−3.39** (0.032)	−4.01** (0.014)	−3.51** (0.026)	−6.74*** (0.000)	−3.67** (0.020)	−2.61 (0.117)	−3.34** (0.034)	−3.63** (0.021)
LNPOP	−5.88*** (0.001)	−0.90 (0.741)	1.71 (0.999)	−1.16 (0.647)	−1.33 (0.581)	0.64 (0.982)	−3.23** (0.041)	−2.36 (0.170)	1.38 (0.997)	−2.88* (0.082)
LNGDP	−2.14 (0.234)	−2.00 (0.282)	−3.35** (0.034)	−2.70 (0.100)	−3.36** (0.035)	−3.31** (0.036)	−2.92* (0.072)	−2.91* (0.072)	−3.98** (0.011)	−2.51 (0.131)
LNEXPICT	−2.25 (0.203)	−3.80** (0.017)	−4.60*** (0.004)	1.32 (0.996)	−3.42** (0.032)	−1.53 (0.480)	−2.73* (0.097)	−4.06*** (0.010)	−3.57** (0.023)	−3.85** (0.014)
LNIMPICT	−2.94* (0.067)	−3.57** (0.025)	−5.59*** (0.001)	−3.97** (0.012)	−3.61** (0.023)	−1.67 (0.417)	−3.24** (0.041)	−3.16** (0.047)	−3.96** (0.012)	−5.04*** (0.002)
LNTI	−2.58 (0.126)	−5.36*** (0.001)	−3.21** (0.048)	−3.86** (0.014)	1.36 (0.996)	−0.48 (0.857)	−1.18 (0.643)	−4.48*** (0.005)	−2.14 (0.235)	−5.87*** (0.001)
LNEU	−1.46 (0.519)	−3.71** (0.018)	−3.20** (0.044)	−3.39** (0.039)	−5.02*** (0.002)	−8.54*** (0.000)	−3.39** (0.031)	−3.18** (0.045)	−3.05* (0.057)	−1.30 (0.589)

Table 3 (continued)

Variables	China	USA	India	Russia	Japan	Germany	South Korea	Canada	Mexico	South Africa
At 2nd difference										
LNCO2	-5.62***	-6.09***	-5.19***	-3.29**	-4.80***	-2.89*	-4.33***	-4.80***	-3.39**	-4.83***
	(0.001)	(0.001)	(0.002)	(0.048)	(0.003)	(0.084)	(0.008)	(0.003)	(0.038)	(0.003)
LNPOP	1.88 (0.999)	-2.76**	-4.93***	-2.61 (0.120)	-3.78**	-3.92**	-3.10*	-3.90**	-4.03**	-0.98 (0.721)
		(0.098)	(0.003)		(0.018)	(0.020)	(0.056)	(0.015)	(0.015)	
LNGDP	-3.70**	-3.34**	-3.29**	-4.56***	-3.18**	-3.28**	-3.82**	-4.50***	-5.06***	-5.99***
	(0.022)	(0.036)	(0.045)	(0.005)	(0.047)	(0.048)	(0.018)	(0.005)	(0.003)	(0.001)
LNEXPICT	-4.23***	-2.72 (0.107)	-7.15***	-5.79***	-5.28***	-0.80 (0.768)	-3.90**	-2.96*	-4.66***	-5.32***
	(0.010)		(0.000)	(0.001)	(0.002)		(0.016)	(0.071)	(0.005)	(0.002)
LNIMPICT	-5.57***	-4.40***	-4.50***	-5.23***	-4.91***	-0.71 (0.796)	-5.26***	-3.26**	-4.58***	-4.95***
	(0.001)	(0.007)	(0.006)	(0.002)	(0.003)		(0.002)	(0.042)	(0.006)	(0.003)
LNTI	-3.41**	-8.24***	-3.39**	-5.44***	-4.98**	-3.62**	-6.23***	-3.77**	-8.05***	-9.11***
	(0.037)	(0.000)	(0.038)	(0.001)	(0.003)	(0.030)	(0.001)	(0.022)	(0.000)	(0.000)
LNEU	-4.44***	-5.06***	-6.09***	-3.72**	-3.21**	-3.48**	-3.84**	-5.65***	-5.10***	-7.00***
	(0.007)	(0.003)	(0.001)	(0.026)	(0.050)	(0.037)	(0.018)	(0.001)	(0.003)	(0.000)

[a]The *p* value are in the parenthesis.

[b]*/**/*** indicates the significance level of 10, 5, and 1%, respectively

Table 4 Results of Panel Unit Root Test

Variables	Breitung			IPS		
	At level	First difference	Second difference	At level	First difference	Second difference
LNCO2	1.95 (0.975)	−1.53* (0.063)	−7.66*** (0.000)	−0.23 (0.407)	−1.25 (0.106)	−6.57*** (0.000)
LNPOP	2.88 (0.998)	1.05 (0.853)	−1.89** (0.029)	−2.63*** (0.004)	−2.26** (0.012)	−2.95*** (0.002)
LNGDP	2.77 (0.997)	−1.29* (0.099)	−6.81*** (0.000)	1.88 (0.970)	−0.73 (0.233)	−5.46*** (0.000)
LNEXPICT	0.17 (0.569)	−0.43 (0.332)	−5.94*** (0.000)	−1.87** (0.031)	−0.22 (0.413)	−6.26*** (0.000)
LNIMPICT	−0.97 (0.166)	−1.95** (0.026)	−6.94*** (0.000)	0.22 (0.585)	−1.29* (0.098)	−6.00*** (0.000)
LNTI	2.57 (0.995)	−1.24 (0.107)	−6.34*** (0.000)	2.18 (0.985)	−1.36* (0.088)	−6.47*** (0.000)
LNEU	2.25 (0.988)	−1.08 (0.140)	−6.82*** (0.0000)	−0.57 (0.284)	−0.09 (0.466)	−6.19*** (0.000)

[a]The p value are in the parenthesis

[b]*/**/*** indicates the significance level of 10, 5, and 1%, respectively

4.3 Normality test by using Shapiro–Wilk and Shapiro–Francia normality test

After having confirmed that the variables have no unit root, we then examined the normal distribution of the variables through widely adopted normality tests namely Shapiro–Wilk and the Shapiro–Francia normality tests (See Table 5). The assumption from the Shapiro–Wilk and Shapiro–Francia tests is that when the value approaches 1, the level of normality in the data also increases. Table 4 shows the results for the both methods. Based on the Shapiro–Wilk normality test, it can be seen that all variables are significant with the p value > 0.05 with the exception of LNEXPICT variable that reject the null hypothesis at 1% significance level because the p value (0.00304) < 0.05. It shows that the variable is not normally distributed. The Shapiro–Francia test shows that all variables are also significant with the p value > 0.05, except for the LNEXPICT variable with the rejection of null hypothesis at 1% significance level because the p value (0.00363) < 0.05. Thus, only LNEXPICT is not normally distributed. In the brief, the results of both tests verify that the variables have asymmetric distributional pattern which strengthens our argument that employing panel quantile regression for our analysis would yield unbiased estimates.

