Chapter 3
The Effect of Internet Use on Air Quality: Evidence from Low-Income Countries

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Abstract This chapter aims at analyzing the effects of information and communications technology (ICT) on air pollution level of low-income country panel over the period 1995–2015. In order to achieve this, the second-generation panel data models allowing for cross-sectional dependence have been employed. The long-run estimation results indicate that percentage of Internet users, a proxy for ICTs, leads to an increase in carbon dioxide (CO_2) emission level in low-income countries. Besides, among the control variables of the model, income and energy consumption appear to increase to CO_2 emission level while financial development and trade openness do not have any significant effects on air quality level of low-income country panel. Based on these results, a number of policy implications could be suggested. For instance, investments into the ICT sector should be encouraged by both government and private sector via subsidies and grants.

Keywords Information and communications technology · Air pollution · Economic growth · Panel data model · Low-income countries

3.1 Introduction

Human being has transformed the world and caused its fragile environment to deteriorate at an increasingly rapid rate, particularly since the beginning of the industrial age in the late eighteenth century (Sui and Rejeski 2002). As such, it could be stated that industrialization has contributed to national growth policies via mechanization of production, but has also created environmental problems as a by-product. In this sense, mechanization of production processes, i.e., sectoral transformation from agrarian-based economy to industrial-based economy, has created more environmental waste and pollution while increasing national output levels. However, in

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the course of time, governments started searching for solutions for rising and upcoming environmental threats at both the national and the international political agendas. In particular, as a result of transformation from an industrial society to a knowledge society in the 1960s, technology and knowledge started being used as policy tools for the struggle against environmental problems. Moreover, the oil price shocks in the 1970s were of great importance because they created a general interest in finding out the ways of reducing national energy demand and air pollution level by adopting a greater usage of information technology (IT) (Salahuddin and Alam 2015). In this way, IT was accepted as a useful and alternative way to gain more efficient economic growth with less energy (Sadorsky 2012).

The above-mentioned developments indicate that energy, in the form of oil and electricity, and information and communications technologies[1] (ICTs) played pivotal roles in the processes of industrialization and economic growth over the last hundred years (Cho et al. 2007). As stated by Funk (2015), for more than 50 years, we have been witnessing some huge and rapid improvements in the IT sector, and those improvements have reduced resource utilization and provided us a higher quality of life by redesigning our world. ICTs have consistently offered innovative products and services that are now an integral part of the daily life (GESI 2008). Therefore, knowledge society takes an advantage of technology and information for fostering a good life for both the current and the future generations by invigorating biological diversity, technological usability, economic wealth for all, political participation of all, and cultural wisdom (Fuchs 2008). As such, knowledge society that arises from the societal change processes driven by the rapid spread of ever-cheaper information and communications technologies takes us gradually forward into a post-industrial society (Hilty 2008). These developments in the areas of information and technology provide a clear evidence of strong relationships between ICTs, economic growth, and environmental quality.

Based on the rising importance of information and technology worldwide, we try to find an answer to the question whether the rising demand for ICT devices alleviates or aggravates environmental quality level based on a sample of low-income countries. Concerning the effect of ICTs on the environment, there exist two opposite viewpoints: The first viewpoint states that ICTs can alleviate environmental pollution by reducing energy demand and creating dematerialization, i.e., substitution of physical goods by virtual good (see Peng 2013; Ropke and Christensen 2012; and Sui and Rejeski 2002), while the second viewpoint indicates that ICTs worsen environmental pollution given that installation and operation of new ICT devices increase demand for electricity (see Al-Mulali et al. 2015; Ropke and Christensen 2012; and Matthews et al. 2001).Therefore, the net environmental effect of ICTs is not known a priori and deserves a special research interest.

[1]"Information and communications technology (ICT) is a broader term for information technology (IT), which refers to all communication technologies, including the Internet, wireless networks, cell phones, computers, software, middleware, videoconferencing, social networking, and other media applications and services enabling users to access, retrieve, store, transmit, and manipulate information in a digital form" (see http://aims.fao.org/es/information-and-communication-technologies-ict).

The sample of analysis is the panel of 23 low-income countries consisting of Bangladesh, Kenya, Benin, Burkina Faso, Burundi, Chad, Gambia, Ghana, Guinea-Bissau, Congo, Madagascar, Malawi, Mali, Mozambique, Nepal, Niger, Central African Republic, Ruanda, Senegal, Sierra Leone, Tanzania, Tonga, and Uganda. The ICT use levels of low-income countries are lower compared to those of middle- and high-income countries. For instance, according to World Development Indicators (World Bank's 2019), the percentage of individuals using the Internet was about 16% in low-income countries, whereas it was about 58% in upper-middle-income countries, 34% in lower-middle-income countries, and 85% in high-income countries in 2017. Therefore, we believe that revealing the net environmental effect of ICT use for the low-income countries will provide policy-makers to develop appropriate political strategies. The remainder of the chapter has been organized as follows: Sect. 3.2 explains the positive and negative effects of ICTs on the environment; Sect. 3.2.1 deals with the substitution effects and dematerialization process; Sect. 3.2.2 explains the compensation effects (income effects) and rebound effects; Sect. 3.3 provides a brief literature summary; Sect. 3.4 describes data and model; Sects. 3.5 and 3.6 explain the methodological approach used and empirical findings, respectively; finally, the chapter is concluded with some important policy implications in Sect. 3.7.

3.2 Effects of ICT on Energy Demand and the Environment

Regarding the environmental effects of ICTs, there exist three different views named "the first-order effects," "the second-order effects," and "the third-order effects" (Fichter 2003; Hilty 2008; Hilty et al. 2006; Houghton 2010; Zhang and Liu 2015; Zadek et al. 2010). The first-order effects indicate that ICT sector is responsible for higher CO_2 emission rate as the production and the use of ICTs create material flows and electronic waste, use hazardous materials, and increase energy consumption (Fichter 2003). In this sense, the first-order effects include the direct effects of ICTs such as energy consumption and e-waste (Houghton 2010). The second-order effects are derived from the usage of ICTs in the other processes because ICTs have an effect on the life cycle of another product, which is optimized (optimization effect) or which is used less often (substitution effect) or more frequently (induction effect) (Hilty 2008). The second-order effects, the indirect effects of ICT applications such as intelligent transport systems, smart buildings, and smart grids, might be beneficial or damaging for the environment (Houghton 2010). Last, the third-order effects, which are derived from the integration of ICTs into everyday life (Zadek et al. 2010), are defined as the adaptive reactions of societies to the availability of ICT services. These effects create structural transformation in the economy and affect lifestyles and consumption patterns of the society, which, in turn, affect the environmental quality level of the society (Hilty et al. 2006).

Based on the above-mentioned views, it could be stated that there is no consensus yet on the net effects of ICTs on energy demand and environmental quality. On the one hand, smartphones and other personal ICT devices allow users to share data, pictures, and videos, creating positive network effects among users; on the other hand, sharing them also increases the demand for electricity (Sadorsky 2012). Moreover, the production of ICT devices has a high energy density; for instance, the production of a desktop computer with a 17-inch CRT monitor consumes 6400 megajoules of total energy and 0.26 tons of fossil fuel (Peng 2013). In addition, the use of ICT products not only consumes electricity, but also leads to CO_2 emissions. Utilization of a desktop computer can result in 0.1 tons of CO_2 emissions per year (Peng 2013).

The effects of the Internet on the energy demand are explained by Romm (2002) as follows:

1. On the one hand, the Internet holds the prospect of increasing energy intensity by
   - increasing delivery of products by relatively inefficient means,
   - increasing shipping in general, as the globalization fostered by the Internet makes it easier to purchase objects from very far away, and
   - increasing the frequency of personal and business travel, as people prefer meeting the widely dispersed people they have met on the Internet in person.
2. On the other hand, the Internet holds the likelihood of reducing transportation energy intensity by
   - replacing some commuting with telecommuting,
   - replacing some shopping with teleshopping,
   - replacing some air travel with teleconferencing,
   - enabling digital transmission or e-materialization of a variety of goods that are today shipped by truck, train, and plane,
   - improving the efficiency of the supply chain, and
   - increasing the capacity utilization of the entire transportation system.

