The Impact of Information and Communication Technologies (ICTs) on Environmental Pollution: Evidence From Developed Countries

Burcu Ozcan[1]

Abstract

This study aims at analyzing the impact of internet users, employed as a proxy for information and communications technologies (ICTs), on CO_2 emissions for a panel of developed countries, spanning the period from 1990 to 2015. On one hand, information technologies (ITs) can produce more efficient economic growth with less energy demand. In this respect, using energy in a more efficient way across all sectors of the economy, IT sector provides a potential solution to reduce CO2 emissions level. On the other hand, given that the installation and the operation of new ICT devices are characterized as highly energy intensive, air pollution may increase because of increased electricity demand. Therefore, the net impact of the ICTs on air pollution is not clear. Using panel data approaches such as unit root, cointegration and causality tests, we analyze whether internet usage alleviates CO2 emissions level of developed countries. Relying on the result that increased Internet access results in lower levels of air pollution, we suggest some crucial policy implications to the governments of developed nations. For instance, increased investment in the ICT sector could be a plausible channel to mitigate air pollution level.

Keywords: Information and communication technology; air pollution; developed countries; panel data models; energy efficiency

JEL Codes : C23, L86, Q53

[1]**Corresponding Author** Department of Economics, Firat University, Elazig, Turkey. bozcan@firat.edu.tr

1. Introduction

In particular, since the beginning of the industrial age in the late eighteenth century, human being has transformed the world and caused its fragile environment to deteriorate at an increasingly rapid rate. (Sui and Rejeski, 2002). Governments struggle to reduce carbon emissions and resource usage for a more sustainable word. Since 1970s, aftermath of the two oil price shocks, countries started showing a general interest in how to reduce energy consumption and CO_2 emissions through the expansion of ICTs (Salahuddin and Alam, 2015). With the advent of the computer age, it is believed that moving from physical resources to information will reduce the resource and pollution intensity of economic growth (Toffel and Horvath, 2004). Therefore, energy, in the form of oil and electricity, and information and communication technologies (ICTs) have played pivotal roles in the processes of industrialization and economic growth over the last hundred years (Cho et al., 2007).

Information technology is accepted as a solution to obtain more efficient economic growth with less energy demand (Sadorsky, 2012). In this respect, there is a special notion “IT for green” (see Cai, Chen and Bose, 2013; Dedrcik, 2010; Salahuddin, Alam and Ozturk, 2016), which accepts ICT sector as a possible solution to reduce CO_2 emissions throughout all sectors of an economy. Herein, IT is accepted as a mean to reach the goal of environmental sustainability in nations through using energy in a more efficient and sustainable way. In this respect, there exist substitution effects (Cho et al., 2007; Coroama, Hilty and Birtel, 2012) whihc can reduce demand for electricity through the replacement of an old energy intensive production technology by a new production technology. For instance, many traditional industries implementing ICTs in their operation processes have been transformed into smart industries, such as smart transportation, smart agriculture, smart management, smart logistic, smart building, and so on. Besides, ICTs can ameliorate air pollution problems via dematerialization (see Ishida, 2015; Ropke and Christensen, 2012). Economic dematerialization refers to an information society, leading to use of ICTs to provide immaterial services where previously material goods were produced, transported and disposed (Hilty, 2008). Virtual goods replace material devices. ICTs are used to substitute ‘bits of information’ such as downloads, virtual meetings and e-commerce for more energy intensive physical products, travel and retail premises (Zadek et al., 2010). Trade and transportation of many products and services over the Internet results in dematerialization that reduces the amount of physical transport and increases the efficiency of transportation (Fuchs, 2008).