4.4 Quantile–quantile (Q–Q) normality test

In order to visualize the distributional pattern of the selected variables, this study have adopted extensively implemented quantile–quantile plot normality test. Suppose the Q-Q plot, which is a plot of the ordered sample quantile versus the standardized quantile corresponding to it, has points located close to a straight line. In that case, it is said that the observation is normally distributed and vice versa. Figures 2, 3, 4, 5, 6, 7, 8 show the distributional pattern of each variable. Based on the normal graph output for each of the above variables, it can be seen that graphs with linear data distribution can be expressed normally. The straight lines was identified as the line that is normally distributed. The graph explains that all variables have a data distribution that is close to a linear line, so it can be stated that the variable is visually normally distributed. Meanwhile, for variable LNEXPICT, it can be seen that the data distribution diverges from the linear line, which indicates the presence of the outliner data, so it can be stated that the LNEXPICT variable is not yet normally distributed.

Table 5 Results of Shapiro–Wilk and Shapiro–Francia normality tests

| Variables	Shapiro–Wilk Normality Test			Shapiro–Francia Normality Test		
	w	z	Prob > z	w	z	Prob > z
$LNCO_2$	0.90677	1.171	0.12083	0.93069	0.714	0.23770
LNPOP	0.96653	−0.855	0.80378	0.98213	−1.679	0.95340
LNGDP	0.92392	0.769	0.22098	0.94798	0.207	0.41795
$LNGDP^2$	0.92257	0.804	0.21083	0.94655	0.255	0.39930
LNEXPICT	0.79351	2.744	0.00304	0.78830	2.684	0.00363
LNIMPICT	0.96031	−0.518	0.69778	0.96853	−0.680	0.75172
LNTI	0.97190	−1.201	0.88508	0.97568	−1.135	0.87172
LNEU	0.91358	1.021	0.15363	0.93682	0.550	0.29114
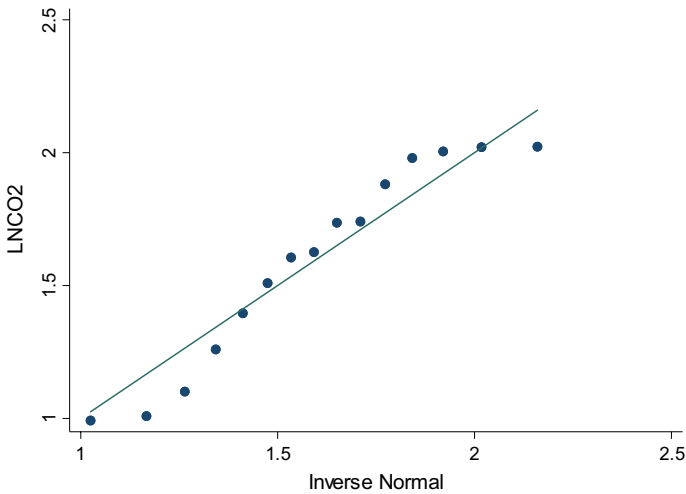
Fig. 2 Normality graph of LNCO2
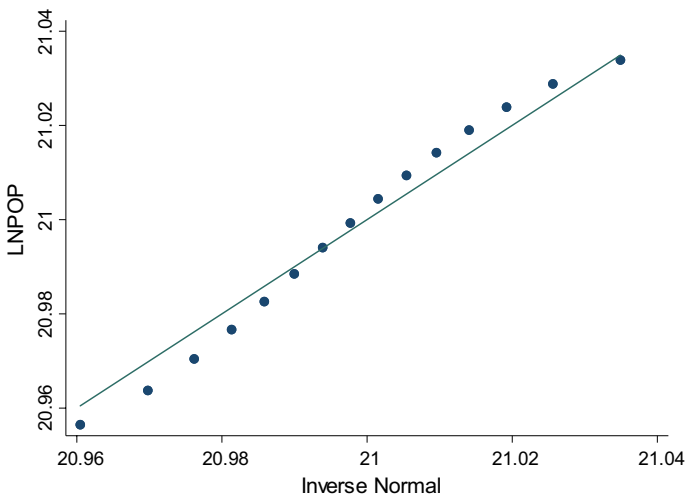
Fig. 3 Normality graph of LNPOP

4.5 Results of panel quantile regression

Table 6 shown the results of panel quantile regression by selecting nine quantile levels from the 15th to 95th levels to analyze each impact in detail. For robustness, we did not add exports in the model, we have developed a model by separating the Export ICT and Import ICT in each model to see the individual results brought about by the two variables. They followed by combining the two variables in the third model. Xie et al. (2021) and Khan et al. (2020), Salman et al. (2019) and other empirical research have used the
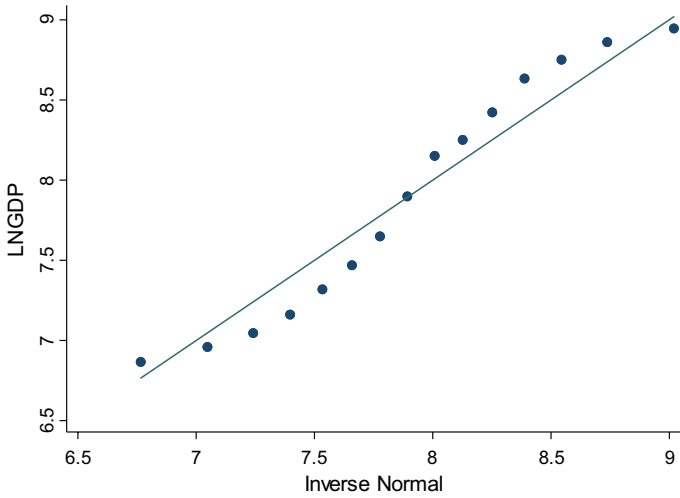
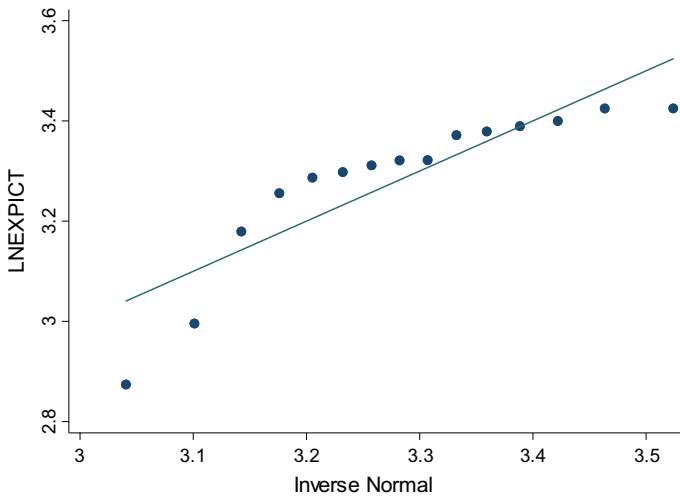**Fig. 4** Normality graph of LNGDP

Fig. 5 Normality graph of LNEXPICT

quantile regression method to show the relationship between independent variables on the dependent variable.

