자원 · 환경경제연구 제 30 권 제 2 호
Environmental and Resource Economics Review
Volume 30, Number 2, June 2021 : pp. 299~323
DOI: https://doi.org/10.15266/KEREA.2021.30.2.299

The Effects of ICT on CO_2 Emissions Along with Economic Growth, Trade Openness and Financial Development in Korea†

Suyi Kim*

ABSTRACT : This study investigated the impact of information and communication technology (ICT), trade openness, financial development, and economic growth on CO_2 emissions in Korea from 1990 to 2016. The cointegration relationship of the variables was confirmed by an autoregressive distributed lag (ARDL) bounds test. In the long-run, economic growth was statistically significant factor in the increase in CO_2 emissions, while other factors, as well as ICT, did not significant factors in the changes in CO_2 emissions. In the long-run, a link between economic growth and CO_2 emissions has been confirmed, but other factors, including ICT, have not been able to confirm the link between CO_2 emissions in the long-run. Meanwhile, in the short-run, economic growth and ICT increased CO_2 emissions, and financial development led to a decrease in CO_2 emissions. Trade openness did not have a significant effect on CO_2 emissions in the short-run as in the long-run. In particular, ICT did not contribute to the reduction of CO_2 emissions in the short-run as well as the long-run. In order to induce CO_2 mitigation through ICT, the development and deployment of technology that efficiently save energy by using ICT should be further promoted.

Keywords : CO_2 emissions, GDP, ICT, Trade openness, Financial development, ARDL

JEL Classifications : Q43, Q56

Received: April 22, 2021. Revised: June 11, 2021. Accepted: June 14, 2021.

† I am grateful to two anonymous referees for helpful comments and suggestions. This work was supported by 2020 Hongik University Research Fund.

* Associate Professor, School of Business Management, College of Business Management, Hongik University, Corresponding author(e-mail: suyikim@hongik.ac.kr)

ICT가 CO_2 배출에 미치는 영향: 경제성장, 무역개방성, 금융발전과의 연관관계하에서 분석†

김수이*

요 약 : 본 연구는 1990년부터 2016년까지 한국의 정보통신기술(ICT), 무역 개방성, 금융 발전, 경제성장이 CO_2 배출량에 미치는 영향을 분석하였다. 변수의 공적분관계는 Autoregressive distributed lag (ARDL)공적분 검증을 통해 확인되었다. 장기적으로 경제성장과 CO_2 배출 간에는 연관관계가 확인되었지만, ICT를 비롯한 다른 요인은 장기적으로 CO_2 배출량과의 연관관계를 확인하지 못하였다. 한편, 단기적으로 경제성장, ICT는 CO_2 배출량을 증가시켰으며, 금융발전은 CO_2 배출량 감소를 가져왔다. 무역개방성은 장기와 마찬가지로 단기에도 CO_2 배출량에 큰 영향을 미치지 못하였다. 특히 ICT는 장기뿐만 아니라 단기적으로도 CO_2 배출량 감소에 기여하지 못하였다. ICT를 통한 CO_2 감축을 유도하기 위해서는 ICT를 활용하여 효율적으로 에너지를 절약할 수 있는 기술의 개발과 보급이 더욱 촉진되어야 할 것이다.

주제어 : CO_2 배출, GDP, ICT, 무역, 금융발전, ARDL

접수일(2021년 4월 22일), 수정일(2021년 6월 11일), 게재확정일(2021년 6월 14일)

† 본 논문을 심사해 주신 익명의 심사자들에게 감사를 드립니다. 이 논문은 2020학년도 홍익대학교 학술연구진흥비에 의하여 지원되었습니다.

* 홍익대학교 상경대학 상경학부 부교수, 교신저자(e-mail:suyikim@hongik.ac.kr)

I. Introduction

Since the 1990s, when personal computers became popular and the Internet was widely introduced, information and communication technology (ICT) has been rapidly developing. In particular, the spread of the Internet and personal mobile phones has brought about various innovations in ICT. According to the World Development Indicators of the World Bank's DataBank, the share of Internet users among the world's population over the past 27 years has increased by about seven times, from 6.7% in 2000 to 49.7% in 2017, and mobile cellular subscriptions (per 100 people) increased from 12.0 in 2000 to 102.8 in 2017. Owing to the spread of the Internet, the number of Internet servers for the exchange and storage of information has rapidly increased, and the demand for personal cell phones has also rapidly increased, along with communication base stations. For this reason, the demand for electricity by ICT has increased. On the other hand, due to the development of ICT, resources and energy can be efficiently managed, and energy efficiency improvement methods using ICT technology have become more efficient. In other words, ICT increases the energy consumption by expanding the spread of related devices, but it also reduces the energy consumption by providing a tool to efficiently use other devices. In particular, technologies that efficiently reduce not only the energy consumption, but also greenhouse gases, are increasingly being developed using ICT technology.

ICT can improve the energy efficiency in the established production and consumption processes related to economic activities. For example, the energy efficiency can be increased by setting target variables such as the productivity in terms of energy consumption. In addition, ICT can be applied to efficiently generate, distribute, allocate, share, and use resources in the environmentally friendly ways. As environmental sustainability has become more important due to addressing climate change and rising energy costs, ICT plays a leading role in large-scale simulation, optimization, and real time control. ICT can help make a series of decisions related to resource and energy consumption more efficiently; examples include the optimization of production and supply chain processes (Ilic et al., 2009), and the development of environmental information systems (Günther, 1997). Investments in energy-saving technologies are often financially rewarded, especially when energy costs are rising. In recent years, the use of ICT embedded energy management systems (EMS), factory energy management systems (FEMS), and building energy management systems (BEMS) has also been expanding.

Empirical research on whether the energy demand and greenhouse gas emissions have actually increased or decreased due to ICT, continues to be actively conducted. Table 1 presents previous studies on the causal relationship and the relationship between ICT and CO_2 emissions that have recently been conducted. The countries and regions involved and the periods analyzed differed from study to study. Panel studies involving several countries were conducted by Park et al. (2018), Haseeb et al. (2019), Faisal et al. (2020), Lu (2018), Lee and Brahmasrene (2014), Ozcan (2018), and Higón et al. (2017). Meanwhile, in-depth research involving a single country was conducted by Zhang and Liu (2015), Amri (2018), and Shehzad (2020).