However, in contrast to the affirmative environmental effects of ICTs we explained above, there exists some views emphasizing the negative impacts of ICTs on air quality. There exists a notion regarding the negative results of ICTs on environment that is called the “Green IT” (see Cai, Chen and Bose, 2013; Dedrcik, 2010; Peng, 2013; Salahuddin et al., 2016). This approach holds ICT sector responsible for the air pollution, and to combat its own carbon footprint, the sector should implement environmentally friendly ICT devices. In this respect, the ***compensation effects (income effect)*** of ICTs, working against the substitution effects, indicates that the installation and the operation of new ICT devices increase demand for electricity (Cho et al., 2007). The usage of smart phones and ICT equipments to share data, videos and pictures creates a positive network effects among users; however, these activities also increase the demand for electricity (Sadorsky, 2012). For instance, Facebook’s global yearly electricity consumption is of 0.5 TWh, amounting approximately to 500 Wh per user. (Gelenbe and Caseau, 2015). Additionally, the *rebound effects* may counteract the positive energy and environmental impacts of ICT equipments because they are accepted to work against energy or resource usage efficiency. The rebound effect denotes the paradox that efficiency gains in devices, machines and systems may lead to increased demand for those devices and machines (Coroama et al., 2012). If a good gets cheaper in terms of its price or any effort necessary to obtain it, the demand for this good usually increases, and thus efficiency improvements do not indicate savings on the input side (Hilty et al., 2006). For instance, the increasing use of ICT products at work and at home has led to significant increase in carbon footprint of the ICT sector and this is one of the most crucial rebound effects concerning ICT (Peng, 2013).

Since the early 1990s, researchers started analyzing the relationships between ICTs and energy demand or ICTs and environmental quality. However, there is still not enough studies in the existing literature. Regarding the nexus of ICTs and air pollution, Zhang and Liu (2015) obtained that ICT industry reduces CO_2 emissions level for the China at national level. Salahuddin et al. (2016) for a panel of OECD economies found that internet usage raises CO_2 emissions level. Additionally, some studies, particularly, analyzed the effects of teleconferencing, digital media, and online retailing on environmental pollution (see Al-Mulali, Ting and Ozturk, 2015; Chavanne et al., 2015; Coroama, Hilty and Birtel, 2012; Toffel and Horvath, 2004; Matthews, Hendrickson and Soh, 2001; Fichter, 2003; Reichart and Hischier, 2003; Siikavirta et al., 2003).

As stated above, there are different effects that work against each other and therefore, we cannot guess before the net and final effect of ICTs on the air quality level of any country. For this reason, we aim to reveal the impact of ICT usage represented by the percentage of Internet users on the air pollution level in the panel including 32 high-income countries based on the some novel panel data tests which allow for cross-sectional dependence and heterogeneity in slope parameters for the period 1990-2015. The rest of the paper is organized as follow. Section 2 discusses data and model used in the paper; methodology and empirical results are discussed in Section 3; and finally Section 4 concludes the study with some policy suggestions.

2. Data and Model

For the current study, the country sample includes the following 32 high-income countries. Germany, USA, Australia, Austria, Belgium, UK, Czech Republic, Denmark, Finland, France, Netherlands, China, Ireland, Spain, Israel, Sweden, Switzerland, Italy, Iceland, Japan, Cyprus, South Korea, Luxembourg, Hungary, Norway, Poland, Portugal, Singapore, Chile, Uruguay, New Zealand, and Greece. Time frame is from 1990 to 2015. As regards the proxy for ICT, Internet users per 100 people measure is used. We added one to each data point to make the log value of zero Internet users to be zero as well (Lin 2015 also utilizes this measure). Air pollution is measured by CO_2 emissions reported in metric tons per capita while economic growth is measured as per capita GDP (constant 2010 US dollar). In addition, we included energy consumption (measured by kg of oil equivalent per capita), financial development (represented by domestic credit to private sector as a share of GDP), and trade openness (the sum of exports and imports divided by GDP) and energy consumption as additional determinants of air pollution. All data come from the World Development Indicators database (2017) of the World Bank, except for CO_2 emissions data, which was obtained from the European Commission's Emissions Database for Global Atmospheric Research (EDGAR, 2018).

Based on the previous studies in the relevant literature (Ozturk and Acaravci 2013; Sadorsky 2012; Salahuddin et al. 2016; Zhang and Liu 2015), we specified the model as in Equation (1):

$$\ln CO_{2_{it}} = \alpha_i + \delta_i t + \beta_{1i} \ln INT_{it} + \beta_{2i} \ln GDPC_{it} + \beta_{3i} \ln FD_{it} + \beta_{4i} \ln TRD_i + \beta_{5i} \ln ENC_{it} + \varepsilon_{it} \quad (1)$$