We have used the OLS approach to estimate the random effect model (REM) based on the Chow test, Hausman test, and LM test for the purpose of comparisons. Based on the panel quantile regression results, population significantly positive affect carbon emissions at the 1*, 5**, and 10%*** levels, respectively, except at the 25th and 45th quantile levels, which implies that a large proportion of the population level contributes
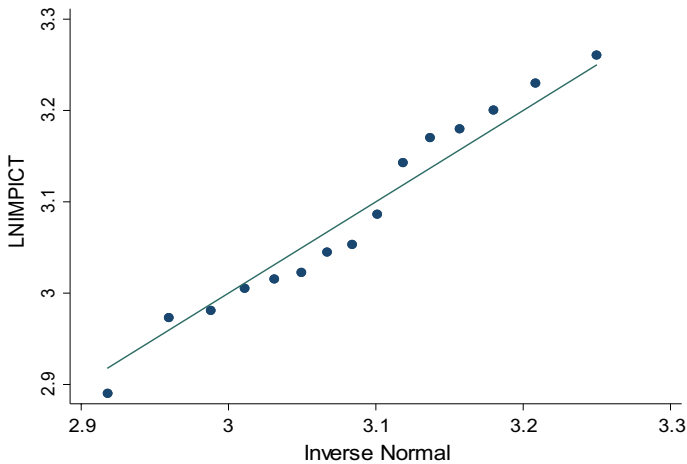
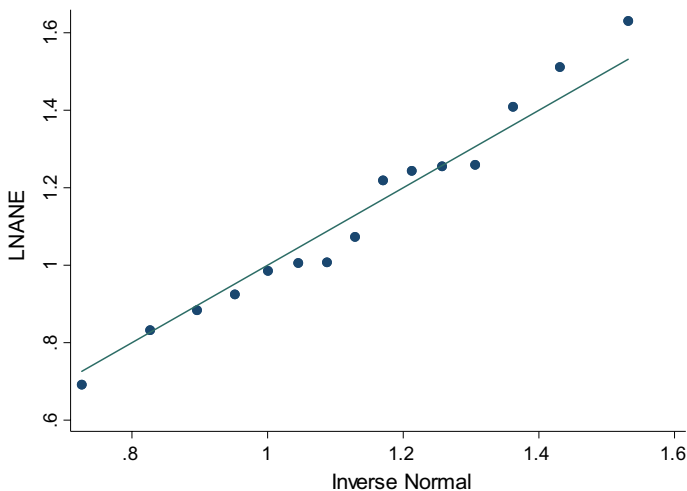**Fig. 6** Normality graph of LNIMPICT

Fig. 7 Normality graph of LNANE

to the increase in carbon emissions (Table 4 and Table 6 in the corresponding indication of the footnote [a, b]).

GDP per capita and quadratic GDP per capita are statistically to be positively and negatively significant at the level significance of 1% except for the 15th; 25th; 45th quantile levels, and these results show that per capita GDP, and it is square term are statistically positive and negative at majority of quantile levels, thereby verifying the presence of EKC hypothesis across the selected countries. In relation to the impact of technology innovation on carbon emissions, we found that effect is negative and significant level at 1% except at 15th, 25th, and 45th quantile levels. The results therefore support the part of the innovation technology hypothesis meaning that innovative technology
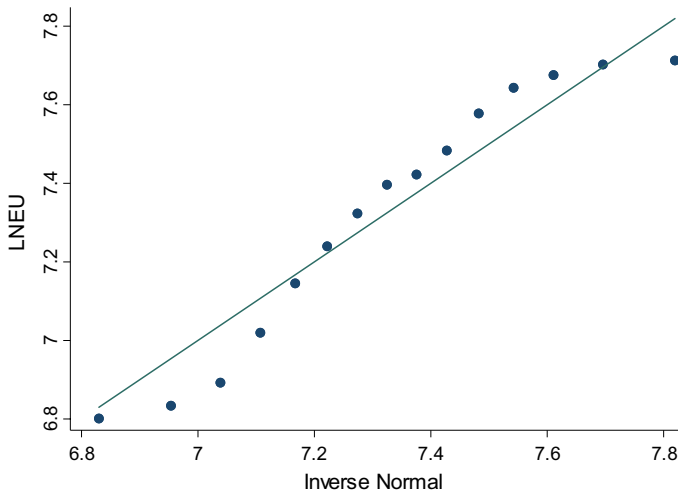
Fig. 8 Normality graph of LNEU

can reduce the level of carbon emissions across the top 10 carbon emitted countries. The results are consistent with Salman et al. (2019).

Regarding Import ICT, we noticed that the effect is statistically positive and significant at 1% except 15th, 25th, 45th, and 65th quantile levels thus indicating that it has a role in reducing carbon emissions in the selected countries. Lastly, energy use has a significant positive effect on the 1% and 5% levels except at the 25th quantile level, and this implied that energy use increased the carbon emissions. The outcomes were in line with Godil et al. (2020). For the summary results, look at Table 6.

Table 7 shows the panel quantile regression results excluding imports. Regarding the explanatory variables, the results are robustness as provided in Table 6. For example, the population's quantile coefficients are positively significant at 1% level except at 15th quantile level, and it indicated almost all level support the hypothesis that the population level enhances the carbon emissions level. Regarding EKC hypothesis, the results also accept the hypothesis at all quantile levels at 1% significance level except 15th quantile level. And the presence of technology innovation has a negative significance effect (1%) on carbon emissions, which implies the innovation contributes to lower the carbon emissions level and supports the hypothesis. It was also positively significant for energy use (1 and 5%) on CO2 except quantile 15th, which partly supports the hypothesis.

And the ICT export was positively significant at all quantile levels except 15th quantile, which indicated that ICT export significantly increase carbon emissions thus, accepting the hypothesis of Export ICT in these countries.

We then incorporated both exports ICT and imports ICT in the model and analyzed their disaggregated effects on carbon emissions. The results are reported in Table 8. Based on the results, we found that the effects of independent variables on carbon emissions remain the same as shown in Tables 5 and 6. Overall, the results of panel quantile regression confirmed that population growth, ICT exports and imports and energy use are the main drivers of carbon emissions in the selected countries. Based on the literature, trade, export, and import activities affect the country's energy use. These findings support the energy use hypothesis where exports and imports of ICT are associated with energy use that has

Table 6 Results of Panel Quantile regression (excluding exports ICT) by Using STATA 13.0

Variables	REM	Quantile levels								
		.15	.25	.35	.45	.55	.65	.75	.85	.95
Total Obs	150	150	150	150	150	150	150	150	150	150
LNPOP	0.46 (0.646)	1.90* (0.058)	−0.02 (0.983)	2.37** (0.018)	−1.52 (0.127)	9.23*** (0.000)	6.22*** (0.000)	44.35*** (0.000)	19.15*** (0.000)	42.65*** (0.000)
LNGDP	8.10*** (0.000)	1.22 (0.221)	0.02 (0.982)	8.60*** (0.000)	1.28 (0.200)	12.38*** (0.000)	15.89*** (0.000)	29.30*** (0.000)	15.10*** (0.000)	57.28*** (0.000)
LNGDP^2	−8.78*** (0.000)	−1.85* (0.064)	−0.02 (0.982)	−12.75*** (0.000)	−1.47 (0.142)	−14.27*** (0.000)	−14.21*** (0.000)	−32.22*** (0.000)	−16.71*** (0.000)	−79.33*** (0.000)
LNIMPICT	−1.70* (0.089)	0.12 (0.904)	−0.02 (0.981)	5.86*** (0.000)	0.01 (0.989)	2.17** (0.030)	1.28 (0.199)	15.42*** (0.000)	17.80*** (0.000)	8.45*** (0.000)
LNTI	−11.00*** (0.000)	−0.41 (0.680)	0.02 (0.983)	−3.88*** (0.000)	0.58 (0.562)	−6.28*** (0.000)	−17.58*** (0.000)	−18.60*** (0.000)	−26.84*** (0.000)	−107.88*** (0.000)
LNEU	40.47*** (0.000)	10.06*** (0.000)	0.02 (0.988)	−84.43*** (0.000)	5.18*** (0.000)	62.26*** (0.000)	49.25*** (0.000)	168.12*** (0.000)	465.54*** (0.000)	238.11*** (0.000)