First, let us evaluate the recent panel studies on multiple countries. Except for the study of Park et al. (2018), which investigated EU countries, the rest of the studies have included both developed and developing countries or only developing countries. Lu (2018) investigated the effects of ICT on CO_2 emissions for twelve Asian countries, including both developed and developing countries (Australia, Hong Kong, Japan, India, Indonesia, South Korea, Malaysia, the Philippines, Singapore, Thailand, and Turkey). Lee and Brahmasrene (2014) examined the Association of South-East Nations (Brunei Darussalam, Cambodia, Indonesia, Lao PDR, Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Vietnam). Additionally, Ozcan (2018), Haseeb et al. (2019), and Faisal et al. (2020) only investigated developing countries. Ozcan (2018) analyzed twenty emerging economies (Brazil, Chile, China, Colombia, the Czech Republic, Egypt, Hungary, Indonesia, India, Greece, Mexico, Malaysia, Peru, the Philippines, Poland, Russia, South Africa, South Korea, Thailand, and Turkey), Haseeb et al. (2019) analyzed BRICS (Brazil, China, Russia, India, and South Africa), and Faisal et al. (2020)

analyzed fast emerging economies such as Brazil, China, India, and South Africa. Furthermore, Higón et al. (2017) investigated 142 economies, split into 116 developing and 26 developed countries. The analysis period varies across the studies, but most of them span the 1990s, 2000s, and 2010s. Various panel analysis methodologies are applied, such as the stochastic impacts by regression on population, affluence, and technology (STIRPAT); mean group (MG); group mean (GM); fully modified ordinary least squares (FMOLS); and dynamic ordinary least squares (DOLS). According to the main empirical results of the studies of Lee and Brahmasrene (2014), Park et al. (2018), and Haseeb et al. (2019), ICT has led to an increase in CO_2 emissions. However, Lu (2018) and Ozcan (2018) found that ICT can lower CO_2 emissions. Higón et al. (2017) and Faisal et al. (2020) found that CO_2 emissions initially increased with the increase in ICT usage and then decreased after the threshold. Specifically, Higón et al. (2017) confirmed that the relationship between ICT and CO_2 emissions was an inverted U-shaped relationship in both developing and developed countries.

Now, let us evaluate the recent studies on a single country. Zhang and Liu (2015) analyzed China, Amri (2018) studied Tunisia, and Shehzad (2020) researched Pakistan. In terms of the analysis method, Zhang and Liu (2015) used STIRPAT models, while Amri (2018) and Shehzad (2020) used the autoregressive distributed lag (ARDL) models. In particular, Shehzad (2020) used both STIRPAT and ARDL models. The effect of ICT on CO_2 emissions varies, depending on the target country analyzed. In some countries, ICT leads to CO_2 reduction, while in others, ICT has little effect on CO_2 reduction. Zhang and Liu (2015) analyzed the effect of the ICT industry on China's CO_2 emissions at national and regional levels, indicating that the ICT industry contributed to reducing China's CO_2 emissions. However, Amri (2018) showed a minimal effect of ICT on CO_2 emissions in Tunisia, and Shehzad (2020) evaluated the impact of ICT investment and ICT goods trade on CO_2 emissions, indicating that investment in ICT could increase CO_2 emissions. Therefore, imports of ICT equipment would be more beneficial for mitigating Pakistan's CO_2 emissions.

〈Table 1〉 Studies on ICT and CO_2 emissions

	Countries and regions	Periods	Factors	Methods
Park et al. (2018)	Selected EU countries[1)]	2001-2014	ICT, GDP, financial development, trade openness	MG estimator
Haseeb et al. (2019)	BRICS countries[2)]	1994-2014	ICTs, globalization, electricity consumption, financial development, GDP	FMOLS and DSUR
Faisal et al. (2020)	Fast emerging countries[3)]	1993-2014	ICT electricity consumption, financial development, trade, GDP	FMOLS, DOLS, Robust least square
Lu (2018)	Twelve Asian countries[4)]	1993-2013	ICT, GDP, energy consumption, financial development	Pedroni cointegration test
Lee and Brahmasrene (2014)	ASEAN countries[5)]	1991-2009	ICT, economic growth, human capital development	FMOLS Canonical Cointegrating Regression Dynamic OLS
Ozcan (2018)	Twenty emerging economies[6)]	1990-2015	Internet users, GDP, financial development, energy consumption, trade openness	MG estimator GM FMOLS
Higón et al. (2017)	116 developing countries and 26 developed countries	1995-2010	ICT, GDP per capita, etc.	Pooled Ordinary Least Squares Driscoll-Kraay Fixed Effects model Instrumental variable Fixed Effect model
Zhang and Liu (2015)	China and Chinese Provinces	2000-2010	ICT industry, energy consumption, urbanization	STIRPAT
Amri (2018)	Tunisia	1975-2014	ICT, total factor productivity, trade, financial development, energy consumption	ARDL
Shehzad (2020)	Pakistan		ICT, FDI, GDP, trade, population	STIRPAT and ARDL

Note: 1) Austria, Belgium, Blgaria, Croatia, Cyprus, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungry, Ireland, Italy, Luxembourg, the Netherlands, Poland, Portugal, Romania, Slovenia, Spain, Sweden, and the UK. 2) Brazil, India, China, and South Africa. 3) Brazil, China, Russia, India, and South Africa. 4) Australia, Hong Kong, Japan, India, Indonesia, South Korea, Malaysia, the Philippines, Singapore, Thailand, and Turkey. 5) Brunei Darussalam, Cambodia, Indonesia, Lao PDR, Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Vietnam. 6) Brazil, Chile, China, Colombia, the Czech Republic, Egypt, Hungary, Indonesia, India, Greece, Mexico, Malaysia, Peru, the Philippines, Poland, Russia, South Africa, South Korea, Thailand, and Turkey.

Although some previous panel analysis such as Lu (2018) and Ozcan (2018) includes Korea, it was difficult to specify the effect of ICT on CO_2 emissions in Korea because it targeted for multiple countries. In particular, Korea has been transitioning from developing country to developed country over the past thirty years. It is meaningful to analyze the impact of ICT on CO_2 emissions for Korea, reflecting the distinctiveness of Korea in the transitional period of economic growth.