The positive and negative effects of ICTs on energy demand and the environment can be explained via some specific notions discussed below.

3.2.1 Substitution Effects and Dematerialization Process

Regarding its positive effects, IT is accepted as a solution to obtain more efficient economic growth with less energy demand (Sadorsky 2012). There exists a special notion named "IT as a solution" or "IT for green" (see Cai et al. 2013; Dedrcik 2010; Salahuddin et al. 2016), which accepts ICT sector as a beneficial solution in reducing CO_2 emissions throughout all economic sectors. In this approach, IT is accepted as a mean to achieve national environmental sustainability goal by using energy in a more efficient and a sustainable way. ICT contributes to energy saving and reduction of CO_2 emissions by improving energy efficiency in different sectors of the economy through the optimization of each link of product systems (Zhang and Liu 2015). The positive effect of ICTs on the environment is reflected in the *substitution effects* that represent the reduction of electricity demand through the replacement of an old energy-intensive production technology by a new one (Cho et al. 2007; Coroama et al. 2012). There is a growing consensus about the idea that ICTs may have a role in reducing the greenhouse gases (GHGs) emissions by both raising the efficiency of existing production processes and enabling the substitution effects (Coroama et al. 2012).

Many traditional industries implementing ICTs in their operation processes have been transformed into smart industries such as smart transportation, smart agriculture, smart management, smart logistics, smart building, and so on. Those ICT-enabled transformations have resulted in better production control and monitoring, more efficient resource management, better transportation and logistics management, less energy waste, and less polluting emissions throughout economy (Peng 2013; Zadek et al. 2010). According to Romm (2002), the Internet provides two types of gains by improving energy intensity: First, the structural gains occur if there is a shift in the industrial structure away from iron and steel, chemicals, and other smokestack industries toward electronics, communications, and other IT industries (Takase and Murota 2004). Second, efficiency gains are obtained with overall efficiency rise throughout the system as a whole, occurring when businesses change their activities in some ways that can reduce energy intensity. According to the Smart 2020 Report (GESI 2008), ICTs will cause higher energy efficiencies in other sectors, and thereby, they will contribute to the reduction of carbon emissions five times larger than the total emissions from the ICT sector in 2020.

The second concept highlighting the positive effects of ICTs on the environment is the *dematerialization,* which represents a knowledge society making use of ICTs to provide immaterial services where material goods were produced, transported, and disposed previously (Hilty 2008). The virtual goods replace material devices. For instance, the shifts from books to bytes, from compact disks to MP3s, from snapshots to JPEGs, and from checkbooks to clicks are the products of the dematerialization process in which electrons substitute for atoms (Sui and Rejeski 2002). In these cases, ICTs are used to substitute "bits of information" such as downloads, virtual meetings, and e-commerce for more energy-intensive physical products, and travel and retail premises (Zadek et al. 2010). Transformation from an "industrial society" to a knowledge society represents a less resource-intensive and a weightless economy given that there is an important process called dematerialization of production (Fuchs 2008). Nowadays, trade and transportation of many products and services over the Internet result in dematerialization, which reduces the amount of physical transport and increases the efficiency of transportation (Fuchs 2008). Thus, it could be stated that ICTs reduce the negative environmental effects of traditional industries by allowing more efficient ways of production and distribution.

E-commerce, online shopping, teleworking, and teleconference, which are likely to have environmental effects, are the products of dematerialization process. We are currently witnessing a growing interest in online shopping. The Internet is turning to be the modern agora free from the limitations of space and time (Sui and Rejeski 2002). However, there are some debates on the effects of the rising interest in online shopping (e-commerce) on the environmental quality, as well. A group of scholars (see Al-Mulali et al. 2015; Ropke and Christensen 2012; Matthews et al. 2001) suggests that online shopping worsens air pollution by causing more energy consumption. For instance, Al-Mulali et al. (2015) suggest that the number of required vehicles to deliver the purchased items to the buyers will increase in the case of online shopping, resulting in more energy consumption in transportation sector. Given that a lorry or a car delivers goods individually, the savings in energy consumption from private transport might be outweighed by the additional energy consumption related to distribution (Ropke and Christensen 2012). Moreover, even though e-commerce can reduce the use of warehouses as well as trips to the shopping malls, it is generally based on a transportation system that is more energy and pollution-intensive; e.g., aircraft may replace trucks and rail (Matthews et al. 2001).

Another group of scholars (see Matthews et al. 2002; Romm 2002; Sui and Rejeski 2002) states that online shopping reduces energy demand and CO_2 emission level compared to shopping by car. In this sense, Romm (2002) argues that a 20-mile round-trip to purchase two 5-pound products at malls consumes about one gallon of gasoline, whereas having those packages transported 1000 miles by truck or air freight consumes nearly 0.1 and 0.6 gallons, respectively. Online sale of products could be beneficial to the environment because in this situation, emissions from vehicles driven to shopping malls can be avoided while retail space, inventories, and waste can be reduced (Matthews et al. 2002). Additionally, by moving businesses online and marketing by pixels instead of packages, e-commerce can reduce the need for such wasteful products such as printed catalogues, telephone books, newspapers, and magazines (Sui and Rejeski 2002). Therefore, the net impact of e-commerce is not known a priori. Teleconference and telework are also the products of dematerialization process. Coroama et al. (2014) state that GHG emissions caused by an international conference could be reduced substantially by organizing it as a teleconference since it will reduce the frequency of traveling. Likewise, telework, allowing knowledge workers to overcome spatiotemporal distances and to work from home, would reduce the need for transport and thus environmental pollution (Fuchs 2008). As sum, through demobilization (i.e., less shopping and business trips), online shopping, teleworking, and telecommuting lead to conservation of energy by reducing fuel consumption (Sui and Rejeski 2002).

3.2.2 Compensation Effects (Income Effects) and Rebound Effects

There is some suspicion about the view that ICT development creates a substantial reduction in energy consumption due to some concerns about the negative side effects of ICT development (Ishida 2015). As stated by Sui and Rejeski (2002), it is so early to paint a rosy picture for the positive environmental effects of the emerging digital economy. There exist two negative environmental effects of ICTs, namely the compensation effects and the rebound effects. The *compensation effects (income effects)* of ICTs work against the substitution effects and indicate that installation and operation of new ICT devices increase the demand for electricity (Cho et al. 2007). The use of smartphones and ICT devices to share data, videos, and pictures creates a positive network effect among users; however, the activity of sharing and using them also raises the demand for electricity (Sadorsky 2012). For instance, Facebook's global yearly electricity consumption is of 0.5 terawatt hours (TWh), amounting approximately to 500 W (Wh) per user (Gelenbe and Caseau 2015). The electricity consumption related to ICT devices, e.g., communication networks, personal computers, and data centers, increases at a rate of nearly 7% per year (Salahuddin and Alam 2015), and the production and use of ICT devices are estimated to be responsible for about 1–3% of global CO_2 emissions (Houghton 2010; Peng 2013; Zadek et al. 2010). Given that production and disposal of ICTs generate waste and toxic emissions, the emergence of knowledge society is accepted as a new stage in the material reality of capitalism instead of an immaterial society (Fuchs 2008). There is a special notion, "green IT" or "IT as a problem" (Cai et al. 2013; Dedrcik 2010; Peng 2013; Salahuddin et al. 2016), which underlines the negative effects of ICTs on the environment. This approach holds ICT sector responsible for the air pollution and asserts that the sector should implement environmentally friendly devices to combat its own carbon footprint. However, the Smart 2020 Report prepared by GESI (2008) stated that ICT sector, by enabling energy efficiencies in other sectors, will save carbon emissions five times larger than the total emissions from the entire ICT sector in 2020.