where $i = 1,2,.....,32$ denotes the number of countries in the panel; $t = 1990,.......,2015$ is the time period; α_i and $\delta_i t$ indicate country-specific fixed effects and deterministic trends, respectively, while ε_{it} represents idiosyncratic errors. All variables are used in their natural logarithms. Thus, the coefficients β_1, β_2, β_3, β_4 and β_5 correspond to the long-run elasticities of CO_2 with respect to related variables. The signs of β_1, β_3 and β_4 are not certain; they could be positive or negative. However, the signs of β_2 and β_5 are expected to be positive. Based on the EKC hypothesis, increases in income raise emissions levels until a threshold level of income is reached after which emissions start to decline (Acaravci and Ozturk, 2010). Therefore, contrary to the squared GDP, GDP in level form is expected to raise CO_2 emissions level. Besides, energy consumption is also a crucial reason of increasing level of air pollution. However, the impact of trade openness could be decomposed into three effects: scale, technique and composition effects (see Grossman and Krueger, 1991). The scale effect supports that pure growth in the scale of the economy would result in growth in pollution if there were no change in the structure or technology of the economy (Stern, 2004). The technique effect explains the positive environmental consequences of economic growth and trade expansion that call for cleaner production methods (Managi, 2004) while the composition effect implies how the environment is impacted by the composition of output determined by the degree of openness as well as by the comparative advantage of the country (Shahbaz, Lean and Shabbir, 2011). The net impact of the composition effect on the level of pollution will depend upon whether pollution-intensive activities expand or contract in the country that on average has the more stringent pollution controls (Grossman and Krueger, 1991).In a similar way, the impact of financial development on air pollution is not certain either. On one hand, by lowering financing costs, expanding financing channels and dispersing operating risks, financial development helps firms to purchase new installations and to invest in new projects, which then increases both energy consumption and carbon emissions (Ozturk and Acaravci, 2013). On the other hand, financial development can provide the opportunity to utilize new production technologies that are clean and environment-friendly and thereby prevent environmental pollution in developing countries (Tamazian et al., 2009).

3. Methodology and Empirical Results

Before proceeding to the empirical part, we first provide some statistical measures of the log values across all the variables in Table 1.

Table 1: Summary statistics

Statistics	lninternet	lngdp	lncarbon	lnenergy	lnfinance	lntrade
Mean	2.964	10.345	2.109	8.199	4.446	4.348
Median	3.693	10.463	2.157	8.232	4.523	4.245
Maximum	4.597	11.625	3.445	9.807	5.743	6.092
Minimum	0.000	8.614	0.228	6.584	2.556	2.773
Std. Dev.	1.577	0.598	0.508	0.510	0.560	0.637
Skewness	-0.744	-0.645	-0.765	-0.168	-0.621	0.563
Kurtosis	1.988	3.179	4.940	3.899	3.091	3.543
Jarque-Bera	112.351	58.946	211.806	32.021	53.890	54.215
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Observations	832	832	832	832	832	832

Source: Authors Calculations from World Bank Development Indicators

3.1 Results for cross-sectional dependence test and panel unit root tests

We first apply the cross-sectional dependence tests developed by Breusch and Pagan (1980, LM), Pesaran (2004, CD and CD_{lm}), and Pesaran et al. (2008, LM_{adj}) to identify the best unit root test. The results reported in Table 2 indicate the presence of cross-sectional dependence across all variables. Therefore, the next step of the analysis employs the panel bootstrap unit root tests proposed by Smith et al. (2004).

Table 2: Cross-sectional dependence test results

Variables	LM (Breusch & Pagan 1980)	CDlm (Pesaran 2004)	LMadj (Pesaran et al. 2008)	CD (Pesaran 2004)
lncarbon	4582.73 (0.000)	129.753 (0.000)	129.113 (0.000)	26.783 (0.000)
lngdp	10831.62 (0.000)	328.156 (0.000)	327.516 (0.000)	103.502 (0.000)
lnenergy	3428.717 (0.000)	93.113 (0.000)	92.473 (0.000)	27.305 (0.000)
lninternet	12287.85 (0.000)	374.391 (0.000)	373.751 (0.000)	110.829 (0.000)
lnfinance	4731.202 (0.000)	134.467 (0.000)	133.827 (0.000)	38.132 (0.000)

lntrade	7002.506 (0.000)	206.581 (0.000)	205.941 (0.000)	75.292 (0.000)
Model	672.627 (0.000)	5.608 (0.000)	10.397 (0.000)	3.051 (0.001)

Source: Author own calculation based on codes.