According to the World Development Indicators of the World Bank's DataBank, ICT has rapidly changed over the past 20 years in Korea (Republic of Korea). The share of individuals using the Internet in the total population in 1990 was only 0.02%, but this increased to 92.8% in 2016, ranking 15th worldwide. Similarly, mobile cellular subscriptions out of 100 people only had a value of 0.19 in 1990, but increased to 120.2 by 2016. Due to the rapid growth of ICT, large-scale data centers have been built, and the demand for Internet servers has also rapidly increased. Secure Internet servers (per 1 million people) of South Korea surged from 175 in 2010 to 4544 in 2019. The growth of ICT has led to an increase in the electricity demand. Meanwhile, energy system management using ICT also improves the energy efficiency through energy saving technologies. Therefore, analyzing how much ICT has affected Korea's CO_2 emissions will be an important foundation for establishing the role of ICT in Korea's greenhouse gas emissions reduction policy.

This study also includes the gross domestic product (GDP), trade openness, and financial development as factors influencing CO_2 emissions, which have been frequently considered in previous studies, such as those of Park et al. (2018), Haseeb et al. (2019), and Faisal et al. (2020). Korea has steadily achieved economic growth over the past 30 years and has a relatively high share of trade in GDP and a well-established private financial system. These factors are also expected to affect CO_2 emissions. Wang and Jin (2007) and Bello and Abimbola (2010) confirm that financial development induces listed companies to use energy-efficient technology, which consequently helps reduce carbon emissions. In contrast, according to Sadorsky (2010) and Zhang (2011), financial development may increase to carbon dioxide emissions. Stock market development assists public companies in reducing financial costs, enlarging financial channels, sharing operational risks and finding a balance between assets and liabilities to acquire new installations and allocate resources for the implementation of new projects, which ultimately increases energy consumption and carbon dioxide emissions.

The empirical methodology used in this research is the ARDL model, which has been widely used by recent studies, as it can produce significant empirical results, even when the sample size is small, for a single country. This study is the first attempt to investigate the effects of ICT on CO_2 emissions incorporating with economic growth, trade openness and financial development in Korea.

This paper is organized as follows. The second section presents the study methodology and discuss data, and the third section presents the empirical results. The conclusions regarding the study findings and policy implications are presented in the last section.

II. Materials and Methods

The long-run empirical model reflecting the effect of the exogenous variables, including ICT, on CO_2 emissions can be specified as the following equation, as modified from the previous studies of Park et al. (2018), Haseeb et al. (2019), and Faisal et al. (2020), etc.:

$$\ln(CO_2)_t = \beta_0 + \beta_1 \ln GDP_t + \beta_2 \ln TR_t + \beta_3 \ln FD_t + \beta_4 \ln ICT_t + \varepsilon_t, \qquad (1)$$

where $\ln$ represents the natural logarithm, CO_2 denotes CO_2 emissions measured by CO_2 emissions per capita (metric tons), GDP denotes economic growth measured by the gross domestic product per capita (constant 2010 US $), TR denotes the trade openness measured by the share of the sum of exports and imports in GDP (%), FD denotes the financial development measured by the share of domestic credit to the private sector in GDP (%), and ICT is measured by Internet users per 100 people. β_1, β_2, β_3 and β_4

represent the elasticity of *GDP*, *TR*, *FD* and *ICT* on CO_2, respectively. ε_t is error terms.

In previous studies which examined the effect of ICT on CO_2 emissions, various factors, such as economic growth, energy consumption, financial development, trade openness, and the population, were considered as factors influencing CO_2 emissions. Although the factors considered in each analysis vary across the studies, economic growth, financial development, and trade openness were considered as common factors. Therefore, this analysis considered four factors (GDP, trade openness, financial development, and ICT) that affect CO_2 emissions.

As Yao and Liu (2011) mentioned, internet and mobile phones are the core technologies of ICT. These two technologies are best used to measure ICT. ICT proxies used in previous studies include 'Internet users' (Lu, 2018; Haseeb et al., 2019; Faisal et al., 2020; Armi, 2018), 'fixed telephone subscription' (Armi, 2018), and 'mobile cellular subscriptions' (Haseeb et al., 2019; Ozcan and Apergis, 2018; Park et al., 2018; Shehzad et al., 2020). This study considered the most popular proxies ('Internet users' and 'mobile cellular subscriptions') used in previous studies. However, the analysis using 'mobile cellular subscriptions (per 100 people)' as an ICT proxy did not provide statistically significant results. Therefore, it is excluded as a proxy variable for ICT in this analysis. Inevitably, 'Internet users per 100 people' is the only proxy that represent ICT in this paper. This proxy includes internet use in terms of individuals using the internet via a computer, mobile phone, personal digital assistant, games machine, digital TV, etc.

This study adopted ARDL methods introduced by Pesaran and Pesaran (1997), Pesaran and Shin (1999), and Pesaran et al. (2001) to evaluate the long-run cointegration among the variables. Compared to Johansen cointegration methods developed by Engle and Granger (1987) and Johansen and Juselius (1990), the ARDL cointegration method is valid, even for a short and finite sample set of data, and provides effective results, even if the variables are integrated at I(0), at I(1), or jointly cointegrated (Pesaran et al., 2001). This method yields valid estimators, even if endogeneity and autocorrelation exist in the model (Harris and Sollis, 2003). This study only sought to analyze Korea, and the period analyzed was relatively short, from 1990 to 2016. This model has also been used in previous studies that involved a single country, such as the studies of Armi (2018) and Shehzad (2020).

There are three steps in estimating ARDL models. The first step is conducting the ARDL bounds test to confirm whether there is a long-run cointegration relationship among variables. The conditional error correction model is formulated as shown in Equation (2):

$$\begin{aligned}\triangle \ln(CO_2)_t = \alpha_0 + \sum_{k=1}^{p}\alpha_{1k}\triangle\ln(CO_2)_{t-k} + \sum_{k=0}^{q_1}\alpha_{2k}\triangle\ln GDP_{t-k} + \sum_{k=0}^{q_2}\alpha_{3k}\triangle\ln TR_{t-k} \\ + \sum_{k=0}^{q_3}\alpha_{4k}\triangle\ln FD_{t-k} + \sum_{k=0}^{q_4}\alpha_{5k}\triangle\ln ICT_{t-k} + \alpha_6\ln(CO_2)_{t-1} + \\ \alpha_7\ln GDP_{t-1} + \alpha_8\ln TR_{t-1} + \alpha_9\ln FD_{t-1} + \alpha_{10}\ln ICT_{t-1} + u_t,\end{aligned} \tag{2}$$

where $\triangle$ denotes the first difference operator; $\alpha_6 - \alpha_{10}$ are the long-run coefficients; and p and $q_1 - q_4$ are the optimal lag length, which is determined by the Akaike information criterion (AIC).