The second concept counteracting the positive energy and environmental effects of ICTs is the *rebound effects* that work against the efficiency of energy and resource use. The rebound effects represent the paradox that efficiency gains in ICT devices and machines can increase the demand for them (Coroama et al. 2012). The rebound effects occur in the case that efficiency of providing a service is increased and that there is not any factor restricting the demand for the service (Hilty 2008). In this sense, if a good gets cheaper in terms of its price or any effort necessary to obtain it, the demand for that good usually increases, and thus, efficiency improvements do not indicate savings on the input side (Hilty et al. 2006). In other words, energy efficiency gains resulting from the deployment of ICTs can create additional pressure on the demand for ICT devices. For instance, the increasing usage level of ICTs at work and home has led to significant increases in carbon footprint of the ICT sector and this might be accepted as one of the most crucial rebound effects (Peng 2013). The new technologies such as LCDs, laptops, and tablets are smaller and more energy efficient; however, the improvements in energy efficiency are outweighed by a fast growth in the number of devices (Heddeghem et al. 2014). Therefore, it appears that the share of electricity consumption of the ICT industry will increase unless the efficiency improvements of the sector can keep up with the growing proliferation of those devices (Zadek et al. 2010).

3.3 Literature Review

Environmental effects of information technologies have started to be analyzed since the early 1990s. The current literature is based on two main research categories: The first category analyzes the effects of ICTs on energy demand (especially electricity demand) (see Collard et al. 2005; Ropke et al. 2010; Sadorsky 2012; Saidi et al. 2017; Salahuddin and Alam 2015; Schulte et al. 2016; Shahbaz et al. 2016; Solarin et al. 2019; Wang and Han 2016). The second category focuses on the effects of ICTs on environmental quality (see Amri et al. 2019; Asongu et al. 2018; Danish et al. 2018; Haseeb et al. 2019; Higón et al. 2017; Lee and Brahmasrene 2014; Lu 2018; Park et al. 2018; Salahuddin et al. (2016); Shabani and Shahnazi 2019).

In the first category, there are time series studies analyzing the effects of ICTs on energy demand. Of them, Collard et al. (2005) modeled electricity demand using a proxy for the ICTs and concluded that increased usage of software and computers in the services sector of France raised the electricity density in production from 1986 to 1998. Ropke et al. (2010) questioned the impact of ICTs on the sectoral electricity consumption of Denmark with a case study from 2007 to 2008. They found that growing usage level of ICTs in daily life increased electricity consumption in the household sector. For the United Arab Emirates (UAE), Shahbaz et al. (2016) examined the effects of ICT and economic growth on electricity consumption for the period 1975–2011 by using Bayer–Hanck cointegration test, the innovative calculation approach, and the Granger causality test. They obtained that ICTs increase the demand for electricity, but they provide lower electricity prices. Additionally, they ascertained an inverted U-shaped relationship between ICT and electricity. In a similar way, Solarin et al. (2019) investigated the effects of ICT, financial development, and economic growth on electricity consumption during the period 1990–2015 for Malaysia by employing the Gregory–Hansen cointegration test and Toda–Yamamoto causality test. Their results confirmed a positive effect of ICTs on electricity consumption. A similar result was obtained by Salahuddin and Alam (2015), who examined the short- and long-term effects of economic growth and Internet use on electricity consumption in Australia for the period 1985–2012 through the autoregressive distributed lag model (ARDL).

Within the nexus of ICT and energy demand, there are some panel data studies. Among them, Schulte et al. (2016) analyzed the relationship between ICT and energy demand for 27 industries from 10 Economic Cooperation and Development Organization (OECD) countries by using the least squares dummy variable (LSDV) estimator and seemingly unrelated regression (SUR) methods for the period 1995–2007. They obtained that ICTs are associated with a significant decrease in total energy demand and electricity consumption. Similarly, Wang and Han (2016), for a panel of 30 Chinese provinces, analyzed the effects of ICT investments on energy intensity during the period 2003–2012 by using the Driscoll–Kraay panel method and panel error correction model. They found that ICT investments reduced energy intensity in the long-run. In contrast, Sadorsky (2012) found that ICTs increased electricity consumption in 19 developing economies from 1993 to 2008 by utilizing the generalized method of moments (GMM). A similar result was gained by Saidi et al. (2017), who found that ICT increased electricity consumption for a panel data set of 67 countries by using GMM from 1990 to 2012.

In the second research category, the studies (time series or panel data studies) examined the effects of ICTs on environmental quality. For instance, Amri et al. (2019) investigated the relationship between CO_2 emission, total factor productivity, and ICT for the Tunisian economy through the autoregressive distributed lag (ARDL) model approach from 1975 to 2014 and obtained an insignificant effect of ICT on CO_2 emissions. Among panel data studies, Salahuddin et al. (2016) obtained that 1% increase in Internet usage caused 0.16% increase in CO_2 emissions in the panel of OECD countries for the period 1991–2012. A similar result was reported by Park et al. (2018), who examined the relationship between ICT, financial development, economic growth, and CO_2 emissions in 23 European Union (EU) countries between 2001 and 2014 through the pooled mean group (PMG) estimator. They found that 1% increase in the number of Internet users raises CO_2 emissions by 0.08%. Another study carried out was by Danish et al. (2018), who explored the relationships between ICT, financial development, economic growth, and electricity consumption for the Next Eleven (N-11) countries by employing the panel mean group (MG) and augmented mean group (AMG) estimators during the period 1990–2014. Their results confirmed a positive relationship between ICT use and CO_2 emissions. Besides, Lee and Brahmasrene (2014) investigated the relationship between ICT, CO_2, and economic growth in 9 Asian countries during the period 1991–2009 by utilizing the Fisher-type Johansen panel cointegration test, and panel FMOLS and DOLS estimators. They confirmed the significant and positive effects of ICTs on both CO_2 emissions and economic growth. Also, Higon et al. (2017) searched the relationship between ICT and environmental sustainability for 142 countries by using the fixed effect panel data model for the period 1995–2010 and obtained an inverted U-shaped relationship between ICT and CO_2 emissions. Finally, Shabani and Shahnazi (2019) examined the relationship between energy consumption, GDP, CO_2 emissions, and ICT for sectors in the Iranian economy through the panel dynamic OLS estimator for the period 2000–2013. Their findings confirmed a positive and a significant effect of ICT on CO_2 emissions in the industrial sector, while a negative effect was discovered in the transportation and service sectors.

Some of the panel data studies confirmed that ICT reduces emission level of CO_2. For instance, Asongu et al. (2018) analyzed the effect of ICT on CO_2 emissions by using GMM model for 44 Sub-Saharan African countries in the period 2000–2012. The results indicate that ICT had no effect on CO_2 emission in the early stages; but there was a negative effect in the later stages. Likewise, Haseeb et al. (2019) searched the effects of ICT, globalization, energy consumption, financial development, and economic growth on environmental quality level in BRICS from 1994 to 2014 by using dynamic seemingly unrelated regression (DSUR). Their results revealed that ICT caused some significant negative effects on CO_2 emissions. A recent study in this group has been carried out by Lu (2018), who investigated the effects of ICT, energy consumption, financial development, and economic growth on CO_2 emissions by employing a common correlated effects mean group (CCEMG) estimator in 12 Asian countries from 1993 to 2013. Their findings provided a negative effect of ICT on CO_2 emissions.