[a]The *p* value are in the parenthesis

[b]*/**/*** indicates the significance level of 10, 5, and 1% respectively

Table 7 Results of Panel Quantile regression (excluding imports ICT) by STATA 13.0

Variables	REM	Quantile levels								
		.15	.25	.35	.45	.55	.65	.75	.85	.95
Total Obs	150	150	150	150	150	150	150	150	150	150
LNPOP	1.20 (0.232)	0.27 (0.790)	27.66*** (0.000)	20.94*** (0.000)	11.86*** (0.000)	8.59*** (0.000)	49.39*** (0.000)	23.19*** (0.000)	50.81*** (0.000)	51.19*** (0.000)
LNGDP	7.91*** (0.000)	−0.23 (0.815)	37.08*** (0.000)	29.74*** (0.000)	37.05 *** (0.000)	48.83*** (0.000)	38.76*** (0.000)	63.72*** (0.000)	79.64*** (0.000)	92.24*** (0.000)
LNGDP[b]	−8.54*** (0.000)	0.21 (0.830)	−34.97*** (0.000)	−37.14*** (0.000)	−52.10*** (0.000)	−50.11*** (0.000)	−43.48*** (0.000)	−69.07*** (0.000)	−85.56*** (0.000)	−111.47*** (0.000)
LNEXPICT	0.58 (0.563)	−0.26 (0.799)	14.48*** (0.000)	30.18*** (0.000)	36.85*** (0.000)	36.73*** (0.000)	43.99*** (0.000)	59.86*** (0.000)	88.29*** (0.000)	85.88*** (0.000)
LNTI	−11.45*** (0.000)	0.25 (0.803)	−53.19*** (0.000)	−57.82*** (0.000)	−18.97*** (0.000)	−5.99*** (0.000)	−74.91*** (0.000)	−28.38*** (0.000)	−74.92*** (0.000)	−159.65*** (0.000)
LNEU	43.80*** (0.000)	0.32 (0.748)	283.85*** (0.000)	231.50*** (0.000)	126.72*** (0.000)	105.52*** (0.000)	316.75*** (0.000)	371.12*** (0.000)	885.17*** (0.000)	1148.83*** (0.000)

[a]The p value are in the parenthesis

[b]*/**/*** indicates the significance level of 10, 5, and 1%, respectively

Table 8 Results of Panel Quantile regression (including exports and imports ICT) by STATA 13.0

Variables	REM	Quantile levels								
		.15	.25	.35	.45	.55	.65	.75	.85	.95
Total Obs	150	150	150	150	150	150	150	150	150	150
LNPOP	0.00 (0.996)	18.09***	27.79***	19.50***	16.43***	50.96***	46.07***	95.28***	78.20***	93.45***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LNGDP	8.03***	36.43***	23.96***	32.53***	25.74***	36.31***	31.51***	57.57***	74.09***	122.65***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LNGDP^2	−8.63***	−34.13***	−28.17***	−38.26***	−30.37***	−42.15***	−34.89***	−61.43***	−87.20***	−132.40 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LNEXPICT	1.36 (0.174)	16.80***	22.29***	20.65***	23.10 ***	19.19***	31.26***	38.55***	27.35***	41.31***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LNIMPICT	−2.20**	2.65***	−0.29 (0.775)	2.06**	2.87***	2.45**	6.15***	2.80***	4.18***	8.59***
	(0.028)	(0.008)		(0.039)	(0.004)	(0.014)	(0.000)	(0.005)	(0.000)	(0.000)
LNTI	−11.13***	−26.62***	−44.29***	−12.86***	−20.43***	−74.81***	−122.11***	−142.99***	−130.65***	−141.17***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LNEU	38.35***	147.92***	415.48***	271.77***	215.59***	238.68***	567.48***	674.08***	654.46***	1801.96***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

[1]The p value are in the parenthesis

[2]*/**/*** indicates the significance level of 10, 5, and 1% respectively

an impact on the level of carbon emissions. Therefore, we conclude that it is important for the ICT industry to realize environmentally friendly productivity activities by adopting innovative technologies to reduce environmental degradation. These findings in line with Shi (2001) with 93 countries, Zhu and Peng (2012) for China, and Ohlan (2015) for India. Ohlan (2015) found that population growth significantly upsurges carbon emissions, and Erdoğan et al. (2020) found that technology innovation is conducive to carbon emissions reduction in G-20 Countries, consistently supporting the Technology Innovation hypothesis, and thus, technological innovation with the use of alternatives and nuclear energy is stated to be able to reduce carbon emissions and play a high role in energy efficiency in the production process. Salman et al. (2019) claimed that exports, imports and energy use are the key impact factors of higher level of carbon emissions across seven ASEAN countries.

Based on the literature, trade, export, and import activities affect the country's energy use. Thus, each country needs to pay attention to energy use on the productivity for producing goods. These findings support the energy use hypothesis where exports and imports of ICT are associated with energy use that has an impact on the level of carbon emissions. Therefore, we conclude that it is important for the ICT industry to realize environmentally friendly productivity activities by adopting innovative technologies to reduce environmental degradation.

Regarding the existence of the EKC, the findings support the EKC hypothesis as indicated by the respective GDP per capita and the squared GDP per capita has a positive and significant negative effect at all quantile levels in the selected countries. These findings support the findings of Li et al. (2016) for China, Isik et al. (2019) for USA, Ketenci (2018) for Russia, Rafindadi (2016) for Japan, Zambrano-Monserrate & Fernandez (2017) for Germany. However, contradictory to Koc and Bulus (2020), the EKC was invalid in South Korea. Based on the results of REM model estimated through OLS approach, LNEXPICT, and LNPOP statistically insignificant. This validates our assumption that using panel quantile regression in case the data exhibits abnormal distribution tendency provides robust results.

5 Conclusions and policy implications

5.1 Conclusions and discussions

The economic aspect of information and communication technology attracts unprecedented attention of economists in designing effective policy for sustainable economic development. However, by prioritizing the green economy, few researchers have paid attention to the role of ICT in controlling carbon emissions. ICT have become one of the most dynamic components of international trade over the last decade and has increased significantly to 3.7 trillion in 2007 (OECD, 2009). Based on the reports of OECD (2009), Republic of China (ROC) is the largest trading center and world's largest exporter of ICT products, while the USA is the largest importer of ICT products, and Germany is the largest European country for the most prominent export and import of ICT products. The impacts of the export and import of ICT on the environment for each country are different according to the manner of adoption and implementation. Ciocoiu et al. (2010) stated that ICT as a digital economy has a different impact on the environment. The importance of ICT on economic growth has proven to be an essential contribution in analyzing the effect of economic consequences and human activities, along with Grossman & Kruenger (1995)

application, which introduced an approach between economic growth and its impact on the environment. Yu & Du (2019) claimed that introducing innovation brings a negative impact on environmental degradation. This research follows the STIRPAT model, which focuses on importing and importing ICT goods and their consequences on the environment. This research reviews the association between variables by involving other STIRPAT's factors: population, GDP per capita, energy use, and technological innovation.