The long-run cointegration relationship among the variables is tested by the joint F-statistics of the long-run coefficients. Therefore, the null hypothesis is $H_0 : \alpha_6 = \alpha_7 = \alpha_8 = \alpha_9 = \alpha_{10}$, while the alternative hypothesis is $H_1 : \alpha_6 \neq 0$ or $\alpha_7 \neq 0$ or $\alpha_8 \neq 0$ or $\alpha_9 \neq 0$ or $\alpha_{10} \neq 0$. The test involves two asymptotic critical value bounds, depending on the number of independent variables, their integration order, the number of short-run coefficients, and the inclusion of intercepts and time trends. In order to verify the validity of the ARDL model, Pesaran et al. (2001) suggested the lower critical bound value, which assumes that the corresponding variables are integrated at I(0), and the upper critical bound value, which assumes that the corresponding variables are integrated at I(I). If the projected F-statistics value is less than the lower critical bound value, then the null hypothesis is accepted, whereas, if the estimated value of F-statistics is higher than the upper critical bound value, then the null hypothesis is rejected, which infers that cointegration among variables is present. Additionally, if the F-statics value falls between the upper and lower critical bound value, then the ARDL model is considered to be inconclusive. If long-run cointegration is identified through this test, the long-run cointegration coefficients and short-run coefficients can be estimated by using this ARDL model (Fernández and Fernández, 2018).

In the second step, if the cointegration relationship is confirmed in the first step, the augmented ARDL model is estimated by the following equation (3):

$$\ln(CO_2)_t = \gamma_0 + \sum_{k=1}^{p}\gamma_{1k}\ln(CO_2)_{t-k} + \sum_{k=0}^{q_1}\gamma_{2k}\ln GDP_{t-k} + \sum_{k=0}^{q_2}\gamma_{3k}\ln TR_{t-k} + \sum_{k=0}^{q_3}\gamma_{4k}\ln FD_{t-k} + \sum_{k=0}^{q_4}\gamma_{5k}\ln ICT_{t-k} + \nu_t. \quad (3)$$

Equation (4) which represents the long-run equilibrium relationship is derived from Equation (3). The long-run coefficients in this ARDL model are estimated from Equation (4):

$$\ln(CO_2)_t = \lambda\gamma_0 + \lambda\sum_{k=0}^{q_1}\gamma_{2k}\ln GDP_{t-k} + \lambda\sum_{k=0}^{q_2}\gamma_{3k}\ln TR_{t-k} + \lambda\sum_{k=0}^{q_3}\gamma_{4k}\ln FD_{t-k} + \lambda\sum_{k=0}^{q_4}\gamma_{5k}\ln ICT_{t-k} + \lambda\nu_t. \quad (4)$$

where, $\lambda = \frac{1}{1-\sum_{k=1}^{p}\gamma_{1k}}$

In the third step, the short-run dynamics are identified through the following associated ARDL error correction model (ARDL-ECM). The short-run coefficients can be deduced from the following equation (5):

$$\triangle\ln(CO_2)_t = \delta_0 + \sum_{k=1}^{p}\delta_{1k}\triangle\ln(CO_2)_{t-k} + \sum_{k=0}^{q_1}\delta_{2k}\triangle\ln GDP_{t-k} + \sum_{k=0}^{q_2}\delta_{3k}\triangle\ln TR_{t-k} + \sum_{k=0}^{q_3}\delta_{4k}\triangle\ln FD_{t-k} + \sum_{k=0}^{q_4}\delta_{5k}\triangle\ln ICT_{t-k} + \delta_6 ECT_{t-1} + \rho_t. \quad (5)$$

where, ρ_t is the error term, and ECT_{t-1} is the error correction term. If the ECT_{t-1} coefficients (δ_6) are negative and statistically significant, the corresponding variables converge into the long-run equilibrium.

The stability of the ARDL model is tested by using the cumulative sum of a recursive residual test (CUSUM) and the cumulative sum of squares of the recursive residual test (CUSUMSQ). The E-views package was used for this ARDL model.

All series in this study covered the period from 1990 to 2016. The data for the variables CO_2, GDP, share of the sum of exports and imports in GDP (TR), financial development (FD), and ICT are from the World Development Indicators of the World Bank's DataBank.

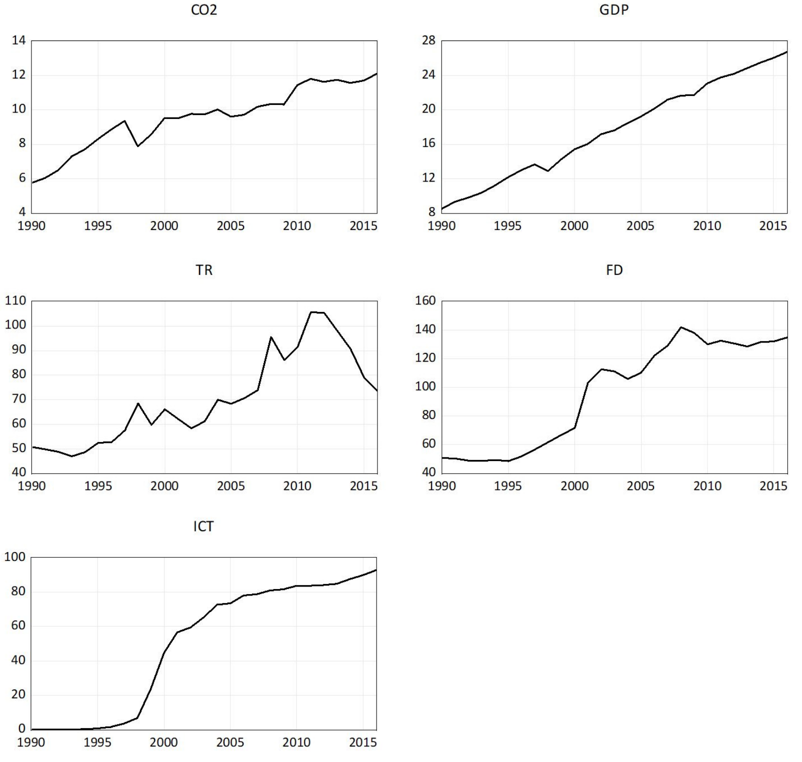
Figure 1 shows the time series of each data set. CO_2 emissions per capita rose rapidly until 1997, but plummeted due to the Asian financial crisis in 1998. From 1999, CO_2 emissions per capita began to increase again. However, since 1999, the rate of increase in CO_2 emissions per capita has been slower than that before 1997. In 1990, CO_2 emissions per capita only had a value of 5.76 tons, but in 1997, it increased to 9.35 tons. It temporarily decreased to 7.88 tons in 1998, but increased to 8.58 tons in 1999. Since 2004, CO_2 emissions per capita have been increasing and decreasing repeatedly, showing an overall increasing trend.