3.4 Model and Data

The sample includes 23 low-income countries, namely Bangladesh, Kenya, Benin, Burkina Faso, Burundi, Chad, Gambia, Ghana, Guinea-Bissau, Congo, Madagascar, Malawi, Mali, Mozambique, Nepal, Niger, Central African Republic, Ruanda, Senegal, Sierra Leone, Tanzania, Tonga, and Uganda. The related countries have been selected based on the classification of the World Bank (2015)[2]. Time period has been determined as the years from 1995 to 2015 due to unavailability of some data points. The dependent variable of the model is the carbon dioxide (CO_2) emission per capita (measured in kilograms). A number of studies, specifically the studies testing the environmental Kuznets curve (EKC) hypothesis (see Al-Mulali 2011; Apergis and Payne 2010; Ghosh 2010; Ozcan 2013), utilize CO_2 emissions as a proxy for air pollution. The main independent variable of the study is the Internet users per 100 people used as a proxy for ICTs in many studies (see Afzal and Gow 2016; Lin 2015; Sadorsky 2012; Saidi et al. 2017; Salahuddin and Alam 2015; Salahuddin and Gow 2016; Salahuddin et al. 2016). Additionally, some other control variables that are likely to affect CO_2 emission level are also included in the model like GDP per capita (constant 2010 US $) and energy use (kg of oil equivalent per capita). GDP and energy consumption are the essential variables mostly included in the models of the EKC studies (see Al-Mulali 2011; Apergis and Payne 2010; Farhani and Rejeb 2012; Haggar 2012; Pao and Tsai 2010). Increases in energy consumption are expected to raise air pollution. According to the EKC hypothesis, air pollution increases with the increase in income level in the early stages of development. However, once the income reaches a certain threshold level, an increase in the income level causes the reduction of air pollution. Therefore, EKC hypothesis posits an inverse U-shaped ($\cap$) relationship between income and CO_2 emissions. Accordingly, while the coefficient of energy consumption is expected to be positive, the coefficient of the income variable is likely to be positive or negative. Another control variable included in the model is the level of financial development (see Dogan and Turkekul; 2016; Jalil and Feridun 2011; Ozturk and Acaravci 2013; Tamazian et al. 2009; Zhang 2011). As a proxy for financial development, domestic credit to private sector (percentage of GDP) is employed. The net effect of financial development on CO_2 emissions is unclear. On the one hand, financial development helps companies to buy new equipment and to invest in new projects by reducing financial costs, enriching financial channels, and distributing operational risks, which increases both energy consumption and CO_2 emissions (Ozturk and Acaravci 2013). On the other hand, financial development provides countries the opportunity to obtain environmentally friendly

[2](See https://datahelpdesk.worldbank.org/knowledgebase/articles/906519).

and clean production technologies and, thus, contributes to the reduction of environmental pollution (Tamazian et al. 2009). The last control variable of the model is trade openness (percentage of total exports and imports of goods and services in GDP) (see Choi et al. 2010; Islam et al. 2013; Karsalari et al. 2014; Shahbaz et al. 2011). The net effect of trade openness on the environment is not certain because there exists a tripartite approach regarding the relationship between trade openness and environmental quality in the literature (Choi et al. 2010; Copeland and Taylor 1994): scale effect, composition effect, and technical effect. The scale effect suggests that the increase in the amount of trade increases output, energy consumption, and, thus, CO_2 emissions. The composition effect emphasizes the reallocation of trade goods of a country. In other words, free trade offers countries a chance to specialize in the production of goods with which they have comparative advantage. Thus, based on whether the sectors in which the country specializes need more energy, energy consumption decreases and environmental quality improves or energy consumption increases and environmental quality deteriorates. Finally, the technical effect indicates that trade liberalization will improve the environmental quality by leading to more efficient use of energy during the production through technology. Therefore, the effect of trade openness on CO_2 emissions depends on which of these three effects are more dominant. If the scale effect is dominant, the coefficient of trade openness is positive; if the technical effect is dominant, the coefficient of trade openness is negative; if the composition effect is dominant, the sign of coefficient is uncertain. The variables, Internet users, GDP, financial development, and trade openness are obtained from the World Bank's (2019) database. CO_2 emission data are from the Emissions Database for Global Atmospheric Research (EDGAR) of the European Commission (2016), while energy consumption data are provided from the U.S. Energy Information Administration (EIA) (2019).

The main model of the study has been determined as follows based on the existing studies in the relevant literature (see Ozcan and Apergis 2018; Ozturk et al. 2016; Salahuddin et al. 2016).

$$\mathrm{PCO_2} = f(\mathrm{PGDP}, \mathrm{ICT}, \mathrm{PENC}, \mathrm{FD}, \mathrm{TO}) \tag{3.1}$$

In Eq. (3.1), per capita CO_2 emission level (PCO_2) is defined as the function of per capita real income level (PGDP), percentage of Internet users (ICT), per capita energy consumption (PENC), trade openness (TO), and financial development (FD). The variables of interest are included in the model in natural logarithmic forms considering the studies in the literature, and thereby, Eq. (3.2) is obtained:

$$\begin{aligned} \mathrm{lnPCO}_{2i} = {} & \alpha_i + \delta_i t + \beta_{1i}\mathrm{lnPGDP}_{it} + \beta_{2i}\mathrm{lnICT}_{it} \\ & + \beta_{3i}\mathrm{lnPENC}_{it} + \beta_{4i}\mathrm{lnTO}_{it} + \beta_{5i}\mathrm{lnFD}_{it} + \varepsilon_{it} \end{aligned} \tag{3.2}$$

where $i = 1, 2, \ldots, N$ refers to the number of countries in the panel and $t = 1995, 1996, \ldots 2015$ is the time period of the study. α_i and $\delta_i t$ represent the country-specific fixed effects and deterministic trend, respectively. ε_{it} is the country-specific random error term with zero mean. β_1, β_2, β_3, β_4, and β_5 denote the long-term elasticity coefficients of CO_2 by the relevant variables.

3.5 Methodology

3.5.1 Cross-Sectional Dependence Tests

The globalizing world order leads to a dependency among the macroeconomic data of the countries. Economic shocks in a country not only affect economic data of that country, but also affect the economic data of other countries. Therefore, it should be tested whether the economic data have interdependencies across cross-sectional units, i.e., countries. The following cross-sectional dependence tests are used in the analysis: the LM tests (Breusch and Pagan 1980), the CD_{LM} and CD tests (Pesaran 2004), and the LM_{adj} test (Pesaran et al. 2008).

The Lagrange multiplier (LM) test, developed by Breusch and Pagan (1980), is based on the mean square estimation of bidirectional correlations. Under the standard continuity condition, it has a chi-square distribution asymptotically ($T \to \infty$) with the N(N − 1)/2° of freedom. The LM test is effective when the time dimension is greater than the cross-sectional dimension ($T > N$). For other cases, Pesaran (2004) developed the CD_{LM} and CD tests. The LM test statistic is shown as follows:

$$\mathrm{LM} = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2 \tag{3.3}$$

where $\hat{\rho}_{ij}$ is a sample estimate of the bidirectional correlation of the residuals, and its properties can be expressed as follows:

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^{T} e_{it} e_{jt}}{\left(\sum_{t=1}^{T} e_{it}^2\right)^{1/2} \left(\sum_{t=1}^{T} e_{ij}^2\right)^{1/2}}, \tag{3.4}$$

where e_{it} is obtained by the ordinary least squares (OLS) method. The *LM* test has asymptotically the chi-square distribution with degree of freedom $N(N-1)/2$, but this test is not valid in the case of $N \to \infty$. For this reason, Pesaran (2004) developed another test statistic (CD_{LM}) that will be used in case that both the cross section and the time dimension are large. Pesaran (2004) describes the test procedure as follows:

$$\mathrm{CD}_{\mathrm{LM}} = \sqrt{\frac{1}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left(T \hat{\rho}_{ij}^2 - 1\right) \tag{3.5}$$

This test statistic does not follow a chi-square distribution as the LM test statistic of Breusch and Pagan (1980), but follows a standard normal distribution.