This study aims at investigating the differential effects of ICT exports and ICT imports under the framework of Environmental Kuznets Curve across top 10 highest carbon emitting countries over the period from 2000 to 2014. This study extended the STIRPAT model by incorporating, ICT Exports and Imports and energy use. To achieve the study's objectives, this study adopts panel quantile regression that provides relatively robust results in case the variables are not normally distributed.

Before applying panel quantile regression, this study explores the stationary properties of the variables through three-unit root tests. Then, the distributional pattern of the variables are investigated by employing three normality tests. After the preliminary tests, the results of panel quantile regression indicate that the effect of each independent variable on carbon emissions differs at the selected quantile levels. Overall, the results found that population, ICT exports, ICT imports and energy use are the major factors of higher level of carbon emissions in the selected countries. Technological innovations proxied by the use of alternative and nuclear energy are found to significant reduce carbon emission. The innovation of ICT products needs to be increased by using renewable energy to decrease the consumption of primary energy and increase energy efficiency during the production process. The use of alternative and nuclear energy during the production process of goods may be applied to minimize the use of energy to reduce CO_2 emissions.

5.2 Policy implications

This study proposes several important policy implications based on the results. First, the governments across these countries should promote and adopt the renewable energy use such as technological innovations in the production process in countries. Further attention should be paid to the selection of energy used in the production process to create green economic growth with low carbon or green innovation, such as developing energy-saving or high level of energy efficiency of IT product. Furthermore, the intensity of exports and imports of ICT goods in countries with high CO_2 levels needs further attention, especially in detail regarding the sources of energy used during the production process and energy generated during product use. They are improving energy-saving or green products through carbon labels or different types of environmental regulations. Finally, it is necessary to control population levels and energy use to mitigate CO_2 emissions in countries with the highest levels of carbon emissions.

Authors contribution ET contributed to original draft preparation, data collection, formal analysis, review and editing; MT contributed to formal analysis, writing—review and editing; LL contributed to rewriting, conceptualization, methodology, writing—review and editing and supervision; MS contributed to validation, writing—review and editing; XL and HS and BZ contributed to writing—review and editing.

References

Acaravci, A., & Ozturk, I. (2010). On the relationship between energy consumption, CO2 emissions and economic growth in Europe. *Energy, 35*(12), 5412–5420.

Acheampong, A. O. (2018). Economic growth, CO2 emissions and energy consumption: What causes what and where? *Energy Economics, 74*, 677–692.

Ali, H. S., Abdul-Rahim, A. S., & Ribadu, M. B. (2017). Urbanization and carbon dioxide emissions in Singapore: Evidence from the ARDL approach. *Environmental Science and Pollution Research, 24*(2), 1967–1974.

Ali, W., Abdullah, A., & Azam, M. (2016). The dynamic linkage between technological innovation and carbon dioxide emissions in Malaysia: An autoregressive distributed lagged bound approach. *International Journal of Energy Economics and Policy, 6*(3), 389–400.

Amri, F., Zaied, Y. B., & Lahouel, B. B. (2019). ICT, total factor productivity, and carbon dioxide emissions in Tunisia. *Technological Forecasting and Social Change, 146*, 212–217.

Ang, J. B. (2007). CO2 emissions, energy consumption, and output in France. *Energy Policy, 35*(10), 4772–4778.

Asongu, S. A., Le Roux, S., & Biekpe, N. (2017). Environmental degradation, ICT and inclusive development in Sub-Saharan Africa. *Energy Policy, 111*, 353–361.

Avom, D., Nkengfack, H., Fotio, H. K., & Totouom, A. (2020). ICT and environmental quality in Sub-Saharan Africa: Effects and transmission channels. *Technological Forecasting and Social Change, 155*, 120028.

Baek, J., & Kim, H. S. (2013). Is economic growth good or bad for the environment? Empirical evidence from Korea. *Energy Economics, 36*, 744–749.

Bakirtas, I., & Cetin, M. A. (2017). Revisiting the environmental Kuznets curve and pollution haven hypotheses: MIKTA sample. *Environmental Science and Pollution Research, 24*(22), 18273–18283.

Balado-Naves, R., Baños-Pino, J. F., & Mayor, M. (2018). Do countries influence neighbouring pollution? A spatial analysis of the EKC for CO2 emissions. *Energy Policy, 123*, 266–279.

Bera, A. K., Galvao, A. F., Montes-Rojas, G. V., & Park, S. Y. (2016). Asymmetric laplace regression: Maximum likelihood, maximum entropy and quantile regression. *Journal of Econometric Methods, 5*(1), 79–101.

Bilgili, F., Koçak, E., & Bulut, Ü. (2016). The dynamic impact of renewable energy consumption on CO2 emissions: A revisited Environmental Kuznets Curve approach. *Renewable and Sustainable Energy Reviews, 54*, 838–845.

Breitung, J. (2001). The local power of some unit root tests for panel data. Emerald Group Publishing Limited.

Chaabouni, S., & Saidi, K. (2017). The dynamic links between carbon dioxide (CO2) emissions, health spending and GDP growth: A case study for 51 countries. *Environmental Research, 158*, 137–144.

Ciocoiu, N., Burcea, S., & Tartiu, V. (2010). Environmental impact of ICT and implications for e-waste management in Romania. *Economia Seria Management, 13*(2), 348–360.

Day, K. M., & Grafton, R. Q. (2003). Growth and the environment in Canada: An empirical analysis. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie, 51*(2), 197–216.

Dietz, T., & Rosa, E. A. (1994). Rethinking the environmental impacts of population, affluence and technology. *Human Ecology Review, 1*(2), 277–300.

EDGAR (2019) https://edgar.jrc.ec.europa.eu/overview.php?v=booklet2019.

Ehrlich, P. R., & Holdren, J. P. (1971). Impact of population growth. *Science, 171*(3977), 1212–1217.

Erdoğan, S., Yıldırım, S., Yıldırım, D. Ç., & Gedikli, A. (2020). The effects of innovation on sectoral carbon emissions: Evidence from G20 countries. *Journal of Environmental Management, 267*, 110637.

Esen, Ö., & Bayrak, M. (2017). Does more energy consumption support economic growth in net energy-importing countries? *Journal of Economics, Finance and Administrative Science*.

Faisal, F., Tursoy, T., & Pervaiz, R. (2020). Does ICT lessen CO_2 emissions for fast-emerging economies? An application of the heterogeneous panel estimations. *Environmental Science and Pollution Research*, 1–12.

Fan, H., & Hossain, M. I. (2018). Technological innovation, trade openness, CO_2 emission and economic growth: Comparative analysis between China and India. *International Journal of Energy Economics and Policy, 8*(6), 240.

Fan, Y., Liu, L. C., Wu, G., & Wei, Y. M. (2006). Analyzing impact factors of CO2 emissions using the STIRPAT model. *Environmental Impact Assessment Review, 26*(4), 377–395.

Farabi, A., Abdullah, A., & Setianto, R. H. (2019). Energy consumption, Carbon Emissions and Economic Growth in Indonesia and Malaysia. *International Journal of Energy Economics and Policy, 9*(3), 338–345.