The GDP per capita declined slightly during the Asian financial crisis and the global financial crisis, but it has shown a steady increase in general, and the rate of increase has been steady. In 1990, the GDP per capita was only $8,496. However, it more than tripled to $26,726 in 2016. In 1998, the GDP per capita declined compared to the previous year, but after that, the growth rate stagnated during the global financial crisis, and has increased steadily since then.

The share of the sum of exports and imports in GDP (TR) fluctuates more than the rate of economic growth. It was only 50.7% in 1990, but almost doubled to 105.6% in 2011. Since 2011, the growth rate of trade has been steadily decreasing, and in 2016, the share reached 73.6%. Meanwhile, financial development (FD) has developed rapidly since the 2000s. In 1990, the share of domestic credit to the private sector in GDP (FD) was only

50.8%, but it gradually increased to 142.1% in 2008. It has declined slightly since then, but in 2016, it remained at a high level of 135.0%. ICT has been the fastest growing variable since 2000. The fastest-growing period was between 1998 and 2005. The share of individuals using the Internet in the population (ICT), which was only 6.8% in 1998, increased to 78.1% in 2006. Since 2006, the growth rate of the percentage has slowed, but the percentage steadily increased to 92.8% in 2016. The descriptive statistics of each variable are specified in Table 2. There is no perfect multicollinearity between two variables.

〈Figure 1〉 Time series plots for each data



Note: Unit of CO_2 is metric tons per capita; unit of *GDP* is 1000$, constant 2010 US $; and unit of share of the sum of exports and imports in GDP (TR), financial development (FD), and information and communication technology (ICT) is %. Each data is from the World Development Indicators of the World Bank's DataBank (https://databank.worldbank.org/source/world-development-indicators).

〈Table 2〉 Descriptive statistics

	CO_2 (metric ton)	GDP (1000$, constant 2010 US$)	TR (%)	FD (%)	ICT (%)
Mean	9.52	17.70	70.07	96.32	49.47
Median	9.72	17.63	68.32	110.30	65.50
Maximum	12.11	26.73	105.57	141.95	92.84
Minimum	5.76	8.50	46.92	48.61	0.02
Standard Deviation	1.81	5.72	18.18	36.41	37.43
Skewness	-0.46	-0.01	0.56	-0.25	-0.38
Kurtosis	2.40	1.70	2.16	1.32	1.36
Jarque-Bera	1.35	1.89	2.23	3.47	3.66
Probability	0.51	0.39	0.33	0.18	0.16
Sum	257.04	477.97	1891.91	2600.57	1335.61
Sum Sq. Dev.	85.35	849.84	8589.36	34,463.86	36,428.24
Observations	27	27	27	27	27

Ⅲ. Results

1. Unit root analysis

To evaluate the long-run cointegration relationships among the variables through the ARDL approach, whether the variables were I(0) or I(1) should be first checked through a unit root test. The Augmented Dickey-Fuller test (Dickey and Feller, 1997) and Phillips-Perron test (Phillips and Perron, 1988) were adopted to test whether each variable was stationary or not. Table 3 summarizes the results of the unit root tests, which reveal that each variable was stationary at different orders. The two tests showed similar results. According to these tests, *lnTR* and *lnFD* had unit roots at the level and did not have unit roots at the first difference. Therefore, these two variables were integrated at I(1). $lnCO_2$, *lnGDP*, and *lnICT* did not have unit roots at the level, which means that these variables were integrated at I(0). The ARDL cointegration method is valid, even if they are of a mixed integrating order. All variables fit I(0) or I(1), which is the requirement for the ARDL model using a bound test approach (Pesaran et al., 2001).

〈Table 3〉 Traditional unit root tests

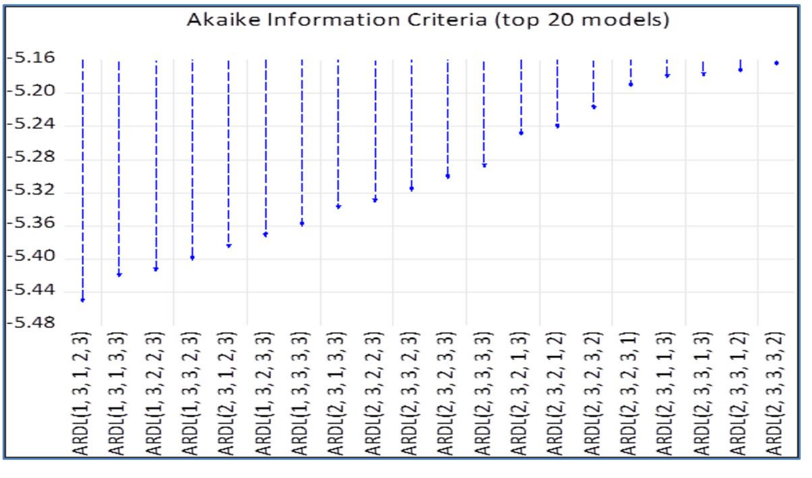
Variables	Augmented Dickey-Fuller (level)	Augmented Dickey-Fuller (first difference)	Phillips-Perron (level)	Phillips-Perron (first difference)
lnCO₂	-2.36**	-3.42**	-3.67***	-4.96***
lnGDP	-2.80*	-5.09***	-10.53***	-5.11***
lnTR	-1.29	-5.02***	-1.29	-5.02***
lnFD	-0.88	-3.43**	-0.90	-3.44**
lnICT	-4.36***	-2.04	-4.31***	-1.79

Notes: *, p-value < 0.1; **, p-value < 0.05; and ***, p-value < 0.01.

2. Lag length criteria

The appropriate lag length should be selected to avoid incorrect estimation and a low reliability of the model. Here, AIC was employed as the appropriate lag length criteria. The top twenty ARDL models by AIC are presented in Figure A1. The ARDL (1, 3, 1, 2, 3) model showed the lowest AIC value. Therefore, the appropriate lag lengths for p, q_1, q_2, q_3, and q_4, corresponded to each variable; for example, *lnCO₂, lnGDP, lnTR, lnFD,* and *lnICT* are 1, 3, 1, 2, and 3, respectively.