Another test statistic, the *CD* test statistic, was proposed by Pesaran (2004) in case of $N > T$; it is defined as:

$$\mathrm{CD} = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \tag{3.6}$$

Finally, Pesaran et al. (2008), for the state of first for $T \to \infty$ and then $N \to \infty$, developed the test statistic in Eq. (3.7) to correct the small sample bias of the LM statistic.

$$\mathrm{LM}_{\mathrm{adj}} = \sqrt{\frac{2}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\frac{(T-k)\hat{\rho}_{ij} - \mu_{Tij}}{v_{Tij}} \tag{3.7}$$

where μ_{Tij} and v_{Tij} indicate the mean and variance, respectively. $\mathrm{LM}_{\mathrm{adj}}$ test statistic has a standard normal distribution ($\mathrm{LM}_{\mathrm{adj}} \to_d N(0, 1)$). The null and the alternative hypotheses of the test statistic are defined as follows:

H_0: There is not any cross-sectional dependence.
H_1: There is a cross-sectional dependence.

3.5.2 Smith et al. (2004) Panel Unit Root Tests

Smith et al. (2004) developed their first test statistic defined in Eq. (3.8) based on the Im et al. (IPS 1997) unit root test.

$$\frac{\sqrt{N}\left\{\bar{t} - E(t_i)\right\}}{\sqrt{\mathrm{Var}(t_i)}} = \bar{t}_s \tag{3.8}$$

The test statistic, $\bar{t}_s$, utilized the Dickey–Fuller (DF) test and has a standard normal distribution. $E(t_i)$ and $\mathrm{Var}(t_i)$ in Eq. (3.8) are the DF mean and variance. The restrictive distributive problems of IPS require the presence of the second moments of t_i. Therefore, the Lagrange multiplier (LM) test statistics, first developed by Solo (1984), should be taken into consideration. In this case, the new test statistic is defined as follows:

$$\frac{\sqrt{N}\left\{\overline{\mathrm{LM}} - E(\mathrm{LM}_i)\right\}}{\sqrt{\mathrm{Var}(\mathrm{LM}_i)}} = \overline{\mathrm{LM}}_s \tag{3.9}$$

where $\overline{\text{LM}}$ is the mean of each LM_i, and thereby, the obtained equation is shown as $\overline{\text{LM}} = N^{-1}\sum_{i=1}^{N}\text{LM}_i$. In addition to the development of DF test statistics with LM test statistics, Leybourne et al. (2002) found two different modifications of DF: the weighted symmetric (WS) test described by Pantula et al. (1994) and the Max test developed by Leybourne (1995). Equations (3.10) and (3.11) describe these two test statistics:

$$\frac{\sqrt{N}\left\{\overline{\text{Max}}_i - E(\text{Max}_i)\right\}}{\sqrt{\text{Var}(\text{Max}_i)}} = \overline{\text{Max}}_s \tag{3.10}$$

$$\frac{\sqrt{N}\left\{\overline{\text{WS}} - E(\text{WS}_i)\right\}}{\sqrt{\text{Var}(\text{WS}_i)}} = \overline{\text{WS}}_i \tag{3.11}$$

The final test is expressed as a more powerful variant of the LM test. This test provides the LM_{f_i} ve LM_{r_i} test statistics based on forward and backward regressions as in previous procedures. The minimums ($\text{Min}_i = \text{Min}\left(\text{LM}_{f_i}, \text{LM}_{r_i}\right)$) are used to achieve the test statistic which is defined in Eq. (3.12) based on the equation of $\overline{\text{Min}} = N^{-1}\sum_{i=1}^{N}\text{Min}_i$.

$$\frac{\sqrt{N}\left\{\overline{\text{Min}} - E(\text{Min}_i)\right\}}{\sqrt{\text{Var}(\text{min}_i)}} = \overline{\text{Min}}_s \tag{3.12}$$

The above-mentioned five test statistics of Smith et al. (2004) have a unit root null hypothesis and allow for heterogeneous autoregressive roots under the alternative hypothesis. Therefore, the rejection of the null hypothesis implies that stationarity does hold for at least one panel member.

3.5.3 Westerlund (2008) and Pedroni (1999, 2004) Cointegration Tests

The Durbin–Hausman (DH) cointegration test, developed by Westerlund (2008), allows the analysis of the cointegration relationship when the dependent variable is not stationary at the level value, i.e., $I(1)$, and the independent variables are stationary at the level, i.e., $I(0)$, or at the first differences, i.e., $I(1)$. The DH test allows cross-sectional dependence with a factor model. In this process, the error terms of Eq. (3.2) are obtained by unique innovations and unobservable factors common to the panel members (Auteri and Constantini 2005). The error terms of Eq. (3.2) are modeled by Eqs. (3.13)–(3.15):

$$\varepsilon_{it} = \lambda_i' \text{F}_t + \text{e}_{it} \tag{3.13}$$

$$F_{jt} = \rho_j F_{jt-1} + u_{jt} \tag{3.14}$$

$$e_{it} = \emptyset_i e_{it-1} + v_{it} \tag{3.15}$$

F_t is a k-dimensional vector of the common factors, while $j = 1, 2, \ldots, \mathrm{k}$ and F_{jt} is a vector compatible with λ_i. The stationarity of F_t is ensured if we assume that $\rho_j < 1$ holds for all j. The statement explains that the combined regression error z_{it} only depends on the integration of the e_{it} during its integration, with its own disruption. Accordingly, testing the null hypothesis of cointegration in the data generation process means testing if $\emptyset_i = 1$. The following two panel test statistics, the panel test statistic (DH_p) and the group-mean test statistic (DH_g), are obtained.

$$\mathrm{DH}_g = \sum_{i=1}^{n} \widehat{S}_i \left(\overline{\emptyset}_i - \widehat{\emptyset}_i\right)^2 \sum_{t=2}^{T} \hat{e}_{it-1}^2 \tag{3.16}$$

$$\mathrm{DH}_p = \widehat{S}_n \left(\overline{\emptyset} - \widehat{\emptyset}\right)^2 \sum_{i=1}^{n} \sum_{t=2}^{T} \hat{e}_{it-1}^2 \tag{3.17}$$

The main difference between DH_p and DH_g test statistics stems from the difference in the formulation of the alternative hypothesis. The hypotheses for the panel tests are

$$H_0^p : \emptyset_i = 1 \text{ for all } i,$$
$$H_1^p : \emptyset_i = \emptyset \text{ for all } i \ \emptyset < 1$$

In this situation, it is assumed that there exists a common value for the autoregressive parameter under both the null and the alternative hypotheses. Therefore, if this assumption is valid, the rejection of the null hypothesis provides evidence in favor of cointegration for all i. The hypotheses for the group tests are specified as:

$$H_0^g = \emptyset_i = 1$$
$$H_1^g = \emptyset_i < 1 \text{ at least for some } i$$

According to the above hypotheses, no common value is assumed for the autoregressive parameter. Thus, the rejection of the null hypothesis does not provide any evidence of cointegration for all units. The rejection of the null hypothesis provides evidence of cointegration at least for some panel members.

As a robustness check, we have also employed Pedroni's (1999, 2004) cointegration tests. There exist seven cointegration tests. Among these seven tests, four tests include within effects and three tests include between effects. Specifically, the within statistics are calculated by summing both shares and denominators separately according to N dimension. The between statistics are obtained by dividing the numerator by denominator before being added to Ndimension. The related test statistics are defined as follows:

$$\text{Panel } v\text{-stat.}: \; T^2 N^{\frac{3}{2}} Z_{\hat{v}_{N,T}} = T^2 N^{\frac{3}{2}} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \widehat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \right)^{-1} \tag{3.18}$$

$$\text{Panel } \rho\text{-stat.}: \; T\sqrt{N} Z_{\hat{\rho}_{N,T}-1} = T\sqrt{N} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \widehat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \right)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \widehat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \left(\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i \right) \tag{3.19}$$

Panel t-stat. (*non-parametric*):

$$Z_{t_{N,T}} = \left(\tilde{\sigma}_{N,T}^2 \sum_{i=1}^{N} \sum_{t=1}^{T} \widehat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \right)^{-\frac{1}{2}} \sum_{i=1}^{N} \sum_{t=1}^{T} \widehat{L}_{11i}^{-2} \hat{e}_{i,t-1}^2 \left(\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i \right) \tag{3.20}$$