Filos, E. (2010). ICT for Sustainable Manufacturing: A European Perspective[C]. In: A. Ortiz, R. D. Franco & P. G. Gasquet (Eds.), Balanced Automation Systems for Future Manufacturing Networks: BASYS 2010. Berlin: IFIP Advances in Information and Communication Technology (Vol. 322). Springer, Heidelberg. https://doi.org/10.1007/978-3-642-14341-0_4.

Ganda, F. (2020). Effect of foreign direct investment, financial development, and economic growth on environmental quality in OECD economies using panel quantile regressions. Environmental Quality Management.

Gill, A. R., Viswanathan, K. K., & Hassan, S. (2018). The Environmental Kuznets Curve (EKC) and the environmental problem of the day. *Renewable and Sustainable Energy Reviews, 81*, 1636–1642.

Godil, D. I., Sharif, A., Agha, H., & Jermsittiparsert, K. (2020). The dynamic nonlinear influence of ICT, financial development, and institutional quality on CO_2 emission in Pakistan: new insights from QARDL approach. *Environmental Science and Pollution Research, 27*(19), 24190–24200.

Gordon, R. J. (2000). Does the" new economy" measure up to the great inventions of the past? *Journal of Economic Perspectives, 14*(4), 49–74.

Granger, C. W., & Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics, 2*(2), 111–120.

Grossman, G.M., & Krueger, A.B. (1991a). NBER Working Paper 3914[C]// National Bureau of Economic Research. Environmental impact of a North American Free Trade Agreement. Cambridge: MA.

Grossman, G. M., & Krueger, A. B. (1991b). Environmental impacts of a North American free trade agreement (No. w3914). National Bureau of economic research.

Grossman, G. M., & Krueger, A. B. (1995). Economic growth and the environment. *The Quarterly Journal of Economics, 110*(2), 353–377.

Guo, W. W. (2018). An Analysis of energy consumption and economic growth of Cobb-Douglas production function based on ECM. *IOP Conference Series: Earth and Environmental Science, 113*, 012071.

Hasanov, F. J., Liddle, B., & Mikayilov, J. I. (2018). The impact of international trade on CO2 emissions in oil exporting countries: Territory vs consumption emissions accounting. Energy Economics, 74, 343–350.

Hasanov, F. J., Mikayilov, J. I., Mukhtarov, S., & Suleymanov, E. (2019). Does CO_2 emissions-economic growth relationship reveal EKC in developing countries? Evidence from Kazakhstan. *Environmental Science and Pollution Research, 26*(29), 30229–30241.

He, J., & Richard, P. (2010). Environmental Kuznets curve for CO2 in Canada. *Ecological Economics, 69*(5), 1083–1093.

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics, 115*(1), 53–74.

Indexmundi. ICT goods exports (% of total goods exports). 2019. https://www.indexmundi.com/facts/indicators/TX.VAL.ICTG.ZS.UN

Işık, C., Ongan, S., & Özdemir, D. (2019). Testing the EKC hypothesis for ten US states: An application of heterogeneous panel estimation method. *Environmental Science and Pollution Research, 26*(11), 10846–10853.

Iwata, H., Okada, K., & Samreth, S. (2010). Empirical study on the environmental Kuznets curve for CO2 in France: The role of nuclear energy. *Energy Policy, 38*(8), 4057–4063.

Ji, X., & Chen, B. (2017). Assessing the energy-saving effect of urbanization in China based on stochastic impacts by regression on population, affluence and technology (STIRPAT) model. *Journal of Cleaner Production, 163*, S306–S314.

Karasoy, A. (2019). Drivers of carbon emissions in Turkey: Considering asymmetric impacts. *Environmental Science and Pollution Research, 26*(9), 9219–9231.

Kasman, A., & Duman, Y. S. (2015). CO_2 emissions, economic growth, energy consumption, trade and urbanization in new EU member and candidate countries: a panel data analysis. *Economic Modelling, 44*, 97–103.

Ketenci, N. (2018). The environmental Kuznets cuve in the case of Russia. *Russian Journal of Economics, 4*(3), 249–265.

Khan, H., Khan, I., & Binh, T. T. (2020). The heterogeneity of renewable energy consumption, carbon emission and financial development in the globe: A panel quantile regression approach. *Energy Reports, 6*, 859–867.

Khan, I., Hou, F., & Le, H. P. (2021). The impact of natural resources, energy consumption, and population growth on environmental quality: Fresh evidence from the United States of America. *Science of the Total Environment, 754*, 142222.

Khan, N., Baloch, M. A., Saud, S., & Fatima, T. (2018a). The effect of ICT on CO2 emissions in emerging economies: Does the level of income matters? *Environmental Science and Pollution Research, 25*(23), 22850–22860.

Khan, N., Baloch, M. A., Saud, S., & Fatima, T. (2018b). The effect of ICT on CO 2 emissions in emerging economies: Does the level of income matters? *Environmental Science and Pollution Research, 25*(23), 22850–22860.

Kharbach, M., & Chfadi, T. (2017). CO2 emissions in Moroccan road transport sector: Divisia, Cointegration, and EKC analyses. *Sustainable Cities and Society, 35*, 396–401.

Knoema. (2019). United States of America - ICT goods imports as a share total goods imports[R]. https://knoema.com/atlas/United-States-of-America/topics/Foreign-Trade/Import/ICT-goods-imports.

Koc, S., & Bulus, G. C. (2020). Testing validity of the EKC hypothesis in South Korea: Role of renewable energy and trade openness. *Environmental Science and Pollution Research, 27*(23), 29043–29054.

Koçak, E., & Şarkgüneşi, A. (2018). The impact of foreign direct investment on CO2 emissions in Turkey: New evidence from cointegration and bootstrap causality analysis. *Environmental Science and Pollution Research, 25*(1), 790–804.

Koenker, R., & Bassett Jr, G. (1978). Regression quantiles. Econometrica: Journal of the Econometric Society, 33–50.

Leal, P. H., & Marques, A. C. (2020). Rediscovering the EKC hypothesis for the 20 highest CO2 emitters among OECD countries by level of globalization. *International Economics, 164*, 36–47.

Li, L., Msaad, H., Sun, H., Tan, M. X., Lu, Y., & Lau, A. K. (2020a). Green Innovation and business sustainability: New evidence from energy intensive industry in China. *International Journal of Environmental Research and Public Health, 17*(21), 7826.

Li, W., Long, R., Chen, H., Chen, F., Zheng, X., He, Z., & Zhang, L. (2020b). Willingness to pay for hydrogen fuel cell electric vehicles in China: A choice experiment analysis. *International Journal of Hydrogen Energy, 45*(59), 34346–34353.

Li, Q., Long, R., & Chen, H. (2018). Differences and influencing factors for Chinese urban resident willingness to pay for green housings: Evidence from five first-tier cities in China. *Applied Energy, 229*, 299–313.

Li, Q., Long, R., Chen, H., Chen, F., & Wang, J. (2020c). Visualized analysis of global green buildings: Development, barriers and future directions. *Journal of Cleaner Production, 245*, 118775.

Li, T., Wang, Y., & Zhao, D. (2016). Environmental Kuznets curve in China: New evidence from dynamic panel analysis. *Energy Policy, 91*, 138–147.