Smith et al. (2004) allow for cross-sectional dependence through a bootstrap procedure and develop five unit root tests: $L\bar{M}$, $\bar{t}$, $Mi\bar{n}$, $Ma\bar{x}$ and $W\bar{S}$ tests. The results of unit root test are tabulated in Table 3.

Table 3: Smith et al. (2005) panel unit root test results

Variables	Level					First-difference				
	$\bar{t}$	$L\bar{M}$	$Mi\bar{n}$	$Ma\bar{x}$	$W\bar{S}$	$\bar{t}$	$L\bar{M}$	$Mi\bar{n}$	$Ma\bar{x}$	$W\bar{S}$
lncarbon	-1.746 (0.913)	4.109 (0.872)	2.553 (0.952)	-1.238 (0.961)	-1.631 (0.980)	-4.753[a] (0.000)	12.56[a] (0.000)	12.20[a] (0.000)	-4.60[a] (0.000)	-5.01[a] (0.000)
lngdp	-1.728 (0.834)	3.705 (0.852)	2.934 (0.751)	-1.492 (0.680)	-1.879 (0.772)	-3.913[a] (0.000)	10.35[a] (0.000)	8.233[a] (0.000)	-3.20[a] (0.000)	-3.62[a] (0.000)
lnenergy	-1.964 (0.714)	4.470 (0.754)	3.395 (0.661)	-1.586 (0.647)	-1.937 (0.821)	-4.747[a] (0.000)	12.46[a] (0.000)	11.59[a] (0.000)	-4.43[a] (0.000)	-4.83[a] (0.000)
lninternet	-1.559 (0.934)	3.261 (0.986)	2.277 (0.954)	-1.046 (0.903)	-1.593 (0.984)	-2.950[a] (0.007)	-2.33[a] (0.003)	7.750[a] (0.002)	5.553[a] (0.004)	-2.78[a] (0.001)
lnfinance	-2.024 (0.661)	4.694 (0.642)	3.396 (0.652)	-1.627 (0.616)	-2.042 (0.643)	-3.526[a] (0.002)	9.56[a] (0.000)	9.297[a] (0.000)	-3.44[a] (0.000)	-3.84[a] (0.000)
lntrade	-2.353 (0.334)	5.419 (0.322)	4.548 (0.226)	-2.098 (0.227)	-2.365 (0.257)	-4.766[a] (0.000)	12.945 (0.000)	12.56[a] (0.000)	-4.61[a] (0.000)	-4.99[a] (0.000)

Source: Author calculation based on code.

Notes: [a] Indicates 1% significance level.

The test results provided in Table 3 document that all variables are nonstationary in their levels, whereas they turn stationary in their first-differences, i.e. they are integrated of order one.

3.2 Results for cointegration tests and long-run parameter estimates

After having defined the integration properties of the variables of interest, the next step is to ascertain the long-run relationship among the variables in Equation (1). To this purpose, we make use of panel cointegration tests proposed by Pedroni (1999) and Westerlund (2008). Their results are tabulated in Tables 4 and 5.

Table 4: Pedroni Panel cointegration tests

Alternative hypothesis: common AR coefs. (within-dimension)				
	Statistic	**Prob.**	**Weighted Statistic**	**Prob.**
Panel v-Statistic	0.703	0.241	-2.305	0.989
Panel rho-Statistic	2.488	0.993	2.561	0.994
Panel PP-Statistic	-7.440[a]	0.000	-8.743[a]	0.000
Panel ADF-Statistic	-7.716[a]	0.000	-8.352[a]	0.000
Alternative hypothesis: individual AR coefs. (between-dimension)				
	Statistic	**Prob.**		
Group rho-Statistic	4.603	1.000		
Group PP-Statistic	-11.896[a]	0.000		
Group ADF-Statistic	-9.107[a]	0.000		
Westerlund (2008) cointegration tests				
	Statistic	**Prob.**		
DHg	-1.986[b]	0.024		
DHp	-1.801[b]	0.036		

Source: Author own calculation based on code

As presented in Table 4, the panel PP- and ADF-statistics and the group-PP and ADF-statistics reject the null hypothesis of nocointegration and provide strong evidence in favor of cointegration. Additionally, it also presents the results from Durbin Hausman-group mean (DHg) and panel (DHp) cointegration tests developed by Westerlund (2008).Both DHg and DHp test statistics reject no cointegration null hypothesis at 5% significance level. Therefore, we conclude that there exists a long-run relationship among variables defined in Eq. (1). Based on the presence of cointegration, we estimate long-run parameters with common correlated effects mean group (CCE-MG) approach developed by Pesaran (2006). CCE allows for both cross-sectional dependence and heterogeneity in slope parameters. Its results are tabulated in Table 5.