Panel t-stat. (*parametric*):

$$Z_{t_{N,T}}^* = \left(\tilde{s}_{N,T}^{*2} \sum_{i=1}^{N} \sum_{t=1}^{T} \widehat{L}_{11i}^{-2} \hat{e}_{i,t-1}^{*2} \right)^{-1/2} \sum_{i=1}^{N} \sum_{t=1}^{T} \widehat{L}_{11i}^{-2} \hat{e}_{i,t-1}^{*} \Delta \hat{e}_{i,t}^{*} \tag{3.21}$$

Group ρ-stat.:

$$TN^{-1/2} \widetilde{Z}_{\hat{\rho}_{N,T}-1} = TN^{-\frac{1}{2}} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \hat{e}_{i,t-1}^2 \right)^{-1} \sum_{t=1}^{T} \left(\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i \right) \tag{3.22}$$

Group t-stat. (*non-parametric*):

$$N^{-1/2} \widetilde{Z}_{t_{N,T}} = N^{-\frac{1}{2}} \sum_{i=1}^{N} \left(\hat{\sigma}_i^2 \sum_{t=1}^{T} \hat{e}_{i,t-1}^2 \right)^{-\frac{1}{2}} \sum_{t=1}^{T} \left(\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i \right) \tag{3.23}$$

Group t-stat. (*parametric*):

$$N^{-\frac{1}{2}} \widetilde{Z}_{t_{N,T}}^* = N^{-\frac{1}{2}} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \hat{s}_i^{*2} \hat{e}_{i,t-1}^{*2} \right)^{-\frac{1}{2}} \sum_{t=1}^{T} \hat{e}_{i,t-1}^{*} \Delta \hat{e}_{i,t}^{*} \tag{3.24}$$

Equations (3.18)–(3.21) represent within effects, while Eqs. (3.22)–(3.24) reflect the between effects. The null and alternative hypotheses for the cointegration tests are defined as follows:

The hypotheses belonging to the equations with within effects are:

$$H_0: \; \gamma_i = 1 \text{ for all } i$$

$$H_1 : \gamma_i = \gamma < 1 \text{ for all } i,$$

The hypotheses belonging to the equations with between effects are:

$$H_0 : \gamma_i = 1 \text{ for all } i$$
$$H_{1:} : \gamma < 1 \text{ for all } i$$

3.5.4 Panel ARDL Estimator of Pesaran et al. (1999)

The panel autoregressive distributed lag (panel ARDL) model developed by Pesaran et al. (1999) is based on the estimation of the unconstrained error correction model by the OLS method. Equation (3.2) is designed as the panel ARDL estimation via Eq. (3.25).

$$\begin{aligned}\ln\mathrm{PCO}_{2_{it}} &= \alpha_i + \sum_{j=1}^{p} \beta_{ij} \ln\mathrm{PGDP}_{i,t-j} + \sum_{j=0}^{q} \delta_{ij} \ln\mathrm{ICT}_{i,t-j} \\ &+ \sum_{j=0}^{k} \theta_{ij} \ln\mathrm{PENC}_{i,t-j} + \sum_{j=0}^{l} \gamma_{ij} \ln\mathrm{TO}_{i,t-j} \\ &+ \sum_{j=0}^{m} \omega_{ij} \ln\mathrm{FD}_{i,t-j} + \varepsilon_{it}\end{aligned} \tag{3.25}$$

Pesaran et al. (1999) additionally suggest that employing the re-parameterized Eq. (3.26) is more suitable.

$$\begin{aligned}\Delta\ln\mathrm{PCO}_{2_{it}} &= \alpha_i + \varphi_i \mathrm{LNPGDP}_{i,t-1} + \delta_i^* \ln\mathrm{ICT}_{it} + \theta_i^* \ln\mathrm{PENC}_{it} + \gamma_i^* \ln\mathrm{TO}_{it} \\ &+ \omega_i^* \mathrm{FD}_{it} + \sum_{j=1}^{p-1} \beta_{ij}^* \Delta\ln\mathrm{PGDP}_{i,t-j} + \sum_{j=0}^{q-1} \delta_{ij}^{**} \Delta\ln\mathrm{ICT}_{i,t-j} \\ &+ \sum_{j=0}^{k-1} \theta_{ij}^{**} \Delta\mathrm{PENC}_{i,t-j} + \sum_{j=0}^{l-1} \gamma_{ij}^{**} \Delta\ln\mathrm{TO}_{i,t-j} \\ &+ \sum_{j=0}^{m-1} \omega_{ij}^{**} \Delta\ln\mathrm{FD}_{i,t-j}\end{aligned} \tag{3.26}$$

The following notations are specified in Eq. (3.26).

$$\varphi_i = -\left(1 - \sum_{j=1}^{p} \beta_{ij}\right), \delta_i^* = \sum_{j=0}^{q} \delta_{ij}, \theta_i^* = \sum_{j=0}^{k} \theta_{ij}, \gamma_i^* = \sum_{j=0}^{l} \gamma_{ij}, \omega_i^* = \sum_{j=0}^{m} \omega_{ij} \tag{3.27}$$

ε_{it} is an error term distributed independently along i and t; φ_i is the error term expected to be negative; $\delta_i^*, \theta_i^*, \gamma_i^*,$ and ω_i^* are the long-run coefficients, while $\beta_{ij}^*, \delta_{ij}^{**}, \theta_{ij}^{**}, \gamma_{ij}^{**}$ ve ω_{ij}^{**} are the short-run coefficients.

Pesaran et al. (1999) propose two estimators, the mean group estimator (MGE) and the pooled mean group estimator (PMGE). The MGE is not sufficiently restrictive because it does not impose any restriction on the ARDL specification parameters and the small sample power is not high. Therefore, while allowing short-term dynamics to differ between countries, the PMGE has been developed to allow long-term parameters to be the same.

3.6 Empirical Results

3.6.1 Results for Cross-Sectional Dependence and Panel Unit Root Tests

Before proceeding to the empirical analysis, we first provide some statistical features of variables of interest, as seen in Table 3.1.

As shown in Table 3.1, GDP per capita has the highest mean (6.27) while CO_2 emissions per capita have the lowest mean (−1.93). Besides, GDP per capita has the highest maximum value (8.21) while CO_2 emissions per capita have the lowest minimum value (−3.15); the standard deviations of variables range from 0.95 (lnFD) to 0.32 (lnTO). After that, to select the right panel unit root test, we first need to test the cross-sectional dependence across variables. In the presence of cross-sectional dependence, the second-generation panel unit root tests should be utilized instead of the first-generation tests. For this goal, the LM test (Breusch and Pagan 1980), the

Table 3.1 Statistical features of variables

Descriptive statistics	$\ln PCO_2$	lnPENC	lnFD	lnPGDP	lnICT	lnTO
Mean	−1.931	4.063	2.235	6.270	0.697	3.927
Median	−2.153	3.944	2.394	6.209	0.271	3.942
Maximum	0.841	6.700	4.171	8.215	3.680	4.879
Minimum	−3.158	1.966	−0.891	5.087	0.000	2.939
Standard dev.	0.704	0.839	0.952	0.533	0.865	0.324
Obs. number	598	598	598	598	598	598

Source Author's own calculation based on data

Table 3.2 Cross-sectional dependence test results

Variables	LM	CD_{LM}	LMadj	CD
$\ln PCO_2$	2785.925[a] (0.000)	112.602[a] (0.000)	112.142[a] (0.000)	41.866[a] (0.000)
lnPGDP	3070.767[a] (0.000)	125.265[a] (0.000)	124.805[a] (0.000)	28.422[a] (0.000)
lnICT	5841.001[a] (0.000)	248.417[a] (0.000)	247.957[a] (0.000)	76.335[a] (0.000)
lnPENC	2103.745[a] (0.000)	82.275[a] (0.000)	81.815[a] (0.000)	6.762[a] (0.000)
lnFD	2143.587[a] (0.000)	84.047[a] (0.000)	83.587[a] (0.000)	35.634[a] (0.000)
lnTO	1171.485[a] (0.000)	40.832[a] (0.000)	40.372[a] (0.000)	18.648[a] (0.000)
Model	569.416[a] (0.000)	14.066[a] (0.000)	12.136[a] (0.000)	10.617[a] (0.000)

Notes The null hypothesis indicates the nonexistence of cross-sectional dependence
[a]refers to the rejection of null hypothesis at 1% significance level

CD and CDLM tests (Pesaran 2004), and the LM_{adj} test (Pesaran et al. 2008) have been employed and their results have been reported for both the variables of and the model in Table 3.2.