Lin, S., Wang, S., Marinova, D., Zhao, D., & Hong, J. (2017). Impacts of urbanization and real economic development on CO2 emissions in non-high income countries: Empirical research based on the extended STIRPAT model. *Journal of Cleaner Production, 166*, 952–966.

Liu, H., Wang, C., & Wen, F. (2020). Asymmetric transfer effects among real output, energy consumption, and carbon emissions in China. *Energy, 208*, 118345.

Mahmood, H., Alkhateeb, T. T. Y., & Furqan, M. (2020). Exports, imports, foreign direct investment and CO2 emissions in North Africa: Spatial analysis. *Energy Reports, 6*, 2403–2409.

Majeed, M. T. (2018). Information and communication technology (ICT) and environmental sustainability in developed and developing countries. *Pakistan Journal of Commerce and Social Sciences, 12*(3), 758–783.

Malmodin, J., & Lundén, D. (2018). The energy and carbon footprint of the global ICT and E&M sectors 2010–2015. *Sustainability, 10*(9), 3027.

Manisalidis, I., Stavropoulou, E., Stavropoulos, A., & Bezirtzoglou, E. (2020). Environmental and health impacts of air pollution: A review. Frontiers in public health, 8–14

Melville, N. P. (2010). Information systems innovation for environmental sustainability. MIS quarterly, 1–21.

Mensah, C. N., Long, X., Boamah, K. B., Bediako, I. A., Dauda, L., & Salman, M. (2018). The effect of innovation on CO_2 emissions of OCED countries from 1990 to 2014. *Environmental Science and Pollution Research, 25*(29), 29678–29698.

Menyah, K., & Wolde-Rufael, Y. (2010). CO2 emissions, nuclear energy, renewable energy and economic growth in the US. *Energy Policy, 38*(6), 2911–2915.

Murad, M. W., Alam, M. M., Noman, A. H. M., & Ozturk, I. (2019). Dynamics of technological innovation, energy consumption, energy price and economic growth in Denmark. *Environmental Progress & Sustainable Energy, 38*(1), 22–29.

Narayan, P. K., & Narayan, S. (2010). Carbon dioxide emissions and economic growth: Panel data evidence from developing countries. *Energy Policy, 38*(1), 661–666.

Nguyen, T. T., Pham, T. A. T., & Tram, H. T. X. (2020). Role of information and communication technologies and innovation in driving carbon emissions and economic growth in selected G-20 countries. *Journal of Environmental Management, 261*, 110162.

OECD. (2009). International trade in ICT goods and services, in OECD Science, Technology and Industry Scoreboard 2009[R]. Paris: OECD Publishing.

OECD. (2013). Exports of ICT goods. OECD Factbook 2013: Economic, Environmental and Social Statistics[R]. Paris: OECD Publishing. https://doi.org/10.1787/factbook-2013-66-en.

Ohlan, R. (2015). The impact of population density, energy consumption, economic growth and trade openness on CO 2 emissions in India. *Natural Hazards, 79*(2), 1409–1428.

Osobajo, O. A., Otitoju, A., Otitoju, M. A., & Oke, A. (2020). The impact of energy consumption and economic growth on carbon dioxide emissions. *Sustainability, 12*(19), 7965.

Ozcan, B., & Apergis, N. (2018). The impact of internet use on air pollution: Evidence from emerging countries. *Environmental Science and Pollution Research, 25*(5), 4174–4189

Ozcan, B., & Ulucak, R. (2020). An empirical investigation of nuclear energy consumption and carbon dioxide (CO2) emission in India: Bridging IPAT and EKC hypotheses. *Nuclear Engineering and Technology*.

Pata, U. K. (2018). Renewable energy consumption, urbanization, financial development, income and CO2 emissions in Turkey: Testing EKC hypothesis with structural breaks. *Journal of Cleaner Production, 187*, 770–779.

Pata, U. K., & Aydin, M. (2020). Testing the EKC hypothesis for the top six hydropower energy-consuming countries: Evidence from Fourier Bootstrap ARDL procedure. *Journal of Cleaner Production, 264*, 121699.

Pham, N. M., Huynh, T. L. D., & Nasir, M. A. (2020). Environmental consequences of population, affluence and technological progress for European countries: A Malthusian view. *Journal of Environmental Management, 260*, 110143.

Rafindadi, A. A., & Ozturk, I. (2016). Effects of financial development, economic growth and trade on electricity consumption: Evidence from post-Fukushima Japan. *Renewable and Sustainable Energy Reviews, 54*, 1073–1084.

Raheem, I. D., Tiwari, A. K., & Balsalobre-Lorente, D. (2020). The role of ICT and financial development in CO 2 emissions and economic growth. *Environmental Science and Pollution Research, 27*(2), 1912–1922.

Roca, J. (2002). The IPAT formula and its limitations. *Ecological Economics, 42*(1–2), 1–2.

Saboori, B., & Sulaiman, J. (2013). Environmental degradation, economic growth and energy consumption: Evidence of the environmental Kuznets curve in Malaysia. *Energy Policy, 60*, 892–905.

Salahuddin, M., Alam, K., & Ozturk, I. (2016). The effects of Internet usage and economic growth on CO_2 emissions in OECD countries: A panel investigation. *Renewable and Sustainable Energy Reviews, 62*, 1226–1235.

Saleem, H., Jiandong, W., Zaman, K., Elashkar, E. E., & Shoukry, A. M. (2018). The impact of air-railways transportation, energy demand, bilateral aid flows, and population density on environmental degradation: Evidence from a panel of next-11 countries. *Transportation Research Part d: Transport and Environment, 62*, 152–168.

Salim, R., Rafiq, S., Shafiei, S., & Yao, Y. (2019). Does urbanization increase pollutant emission and energy intensity? Evidence from some Asian developing economies. *Applied Economics, 51*(36), 4008–4024.

Salman, M., Long, X., Dauda, L., Mensah, C. N., & Muhammad, S. (2019). Different impacts of export and import on carbon emissions across 7 ASEAN countries: A panel quantile regression approach. *Science of the Total Environment, 686*, 1019–1029.

Shahbaz, M., Hye, Q. M. A., Tiwari, A. K., & Leitão, N. C. (2013). Economic growth, energy consumption, financial development, international trade and CO2 emissions in Indonesia. *Renewable and Sustainable Energy Reviews, 25*, 109–121.

Shahbaz, M., Lean, H. H., & Shabbir, M. S. (2012). Environmental Kuznets curve hypothesis in Pakistan: Cointegration and Granger causality. *Renewable and Sustainable Energy Reviews, 16*(5), 2947–2953.

Shi, A. (2001, August). Population growth and global carbon dioxide emissions. In *IUSSP Conference in Brazil/session-s09*.

Sinha, A. (2018). Impact of ICT exports and internet usage on carbon emissions: A case of OECD countries. *International Journal of Green Economics, 12*(3–4), 228–257.

Sugiawan, Y., & Managi, S. (2016). The environmental Kuznets curve in Indonesia: Exploring the potential of renewable energy. *Energy Policy, 98*, 187–198.

Sulaiman, C., & Abdul-Rahim, A. S. (2018). Population growth and CO_2 emission in Nigeria: A recursive ARDL approach. *Sage Open, 8*(2), 2158244018765916.

Sun, H., Enna, L., Monney, A., Tran, D. K., Rasoulinezhad, E., & Taghizadeh-Hesary, F. (2020a). The long-run effects of trade openness on carbon emissions in Sub-Saharan African Countries. *Energies, 13*(20), 5295.