〈Figure 2〉 Lag length criteria



3. ARDL bounds tests

The ARDL bounds tests were used to identify the existence of a long-run cointegration relationship among the variables, where $ln CO_2$ is the dependent variable and the other variables are the explanatory variables. The results of the bounds test for the selected ARDL (1, 3, 1, 2, 3) model are shown in Table 4. Here, the null hypothesis of the F-statistic bounds test was that there was no cointegration among variables. The critical bound values given by Narayan (2005) were used to identify a long-run cointegrating relationship, because the sample size was relatively small.

The calculated F-statistic was 16.31, which is above the upper bound of 6.67 at the 1% significance level, which confirms that there exists a long-run cointegrating relationship among the corresponding variables.

〈Table 4〉 ARDL bounds test

ARDL (1, 3, 1, 2, 3)				
Null Hypothesis (H_0) : $\alpha_6 = \alpha_7 = \alpha_8 = \alpha_9 = \alpha_{10} = 0$				
F-statistic k = 4	16.312		Lower bound	Upper bound
		10%	2.75	3.99
		5%	3.35	4.77
		1%	4.77	6.67

4. Long-run equilibrium

The estimated coefficients of the augmented ARDL model, as in Equation (3), are shown in Table 5. Eleven of fifteen coefficients are statistically significant at 5% significance level. In order to confirm the accuracy of this ARDL model, this study applied the normality test, Breusch-Godfrey serial correlation Lagrange multiplier test, and Breusch-Pagan-Godfrey heteroskedasticity test. According to the results, this ARDL model is well-fitted, and shows no serial correlation and heteroscedasticity.

The reduced equation, as shown in Equation (4), is represented in Table 6. The long-run coefficient of *lnGDP* was statistically significant at the 5% significance level.

However, the long-run coefficients of *lnTR* and *lnFD* were not statistically significant, which means that trade openness and financial development didn't affect CO_2 emissions in the long-run. The long-run coefficient of *lnICT* also was insignificant, which means that ICT had not played in mitigating CO_2 emissions in the long-run.

〈Table 5〉 Estimated coefficients of the ARDL (1, 3, 1, 2, 3) model

dependent variable: $lnCO_2$				
Explanatory Variables	Coefficient	standard error	t-statistic	p-value
$lnCO_2(-1)$	0.79***	0.183	4.317	<0.01
lnGDP	1.73***	0.132	13.143	<0.01
lnGDP(-1)	-0.90**	0.297	-3.028	<0.05
lnGDP(-2)	0.06	0.180	0.326	0.752
lnGDP(-3)	-0.61**	0.200	-3.029	<0.05
lnTR	0.05	0.040	1.245	0.245
lnTR(-1)	-0.11**	0.047	-2.352	<0.05
lnFD	-0.13	0.125	-1.065	0.314
lnFD(-1)	0.35***	0.079	4.409	<0.01
lnFD(-2)	0.11**	0.051	2.074	<0.05
lnICT	0.10***	0.026	3.842	<0.01
lnICT(-1)	0.01	0.030	0.447	0.666
lnICT(-2)	-0.07**	0.030	-2.480	<0.05
lnICT(-3)	-0.07**	0.022	-2.979	<0.05
constant	-1.64***	0.438	-3.736	<0.01
R^2	0.996	Akaike info criterion	-5.450	
Adjusted R^2	0.991	Schwarz criterion	-4.714	
Jarque-Bera statistic	0.277	p-value: 0.871		
Breusch-Godfrey serial correlation LM test statistic	2.147	p-value: 0.143		
Breusch-Pagan-Godfrey heteroskedasticity test statistic	17.707	p-values: 0.22		

Notes: *, p-value < 0.1; **, p-value < 0.05; and ***, p-value < 0.01. (-k) means the k period before.

〈Table 6〉 Estimated long-run cointegration relationship

dependent variable: $lnCO_2$				
Explanatory Variables	Coefficient	standard error	t-statistic	p-value
lnGDP	1.354**	0.624	2.169	< 0.05
lnTR	-0.292	0.407	-0.718	0.491
lnFD	1.528	1.821	0.839	0.423
lnICT	-0.121	0.152	-0.797	0.446

Notes: *, p-value < 0.1; **, p-value < 0.05; and ***, p-value < 0.01. (-k) means the k period before.

5. Short-run Analysis

Table 7 shows the results regarding the short-run dynamic coefficients from the ARDL-ECM represented by Equation (5). The advantage of the ARDL model is that it enables a short-term dynamic analysis of independent variables based on a dependent variable. The coefficients for the ARDL-ECM excluding trade openness are statistically significant. Hence, the changes in economic growth, financial development, and ICT cause changes in CO_2 emissions in the short-run. Specifically, the coefficients of $\triangle lnGDP$, $\triangle lnGDP(-1)$ and $\triangle lnGDP(-2)$ on $\triangle lnCO_2$ are 1.73, 0.55, and 0.61 respectively, and are statistically significant at the 1% significance level. This means that economic growth has a big effect on CO_2 emissions in the short-run, as well as the long-run. The coefficients of $\triangle lnICT$, $\triangle lnICT(-1)$ and $\triangle lnICT(-2)$ on $\triangle lnCO_2$ are 0.10, 0.14 and 0.07 respectively, and are statistically significant at the 1% significance level. This means ICT increases CO_2 emissions in the short-run. Although ICT did not significantly affect CO_2 emissions in the long-run, it was shown to increase CO_2 emissions in the short-run. This is because the electricity consumption has been increased due to the rapid growth of information and communication equipment and facilities, and the energy saving effects of ICT were not so great during the period. Meanwhile, the coefficients of $\triangle lnFD$ and $\triangle lnFD(-1)$ on $\triangle lnCO_2$ are -0.13 and -0.11 respectively and are statistically significant at the 1% significance level. This means that financial development played a role in reducing CO_2 emissions in the short-run. With the development of private finance, an efficient transaction system seems to have brought about the improvement in the energy efficiency of economic activities. Furthermore, the coefficient of $\triangle lnTR$ on $\triangle lnCO_2$ is statistically insignificant. This means that the coefficients of trade openness had no effect on the changes in CO_2 emissions in the short-run, as well as in the long-run.

The coefficient of error correction term is -0.21 and significant at 1% significance level, and has a negative sign between 0 and -1, which implies that the model can quickly converge back to long-run equilibrium after a temporary shock. The coefficient of error correction term indicates that the disequilibria from shock in this period can be adjusted by about 20% in the next period. Here, any disequilibrium will converge back in about five years.