As can be seen in Table 3.2, the null hypothesis of cross-sectional independence is rejected at 1% significance level for both the variables of interest and the model defined in Eq. (3.2). Therefore, we have to employ the unit root tests and cointegration tests that take cross-sectional dependence into account. For this purpose, we utilize the panel unit root test, modeling the cross-sectional dependence via bootstrap, developed by Smith et al. (2004). The results of panel unit root test are given in Table 3.3.

As provided in Table 3.3, except trade openness (TO) variable, all variables are nonstationary, i.e., they have unit root, whereas they are stationary in their first differences, i.e., they do not have unit root. As such, trade openness is integrated of order zero, i.e., $I(0)$, while the remaining variables are integrated of order one, i.e., $I(1)$. Based on these results, we can ascertain if there is a cointegration, a long-run relationship between the variables defined in Eq. (3.2). To achieve this purpose, we utilize the cointegration test proposed by Westerlund (2008), which allows for cross-sectional dependence and that independent variables to be $I(0)$ or (1). Additionally, the panel cointegration tests of Pedroni (1999, 2004) are utilized as robustness aim. The results of cointegration tests are given in Table 3.4.

Based on the Durbin–Hausman group test (DH_g test statistic), the null hypothesis of no cointegration is rejected at 5% significance level. Besides, four out of seven Pedroni's (1999, 2004) cointegration tests, the panel PP, the panel ADF, the group PP, and the group ADF, have evidence of a long-run relationship (cointegration) between variables at 1% significance level.

Table 3.3 Results for Smith et al. (2004) unit root tests

	Level					First differences				
Variables	$\bar{t}$	$\overline{LM}$	$\overline{Min}$	$\overline{Max}$	$\overline{WS}$	$\bar{t}$	$\overline{LM}$	$\overline{Min}$	$\overline{Max}$	$\overline{WS}$
$lnPCO_2$	−3.17[a] (0.00)	8.63 [a] (0.00)	4.39 (0.25)	−1.88 (0.30)	−2.34 (0.21)	−5.16 [a] (0.00)	14.11[a] (0.00)	13.25[a] (0.00)	−4.78[a] (0.00)	−5.25[a] (0.00)
lnPGDP	−2.29 (0.17)	5.34 (0.21)	2.50 (0.94)	−1.29 (0.93)	−1.72 (0.95)	−4.79[a] (0.00)	12.91[a] (0.00)	12.13[a] (0.00)	−4.51[a] (0.00)	−4.86[a] (0.00)
lnPENC	−2.30 (0.26)	5.27 (0.28)	3.65 (0.48)	−1.82 (0.39)	−2.06 (0.55)	−5.36[a] (0.00)	14.19[a] (0.00)	13.51[a] (0.00)	−5.00[a] (0.00)	−5.43[a] (0.00)
lnICT	−0.57 (1.00)	2.60 (0.99)	1.15 (1.00)	−0.03 (1.00)	−0.42 (1.00)	−3.28[a] (0.01)	8.54[a] (0.00)	8.16[a] (0.00)	−3.26[a] (0.00)	−3.74[a] (0.00)
lnFD	−2.23 (0.33)	5.24 (0.35)	2.39 (0.98)	−1.25 (0.98)	−1.67 (0.97)	−4.61[a] (0.00)	12.64[a] (0.00)	11.64[a] (0.00)	−4.26[a] (0.00)	−4.71[a] (0.00)
lnTO	−2.09[a] (0.00)	4.73[a] (0.00)	3.63[a] (0.00)	−1.71[a] (0.00)	−1.85[a] (0.00)	−5.54[a] (0.00)	14.60[a] (0.00)	13.38[a]nnn (0.00)	−4.87[a] (0.00)	−5.30[a] (0.00)

Notes [a]refers to the rejection of unit root null hypothesis at 1% significance level. Maximum lag number has been defined as 3; block size has been set to 100; the number of bootstraps has been selected as 5000. Constant and trend have been used as deterministic terms

Table 3.4 Westerlund (2008) and Pedroni (1999, 2004) cointegration test results

Westerlund (2008) cointegration test results				
DH_g test statistic	−1.828[b]	Prob. value		0.034
DH_p test statistic	−0.720	Prob. value		0.236
Pedroni (1999, 2004) cointegration test results				
Alternative hypothesis: common AR coefficients (within dimension)				
Tests	Statistics	Prob.	Weighted statistics	Prob.
Panel v-stat.	0.676	0.249	−1.274	0.898
Panel rho-stat.	2.526	0.994	1.825	0.966
Panel PP-stat.	−3.632[a]	0.000	−4.955[a]	0.000
Panel ADF-stat.	−3.882[a]	0.000	−5.030[a]	0.000
Alternative hypothesis: individual AR coefficients (between dimensions)				
Tests	Statistics	Prob.		
Group rho-stat.	3.493	0.999		
Group PP-stat.	−4.877[a]	0.000		
Group ADF-stat.	−4.608[a]	0.000		

Notes Westerlund (2008) has a null hypothesis that there is no cointegration. The number of maximum factors is 2, and Newey and West (1994) are used as bandwidth selection. In Pedroni (1999, 2004) cointegration tests, Schwarz information criterion, and the Newey–West automatic selection as bandwidth are used. Constant and trend are used as deterministic terms
[a], [b], and [c]denote significance at 1%, 5%, and 10% significance levels, respectively

After having decided on a long-run relationship between the variables of interest, we can estimate the long-run parameters of variables, i.e., estimations of β_1, β_2, β_3, β_4, and β_5 coefficients in Eq. (3.2). The panel ARDL approach, which allows for the possibility of independent variables to be $I(1)$ or $I(0)$ in the model, is utilized because the trade openness variable is stationary at level. Hausman (1978) test has been employed to decide among the pooled mean group estimator (PMGE) and the mean group estimator (MGE) of the panel ARDL approach. Hausman (1978) test supports the PMG estimation because it confirms homogeneity in the long-run parameters and heterogeneity in short-run parameters. The joint Hausman (1978) test signals that the null hypothesis of homogeneity in long-run parameters cannot be rejected, and thus, we depend on the results of PMGE.