Sun, H., Pofoura, A. K., Mensah, I. A., Li, L., & Mohsin, M. (2020b). The role of environmental entrepreneurship for sustainable development: evidence from 35 countries in Sub-Saharan Africa. *Science of the Total Environment, 741*, 140132.

Tiba, S., & Belaid, F. (2020). The pollution concern in the era of globalization: Do the contribution of foreign direct investment and trade openness matter? *Energy Economics, 92*, 104966.

Tursun, H., Li, Z., Liu, R., Li, Y., & Wang, X. (2015). Contribution weight of engineering technology on pollutant emission reduction based on IPAT and LMDI methods. *Clean Technologies and Environmental Policy, 17*(1), 225–235.

Ulucak, R., & Bilgili, F. (2018). A reinvestigation of EKC model by ecological footprint measurement for high, middle and low income countries. *Journal of Cleaner Production, 188*, 144–157.

UNCTAD (2011). Implication of Applying The New Defenition of ICT Goods. Division on Technology and Logistics Science, Technology and ICT Branch ICT Analysis Section, Technical Note No.1[R].

UNCTAD (2019). Trade in electronic components drives growth in technology goods. https://unctad.org/news/trade-electronic-components-drives-growth-technology-goods

Wagner, M., Hlouskova, J. (2005). CEEC growth projections: Certainly necessary and necessarily uncertain. *Economics of Transition, 13*(2), 341–372.

Waheed, R., Sarwar, S., & Wei, C. (2019). The survey of economic growth, energy consumption and carbon emission. *Energy Reports, 5*, 1103–1115.

Wang, C., Wood, J., Wang, Y., Geng, X., & Long, X. (2020a). CO2 emission in transportation sector across 51 countries along the Belt and Road from 2000 to 2014. *Journal of Cleaner Production, 266*, 122000.

Wang, S., Tang, Y., Du, Z., & Song, M. (2020b). Export trade, embodied carbon emissions, and environmental pollution: An empirical analysis of China's high-and new-technology industries. *Journal of Environmental Management, 276*, 111371.

Wang, S., Zhao, T., Zheng, H., & Hu, J. (2017). The STIRPAT analysis on carbon emission in Chinese cities: An asymmetric laplace distribution mixture model. Sustainability, 9(12), 2237.

Wang, Z., & Zhu, Y. (2020). Do energy technology innovations contribute to CO_2 emissions abatement? A spatial perspective. *Science of the Total Environment, 726*, 138574.

Wei, T. (2011). What STIRPAT tells about effects of population and affluence on the environment? *Ecological Economics, 72*, 70–74.

World Bank (2020). http://datatopics.worldbank.org/world-development-indicators/.

Wu, H., Xu, L., Ren, S., Hao, Y., & Yan, G. (2020). How do energy consumption and environmental regulation affect carbon emissions in China? New evidence from a dynamic threshold panel model. *Resources Policy, 67*, 101678.

Xie, Z., Wu, R., & Wang, S. (2021). How technological progress affects the carbon emission efficiency? Evidence from national panel quantile regression. Journal of Cleaner Production, 127133.

Xu, Y., Dietzenbacher, E., & Los, B. (2020). International trade and air pollution damages in the United States. *Ecological Economics, 171*, 106599.

Yang, L., Xia, H., Zhang, X., & Yuan, S. (2018). What matters for carbon emissions in regional sectors? A China study of extended STIRPAT model. *Journal of Cleaner Production, 180*, 595–602.

Yeh, J. C., & Liao, C. H. (2017). Impact of population and economic growth on carbon emissions in Taiwan using an analytic tool STIRPAT. *Sustainable Environment Research, 27*(1), 41–48.

York, R., Rosa, E. A., & Dietz, T. (2003). STIRPAT, IPAT and ImPACT: Analytic tools for unpacking the driving forces of environmental impacts. *Ecological Economics, 46*(3), 351–365.

Yu, Y., & Du, Y. (2019). Impact of technological innovation on CO2 emissions and emissions trend prediction on 'New Normal' economy in China. *Atmospheric Pollution Research, 10*(1), 152–161.

Zambrano-Monserrate, M. A., & Fernandez, M. A. (2017, May). An environmental Kuznets curve for N2O emissions in Germany: an ARDL approach. In Natural resources forum (Vol. 41, No. 2, pp. 119–127). Oxford, UK: Blackwell Publishing Ltd.

Zambrano-Monserrate, M. A., Carvajal-Lara, C., & Urgiles-Sanchez, R. (2018). Is there an inverted U-shaped curve? Empirical analysis of the environmental Kuznets Curve in Singapore. *Asia-Pacific Journal of Accounting & Economics, 25*(1–2), 145–162.

Zambrano-Monserrate, M. A., Valverde-Bajaña, I., Aguilar-Bohórquez, J., & Mendoza-Jiménez, M. (2016). Relationship between economic growth and environmental degradation: Is there an environmental evidence of kuznets curve for Brazil? *International Journal of Energy Economics and Policy, 6*(2), 208–216.

Zha, C., Chen, B., Hayat, T., Alsaedi, A., & Ahmad, B. (2014). Driving force analysis of water footprint change based on extended STIRPAT model: Evidence from the Chinese agricultural sector. *Ecological Indicators, 47*, 43–49.

Zhang, C., & Liu, C. (2015). The impact of ICT industry on CO2 emissions: A regional analysis in China. *Renewable and Sustainable Energy Reviews, 44*, 12–19.

Zhang, Y., & Zhang, S. (2018). The impacts of GDP, trade structure, exchange rate and FDI inflows on China's carbon emissions. *Energy Policy, 120*, 347–353.

Zhang, J., Wang, B., & Latif, Z. (2019). Towards cross-regional sustainable development: The nexus between information and communication technology, energy consumption, and CO_2 emissions. *Sustainable Development, 27*(5), 990–1000.

Zhou, T., & Zhang, J. (2020). Behavioral research on transport and energy in the context of aviation. Transport and Energy Research, 279–294.

Zhou, X., Zhou, D., Wang, Q., & Su, B. (2019). How information and communication technology drives carbon emissions: A sector-level analysis for China. *Energy Economics, 81*, 380–392.

Zhu, Q., & Peng, X. (2012). The impacts of population change on carbon emissions in China during 1978–2008. *Environmental Impact Assessment Review, 36*, 1–8.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Authors and Affiliations

Ellen Thio[1] · MeiXuen Tan[1] · Liang Li[1,2] · Muhammad Salman[3] · Xingle Long[4] · Huaping Sun[5] · Bangzhu Zhu[1]

Ellen Thio
thio_ellen@yahoo.com

MeiXuen Tan
mathevas93@hotmail.com

Muhammad Salman
dawarsalman@gmail.com

Xingle Long
longxingle@163.com

Huaping Sun
shp797@163.com

Bangzhu Zhu
wpzbz@126.com

[1]   School of Business, Nanjing University of Information Science and Technology, Nanjing 210044, China

[2]   Research Institute for Environment and Health, Nanjing University of Information Science and Technology, Nanjing 210044, China

[3]   College of Economic and Management, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, China

4   School of Management, Jiangsu University, Zhenjiang 212013, China

5   School of Finance and Economics, Jiangsu University, Zhenjiang 212013, China