Table 5: CCE Estimation Results

Countries	lngdp		lninternet		lnenergy		lnfinance		lntrade	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Germany	-0.073	-0.343	-0.004	-0.174	0.892^{a}	7.372	-0.212^{a}	-3.926	0.045	0.672
USA	-0.398	-1.118	0.002	0.125	1.288^{a}	8.822	0.076^{c}	1.727	-0.122^{b}	-2.103
Australia	0.804^{b}	2.344	0.033^{a}	5.500	-0.065	-0.565	-0.246	-1.323	-0.004	-0.061
Austria	-0.554^{b}	-2.441	-0.029^{a}	-2.900	1.188^{a}	15.840	-0.124^{a}	-2.818	0.281^{a}	2.555
Belgium	-0.123	-0.239	-0.008	-0.296	0.792^{a}	7.009	-0.007	-0.636	0.324	1.227
UK	0.753^{a}	3.486	0.013	0.448	0.936^{a}	6.882	0.132^{b}	2.129	-0.108^{c}	-1.770
Czech Republic	0.029	0.207	-0.066^{b}	-2.357	0.589^{a}	3.681	-0.104^{b}	-2.476	-0.092	-1.333
Denmark	1.377^{a}	3.046	-0.074^{b}	-2.000	1.767^{a}	17.848	-0.006	-0.462	-0.030	-0.153
Finland	0.184	0.395	0.142^{a}	5.071	1.718^{a}	4.994	0.086	0.688	0.105	0.761
France	0.51^{c}	1.759	-0.068^{a}	-3.238	0.883^{a}	3.790	-0.034	-0.281	0.252^{a}	2.625
Netherlan ds	0.547^{a}	3.440	-0.035^{b}	-2.333	0.724^{a}	8.829	-0.073^{c}	-1.738	-0.078	-0.565
China	1.135^{a}	3.234	-0.070^{c}	-1.667	0.114^{b}	2.111	0.392^{a}	4.612	0.530^{a}	5.464
Ireland	0.13	0.844	0.068	1.046	1.381^{a}	9.395	-0.004	-0.235	-0.107	-1.466
Spain	-0.228	-0.905	0.005	0.417	1.478^{a}	13.080	0.014^{c}	0.179	0.273^{a}	3.033
Israel	0.39^{a}	2.977	-0.006	-0.240	0.712^{a}	6.980	-0.082	-1.608	0.272^{a}	6.634
Sweden	-0.08	-0.221	-0.061^{c}	-1.694	0.409	1.262	-0.058^{b}	-2.000	0.024	0.188
Switzerlan d	0.397	0.639	-0.005	-0.192	0.446^{a}	3.457	0.037	0.287	-0.047	-0.246
Italy	0.388	1.232	0.045^{b}	2.500	1.066^{a}	7.560	-0.018	-0.383	-0.123	-1.098
Iceland	0.599^{c}	1.783	-0.014	-0.737	0.275^{a}	2.523	-0.048	-1.455	0.045	0.391
Japan	0.421	1.196	-0.113^{a}	-4.185	0.379^{a}	2.650	-0.132^{a}	-3.568	0.046	0.885
Cyprus	0.696^{b}	2.425	0.059^{a}	2.682	0.393^{a}	3.023	0.265^{b}	2.325	-0.106^{a}	-2.524
South Korea	0.474^{a}	2.821	0.026	1.529	0.875^{a}	5.795	0.032	0.744	-0.035	-0.714
Luxembou rg	-0.165	-0.912	0.012	0.480	1.354^{a}	20.209	-0.102^{b}	-2.040	0.434^{a}	3.875
Hungary	0.443^{b}	2.382	-0.037	-1.057	0.724^{a}	4.000	-0.004	-0.058	0.005	0.055
Norway	1.012^{a}	2.976	-0.106^{a}	-3.786	-0.083	-0.529	-0.093	-1.525	0.095	0.537
Poland	0.215	1.473	-0.054^{a}	-7.714	0.814^{a}	11.306	0.023^{a}	3.833	0.081^{b}	2.382
Portugal	0.061	0.265	-0.078^{a}	-2.600	1.391^{a}	10.304	0.082	1.188	-0.073	-0.518
Singapore	-0.107	-0.259	-0.023	-0.184	-0.398^{a}	-2.970	0.186	0.514	-0.217	-0.835
Chile	-0.752^{a}	-4.347	-0.189^{a}	-5.559	0.639^{a}	2.803	0.424^{c}	1.868	-0.275	-1.396
Uruguay	0.264	0.714	-0.012	-0.158	1.391^{a}	10.538	0.018	0.353	0.097	0.708
New Zealand	0.304	0.661	-0.107^{a}	-5.095	0.308	1.413	0.327^{c}	1.730	0.445^{a}	2.834
Greece	-0.007	-0.040	-0.006	-0.109	0.793^{a}	3.290	0.018	0.305	0.071	1.183
Panel	0.270^{a}	3.226	-0.024^{b}	-2.138	0.787^{a}	8.382	0.024	0.868	0.063^{c}	1.806