Hausman (1978) test results have evidence in favor of PMG estimation, indicating homogeneity in the long-run parameters, but heterogeneity in short-run parameters. According to the results of PMG, given in Table 3.5, increases in GDP per capita, energy consumption per capita, and percentage of Internet users cause more CO_2 emissions; i.e., income, energy demand, and Internet usage aggravate the air pollution level of low-income countries, by emitting more CO_2 into the air. In short, countries in this group use air-polluting production processes to grow further. Likewise, increases in energy consumption worsen the air quality of the low-income country panel. Although the share of fossil energy resources in total energy consumption for the

Table 3.5 Results for panel ARDL estimation

Pooled mean group estimator (PMGE)				Mean group estimator (MGE)			Hausman test	
Variables	Long-run results							
	Coeff.	Standard deviation	t stat.	Coeff.	Standard deviation	t stat.	Test stat.	Prob.
lnPGDP	0.223[a]	0.042	5.309	0.392	1.026	0.382	0.03	0.87
lnICT	0.097[a]	0.018	5.428	−0.101	0.139	−0.726	2.07	0.15
lnPENC	0.167[a]	0.021	7.990	0.190	0.318	0.597	0.01	0.94
lnFD	−0.021	0.015	−1.394	0.080	0.199	0.402	0.26	0.61
lnTO	−0.026	0.025	−1.065	−0.303	0.587	−0.515	0.22	0.64
Error correction term	0.443[a]	0.080	−5.520	−0.744[a]	0.096	−7.739		
Joint Hausman test							6.07	0.30
Short-run results								
Variables	Coeff.	Standard deviation	t stat.	Coeff.	Standard deviation	t stat.		
lnPGDP	0.099[a]	0.018	5.520	0.464	0.376	1.234		
lnPENC	0.074[a]	0.013	5.520	0.022	0.114	0.196		
lnICT	0.043[a]	0.008	5.520	−0.004	0.059	−0.060		
lnFD	−0.009[a]	0.002	−5.520	0.027	0.061	0.449		
lnTO	−0.012[a]	0.002	−5.520	−0.100	0.129	−0.774		
dlnPCO$_2$(−1)	−0.034	0.033	−1.037	−0.044	0.063	−0.689		
dlnPGDP	0.175	0.193	0.904	−0.218	0.347	−0.63		
dlnPGDP(−1)	0.093	0.234	0.398	−0.33	0.407	−0.811		
dlnPENC	0.021	0.065	0.33	0.022	0.099	0.218		
dlnPENC(−1)	−0.036	0.03	−1.217	−0.082	0.065	−1.266		
dlnICT	−0.002	0.018	−0.135	0.008	0.034	0.245		
dlnICT(−1)	0.027	0.017	1.567	0.064	0.046	1.383		
dlnFD	−0.044	0.029	−1.52	−0.095[c]	0.055	−1.75		
dlnFD(−1)	0.034	0.048	0.702	−0.012	0.048	−0.25		
dlnTO	0.018	0.032	0.563	0.085	0.08	1.064		
dlnTO(−1)	−0.023	0.026	−0.895	−0.01	0.058	−0.176		
Sabit	0.046	0.08	0.575	−0.002	0.247	−0.009		
Diagnostic test results								
	PMGE			MGE				
	χ^2_{SC}	χ^2_{NO}	χ^2_{HE}	χ^2_{SC}	χ^2_{NO}	χ^2_{HE}		
	1.48	1.07	0.00	5.00	0.78	2.13		

Notes χ^2_{SC} is the autocorrelation test statistic of Breusch–Godfrey; χ^2_{NO} is the Jarque–Bera normality test statistic; χ^2_{HE} is the White heteroscedasticity test statistic

[a], [b], and [c]represent 1%, 5%, and 10% significance levels, respectively

low-income countries is quite low (around 21% according to the World Development Indicators, 2019), high utilization level of renewable energy sources such as biofuels and overconsumption of natural resources as energy sources in meeting the basic needs appear to lead to air pollution. These results in terms of income and energy consumption are similar to those of many studies in the EKC literature (see Ang 2007; Halicioglu 2009; Narayan and Narayan 2010; Ozcan 2013; Ozcan and Apergis 2018). Concerning the environmental effect of the Internet usage, as the percentage of Internet users in the low-income countries increases, air pollution increases as well because ICTs are not energy efficient and environmentally friendly as well as residents of low-income countries are not conscious Internet users. The negative effect of ICTs on air quality indicates technological underdevelopment in the low-income countries. Given that substitution effects and dematerialization process are rather low in this country group, the increased Internet usage level results in more air pollution. This finding is in line with those of Park et al. (2018), Danish et al. (2018), and Salahuddin et al. (2016).

Other variables of the model, financial development, and trade openness have not any significant effect on the CO_2 emission level of low-income country panel. In this sense, financial development and trade openness in these countries are not high enough to affect air quality. Besides, the error correction term in the cointegrating equation, as expected, is negative and significant, which, in turn, signals a long-run relationship between the variables defined in Eq. (3.2). In other words, short-term deviations from the equilibrium value of CO_2 will be corrected over time. Besides, the results of diagnostic tests have provided evidence against problems of autocorrelation and heteroscedasticity for the model defined in Eq. (3.2). Finally, our results concerning the financial development are consistent with those of Dogan and Turkekul (2016), Omri et al. (2015), and Ozturk and Acaravci (2013) while our findings about the trade openness are in line with those of Ertugrul et al. (2016), Farhani et al. (2014), and Jalil and Mahmud (2009).

3.7 Conclusion and Policy Implication

In this study, the effects of ICT use on air pollution have been analyzed by using second-generation panel data models over the period 1995–2015 by considering the low-income country panel. To this end, as being proxies for ICTs and air pollution, the percentage of Internet users and CO_2 emissions per capita, respectively, has been used. In addition, per capita income, energy consumption per capita, financial development, and trade openness variables, which are thought to affect CO_2 emission level, have been added to the model as control variables. Firstly, cross-sectional dependence for both the variables of interest and the model has been tested to select the right panel data tests. The presence of cross-sectional dependence has led us to utilize the second-generation panel tests.

The results indicate that energy-inefficient ICT devices, by boosting energy demand, emit more CO_2 into the air because technological development level is rather low in the low-income countries. In addition, the residents of low-income countries do not deliberatively make use of the Internet because their education levels are lower compared to those of high-income countries. Among other determinants of air pollution, income and energy consumption variables appear to worsen air quality of the low-income country panel. The results in terms of income level show that low-income countries have not yet reached the threshold level of income after which economic growth improves air quality. Besides, excessive usage of renewable energy and natural resources to meet the basic needs seems to create more air pollution. The remaining two variables of the model, financial development and trade openness, do not have any significant influence on the air quality level given that commercial and financial relations are not sufficiently developed to have an environmental influence in the low-income country panel.

Based on the above-mentioned results, some crucial policy implications could be suggested. First, due to the fact that economic growth and energy consumption cause air pollution, a revision for the economic development policy of low-income countries on the axis of sustainable development seems necessary. Instead of a development strategy that focuses solely on the purpose of economic growth, a development policy that considers environmental quality as well as growth seems more reasonable. The choice of a growth model in which natural resources and the environment are not sacrificed for further growth is necessary. In terms of energy sources, although the low-income countries have rich natural resources and renewable energy sources, their residents have not been able to benefit from alternative energy sources effectively due to their unawareness. Therefore, public awareness among residents should be established in order to use renewable energy resources more effectively, and thereby, the excessive exploitation of natural resources will be prevented.

In terms of ICT, which is the main variable of the research, investments in the ICT sector should be encouraged through the channel of government and private sector in the form of subsidies and grants. Residents should be made aware of ICTs, in general, and the Internet in particular, through various trainings, courses, and seminars in order to use them with more awareness. Besides, the outputs of the dematerialization process should be utilized more actively. For example, monitoring of newspapers over the Internet instead of buying printed newspapers, meeting the needs of online shopping instead of driving to shopping centers, and conducting conferences in the form of teleconferences instead of long-distance conferences are some solutions of the dematerialization process that may have positive effects on the environment.

Regarding financial development, precautions should be taken to convert the insignificant effect of financial development on the environment to positive. Companies should include more environmentally friendly technologies in their production processes via credit opportunities provided by financial development. The purchased new equipment and new project investments should be arranged in a way that does not harm the environment. Consumers should purchase environmentally friendly ICT equipment with loans provided by financial development. Increasing the share of firms investing in renewable energy (green) in the capital markets and deepening voluntary carbon markets aimed at granting voluntary emission reduction certificates to companies are among the other alternatives to be considered. The insignificant effect of the trade openness, the last determinant of air quality, on the air quality of the low-income country panel can be remedied through advanced and modern technology transfer, which will be accompanied by trade liberalization. Finally, the neutral effect of international trade on the environment in low-income countries can be transformed into a positive one thanks to the import of modern technologies that enables more efficient use of energy in production processes.

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