〈Table 7〉 ARDL-ECM representation

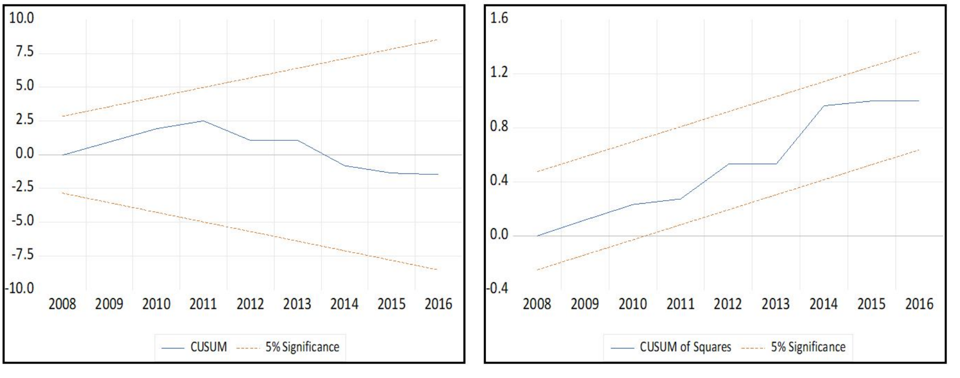
dependent variable: $\triangle lnCO_2$				
Expalnatory Variables	coefficient	standard error	t-statistic	p-value
constant	-1.64***	0.147	-11.108	< 0.01
$\triangle lnGDP$	1.73***	0.087	19.848	< 0.01
$\triangle lnGDP(-1)$	0.55***	0.107	5.094	< 0.01
$\triangle lnGDP(-2)$	0.61***	0.102	5.935	< 0.01
$\triangle lnTR$	0.05	0.029	1.743	0.115
$\triangle lnFD$	-0.13***	0.040	-3.292	< 0.01
$\triangle lnFD(-1)$	-0.11***	0.032	-3.267	< 0.01
$\triangle lnICT$	0.10***	0.014	7.021	< 0.01
$\triangle lnICT(-1)$	0.14***	0.017	8.367	< 0.01
$\triangle lnICT(-2)$	0.07***	0.016	4.114	< 0.01
$\triangle ECT(-1)$*	-0.21***	0.019	-10.854	< 0.01
R^2	0.978		Akaike info criterion	-5.783
Adjusted R^2	0.961		Schwarz criterion	-5.243

Notes: *, p-value < 0.1; **, p-value < 0.05; and ***, p-value < 0.01.

6. Model stability

The stability of the coefficients in the estimated models is tested by using CUSUM and CUSUMSQ tests to avoid misspecification of the functional form (Pesaran and Pesaran, 1997). If the statistic lies between red confidence intervals, then the estimated coefficients are stable (Brown et al., 1975). Figure 2 depicts the results of these stability tests, where the left plot (a) shows CUSUM and the right plot (b) shows CUSUMSQ. As demonstrated, the stability of this ARDL model was confirmed for the chosen sample period because the estimated values for both tests lied between confidence intervals at the 5% significance level.

〈Figure 2〉 Plot of CUSUM (a) and CUSUMSQ (b)



(a) (b)

IV. Discussions and Conclusions

This study investigated the effects of ICT, trade openness, and financial development, incorporating economic growth, on Korean CO_2 emissions from 1990 to 2016. The ARDL model was used because only a single country was analyzed and the data period was relatively short. The results of the ARDL bounds test confirmed a long-run equilibrium among the corresponding variables.

After confirming the long-run cointegration relationship, the long-run and short-run coefficients were estimated using ARDL-ECM. In the long-run, CO_2 emissions mainly increased by GDP. The progress in ICT by spread of Internet did not affect CO_2 emissions. The increase in electricity demand caused by ICT seems to have been offset by the energy-saving effect of ICT in the long-run. Compared with previous studies, this result doesn't match with the panel studies which include Korea. The empirical outcomes of Lu (2018) and Ozcan (2018) showed a negative effect of ICT on CO_2 emissions. Their result indicated that the progress of ICT had contributed to the reduction of CO_2 emissions.

In the short-run, CO_2 emissions are also accompanied by GDP growth. Trade openness also did not affect CO_2 emissions in the short-run, as well as in the long-run. Financial development led to a decrease in CO_2 emissions in the short-run, although it did not affect CO_2 emissions in the long-run. The progress of ICT induced by Internet led to an increase in CO_2 emissions in the short-run. However, the coefficients of the ICT were not so high, it is difficult to say that ICT has a substantial effect on the increase in CO_2 emissions. It can be concluded that ICT has not contributed to the mitigation of CO_2 emissions in the both short and long-run.

The progress of ICT may increase or decrease CO_2 emissions. The increase in electricity consumption by the progress of ICT is directly related to the increase in CO_2 emissions. In other words, the spread of Internet related devices, such as mobile phones, internet servers, and personal computers, is accompanied by an increase in electricity use. However, along with the spread of such hardware, the development of software for efficient energy consumption is also accompanied. Therefore, the two effects have the effect of increasing the energy consumption on the one hand, but also reducing the energy consumption on the other hand. Therefore, the progress of ICT may have a different effect on CO_2 emissions, depending on how ICT is used technologically to mitigate CO_2 emissions.

To efficiently mitigate CO_2 emissions and address climate change, energy-saving methods using ICT should be further implemented. Energy-saving through the use of an

EMS, FEMS, and BEMS should be encouraged, and economic incentives should also be given to companies that have efficiently accomplished energy saving through these technologies. In Korea, the national emission trading scheme has already been implemented for large-scale greenhouse gas emission facilities since 2015, but there is a limitation to mitigating greenhouse gas emissions using only the emission trading scheme. When the emission trading scheme is combined with CO_2 reduction technology, the effect of CO_2 mitigation can be maximized. Therefore, the deployment of CO_2 reduction technologies using ICT should be further implemented.