Source: Author own calculation based on code.

Notes: [a], [b] and [c] indicate significance levels at 1%, 5% and 10% levels, respectively.

As tabulated in Table 5, the findings from CCE indicate that Internet usage has a negative and statistically significant effect on CO_2 emissions. A 1% increase in the Internet users decreases CO_2 emissions by 0.02%. Despite the small impact, ICTs use in general and the Internet use in particular appear to alleviate air pollution in the high-income countries panel. This result is an indication that ICT-induced higher energy saving in some areas of life is likely to surpass ICT-induced additional energy consumption in other areas. The gains in energy efficiency derived from the substitution effects of ICTs appear to surpass the additional energy demand derived from both the compensation and the rebound effects. Regarding the country-level results, for thirteen countries namely Austria, Czech Republic, Denmark, France, Netherlands, China, Sweden, Japan, Norway, Poland, Portugal, Chile, New Zealand, Internet usage appears to reduce CO_2 emissions level, whereas for four countries (Australia, Finland, Italy, and Cyprus) the Internet use leads more air pollution. This result is similar to the results of Zhang and Liu (2015) for China and Ozcan and Apergis (2018) for a panel consisting of 20 emerging market economies; however, it is in sharp contrast to that of Salahuddin et al. (2016) for a panel of OECD countries. Concerning the effect of income per capita, economic growth appears to raise CO_2 emissions level for the panel of high-income countries. At country-level, twelve countries (Australia, UK, Denmark, France, Netherlands, China, Israel, Iceland, Cyprus, South Korea, Hungary, and Norway), economic growth causes more air pollution, whereas only for two countries (Austria and Chile), growth appears as a cure for air pollution problems. Regarding energy consumption, more energy use creates more CO_2 emissions as expected theoretically in twenty eight countries, namely Germany, USA, Austria, Belgium, UK, Czech Republic, Denmark, Finland, France, Netherlands, China, Ireland, Spain, Israel, Switzerland, Italy, Iceland, Japan, Cyprus, South Korea, Luxembourg, Hungary, Poland, Portugal, Singapore, Chile, Uruguay, and Greece. However, the influence of financial development is insignificant for the panel as a whole. As such, financial development does not seem to have any statistically significant impact on air pollution. In other words, financial development in emerging markets has not taken place at the expense of environmental pollution. The beneficial and harmful environmental impacts of financial development cancel each other. At country level, for eight countries (Germany, Australia, Austria, Czech Republic, Netherlands, Sweden, Japan, and Luxembourg), financial development reduces air pollution, whereas for USA, UK, China, Spain, Cyprus, Poland, Chile, and New Zealand, more financial development appears to increase air pollution level. For the remaining high-income countries, financial development has no significant effect on air quality. Lastly, trade openness worsens air quality level for the panel of high-income countries. It means that trade openness is harmful for environment because the technological effect is not greater than the composition effect and scale effect (see Grossman and Krueger, 1991). Trade openness creates more air pollution for Austria, France, China, Spain, Israel, Luxembourg, Poland and New Zealand, while it reduces emissions level for only three countries (USA, UK, and Cyprus). However, for the rest of countries, trade openness has not significant influences on air quality level.