The limitations of this paper are as follows. First, the Internet users per 100 people was used as an index to measure ICT. However, although this index is most important indicator representing ICT technology, it is difficult to say that it presents the entire ICT technology. However, it is currently difficult to find other indicators with enough time series to analyze for Korea. Second, the effect of ICT on CO_2 emissions vary by economic sector, such as household, industrial, transportation, and general sectors. For example, the changes in electricity consumption due to ICT can appear differently in the household and industrial sectors. The impact of ICT on CO_2 emissions is expected to be different in each sector. Therefore, analyzing the impact of ICT on CO_2 emissions in each sector will lead to more precise policy implications. Therefore, the impact of ICT on CO_2 emissions in each sector will be explored through further studies. Third, the productivity of ICT industry can also affect the dynamics of CO_2 emissions. The effect of the productivity of the ICT industry on CO_2 emissions will also be analyzed in the further studies.

[References]

Amri, F. “Carbon dioxide emissions, total factor productivity, ICT, trade, financial development, and energy consumption: testing environmental Kuznets curve hypothesis for Tunisia,” *Environmental Science and Pollution Research*, Vol. 25, 2018, pp. 33691~33701.

Bello, A, K., and Q. M. Abimola, "Does the level of Economic Growth influence Environmental Quality in Nigeria: A test of environmental Kuznets curve (EKC) Hypothesis," *Pakistan Journal of Social Science*, Vol. 7, 2010, pp. 325~329.

Brown, R. L., J. Durbin, and J. M. Evans, "Techniques for testing the constancy of regression relations over time", *Journal of Royal Statistical Society*, Vol. 37, 1975, pp. 149~163.

Dickey, D. A., W. A. Fuller, "Distribution of the estimators for autoregressive time series with a unit root," *Journal of the American Statistical Association*, Vol. 74, No. 366, 1979, pp. 427~431.

Engle, R. F., and C. W. J. Granger, "Cointegration and error correction: representation, estimation, and testing," *Econometrica*, Vol. 55, 1987, pp. 251~276.

Faisal, F., Azizullah. T. Tursoy, and R. Pervaiz, "Does ICT lessen CO_2 emissions for fast-emerging economies? an application of the heterogeneous panel estimations," *Environmental Science and Pollution Research*, Vol. 27. 2020, pp. 10778~10789.

Fernández, V. C., and J. T. Fernández, "The long run impact of foreign direct investment, exports, imports and GDP: evidence for Spain from an ARDL approach," *EHES Working Paper*, Vol. 128, 2018, pp. 1~21.

Günther, O., "Environmental information systems," *SIGMOD Rec*. Vol. 3, No. 1, 1997, pp. 3~4.

Harris, R., and R. Sollis, *Applied Time Series Modeling and Forecasting*, Wiley, West Sussex, 2003.

Haseeb, A. E. Xia, S. Saud, A. Ahmad, and H. Khurshid, "Does information and communication technologies improve environmental quality in the era of globalization? an empirical analysis," *Environmental Science and Pollution Research*, Vol. 26, 2019, pp. 8594~8608.

Higón, D., R. Gholami, and F. Shirazi, "ICT and environmental sustainability: a global perspective," *Telematics and Informatics*, Vol. 34, 2017, pp. 85~95

Ilic, A., P. Bowman, J. Ng, and T. Staake, "The value of RFID for RTI management," *Electronic Markets*, Vol. 19, No. 2-3, 2009, pp. 125~135.

Johansen, S., and K. Juselius, "Maximum likelihood estimation and inference on cointegration with applications to the demand for money," *Oxford Bulletin of Economics and Statistics*, Vol. 52, 1990, pp. 169~210.

Lee, J. W., and T. Brahmasrene, "ICT, CO_2 emissions and economic growth: evidence from a panel of ASEAN," *Global Economic Review*, Vol. 43, 2014, pp. 93~109.

Lu, W. C., "The impacts of information and communication technology, energy consumption, financial development, and economic growth on carbon dioxide emissions in 12 Asian countries," *Mitigation and Adaptation Strategies for Global Change*, Vol. 23, 2018, pp. 1351~1365.

Narayan, P. K. "The saving and investment nexus for China: evidence from cointegration tests," *Applied Economics*, Vol. 37, 2005, pp. 1979~1990.

Ozcan, B., and N. Apergis, "The impact of internet use on air pollution: evidence from emerging countries," *Environmental Science and Pollution Research*, Vol. 25, 2018, pp. 4174~4189.

Park, Y., F. Meng, and M.A. Baloch, "The effect of ICT, financial development, growth, and trade openness on CO_2 emissions: an empirical analysis," *Environmental Science and Pollution Research*, Vol. 25, 2018, pp. 30708~30719.

Pesaran, M. H., and B. Pesaran, *Working with Microfit 4.0: interactive econometric analysis*, Oxford: Oxford University Press, 1997.

Pesaran, M. H., and Y. Shin, *An autoregressive distributed lag modelling approach to cointegration analysis*, In: Strom S, Holly A, Diamond P, eds. Econometrics and Economic Theory in the 20th Century: The Ranger Frisch Centennial Symposium. Cam-bridge: Cambridge University Press, UK, 1999.

Pesaran, M. H., Y. Shin, and R. J. Smith, "Bounds testing approaches to the analysis of level relationships," *Journal of Applied Econometrics*, Vol. 16, 2001, pp. 289~326.

Phillips, P. C. B., and P. Perron, "Testing for a unit root in time series regression," *Biometrika*, Vol. 75, No. 2, 1988, pp. 335~346.

Sadorsky, P., "The impact of financial development on energy consumption in emerging economies," *Energy Policy*, 38, 2010. pp. 2528~2535.

Shehzad, K., L. Xiaoxing, M. Sarfraz, and M. Zulfiqar, "Signifying the imperative nexus between climate change and information and communication technology development: a case from Pakistan," *Environmental Science and Pollution Research Environmental Science and Pollution Research*, Vol. 27, 2020, 30502~30517. https://doi.org/10.1007/s11356-020-09128-x.

Wang, H., and Y, Jin, "Industrial ownership and environmental performance: evidence from China," *Environmental and Resource Economics*, Vol. 36, 2007, pp. 255~273.

World development indicators of the World Bank DataBank, Available: https://databank.worldbank.org/source/world-development-indicators (accessed on 1 June 2020).

Yao, X-N., and J-Y. Liu, *The potential of economic growth and technology advancement in the BRICs*, Proceeding of the 2011 International Conference on Machine Learning and Cybernetics.

Zhang, C., and C. Liu, “The impact of ICT industry on CO_2 emissions: a regional analysis in China,” *Renewable & Sustainable Energy Reviews*, Vol. 44, 2015, pp. 12~19.

Zhang, Y. J. “The impact of financial development on carbon emissions: an empirical analysis in China,” *Energy Policy*, Vol. 39, 2011, pp. 2197~2203.