3.3 Dumitrescu-Hurlin (DH, 2012) panel causality test results

We employ panel causality test proposed by Dumitrescu and Hurlin (DH 2012) to define the directions of causality linkages between the variables. DH (2012) test is a simple Granger (1969) non-causality test in heterogeneous panel data models with fixed coefficients and allows for two dimensions of heterogeneity: (i) The heterogeneity of regression models used to test the Granger causality and (ii) the heterogeneity of the causal relationships. The null hypothesis assumes that there is no causal relationship for any of the cross-sectional units in the panel, whereas the alternative hypothesis proposes a causal relationship for a subgroup of panel. DH (2012) test results are provided in Table 6.

Table 6. Results from the Pairwise Dumitrescu-Hurlin (2012) panel causality test

Null Hypothesis:	W-Stat.	Zbar-Stat.	Prob.
lngdp does not homogeneously cause lncarbon	3.029[c]	1.728	0.083
lncarbon does not homogeneously cause lngdp	2.236	-0.029	0.976
lnenergy does not homogeneously cause lncarbon	1.753	-1.101	0.270
lncarbon does not homogeneously cause lnenergy	2.397	0.327	0.743
lninternet does not homogeneously cause lncarbon	3.551[a]	2.886	0.003
lncarbon does not homogeneously cause lninternet	3.843[a]	3.534	0.000
lntrade does not homogeneously cause lncarbon	2.227	-0.049	0.960
lncarbon does not homogeneously cause lntrade	2.263	0.0309	0.975
lnfinance does not homogeneously cause lncarbon	2.032	-0.481	0.630
lncarbon does not homogeneously cause lnfinance	1.776	-1.048	0.294
lnenergy does not homogeneously cause lngdp	1.962	-0.637	0.523
lngdp does not homogeneously cause lnenergy	3.051[c]	1.777	0.075
lninternet does not homogeneously cause lngdp	2.888	1.414	0.157
lngdp does not homogeneously cause lninternet	1.879	-0.822	0.410
lntrade does not homogeneously cause lngdp	3.690[a]	3.192	0.001
lngdp does not homogeneously cause lntrade	3.135[b]	1.963	0.049
lnfinance does not homogeneously cause lngdp	3.311[b]	2.354	0.018
lngdp does not homogeneously cause lnfinance	3.360[b]	2.461	0.013
lninternet does not homogeneously cause lnenergy	2.462	0.472	0.636
lnenergy does not homogeneously cause lninternet	3.437[a]	2.633	0.008
lntrade does not homogeneously cause lnenergy	2.565	0.699	0.484
lnenergy does not homogeneously cause lntrade	2.002	-0.548	0.583
lnfinance does not homogeneously cause lnenergy	3.298[b]	2.324	0.020
lnenergy does not homogeneously cause lnfinance	1.740	-1.130	0.258
lntrade does not homogeneously cause lninternet	2.594	0.763	0.444
lninternet does not homogeneously cause lntrade	5.042[a]	6.191	0.000
lnfinance does not homogeneously cause lninternet	2.413	0.362	0.716
lninternet does not homogeneously cause lnfinance	1.621	-1.393	0.163
lnfinance does not homogeneously cause lntrade	2.151	-0.217	0.827
lntrade does not homogeneously cause lnfinance	2.783	1.183	0.236

Source: Author own calculation based on code.
Notes: [a], [b] and [c] denote significance at 1%, 5% and 10% levels, respectively.

Based on the causality test results tabulated in Table 6, there exists a reciprocal relationship between CO_2 emissions and the Internet users. The increasing number of internet users appears to reduce CO_2 emissions level as obtained in CCE estimation results. Additionally, rising level of air pollution Granger causes the Internet use. For instance, conscious inhabitants of high-income countries are likely to choose using the online shopping instead of going to shopping centers by driving car. Besides, inhabitants may utilize energy efficient ICTs such as smart phone, computer, refrigerator, television unit, and so on, which results in less energy consumption and more energy saving. Apart from the significant relationship between the Internet users and CO_2 emissions, we also obtain some feedback relationships between the pairs of economic growth and trade openness and economic growth and financial development. In this regard, financial markets develop as a result of economic growth, which in turn feeds back as a stimulant to the growth process (Al-Yousif, 2002). Likewise, trade liberalization and economic growth appear to reinforce each other. We also found some unidirectional causality relationships running from economic growth to CO_2 emissions; from economic growth to energy consumption; from energy consumption to the Internet users; from financial development to energy use; and from the Internet use to trade openness. However, we didn't explain the theoretical mechanisms behind these causality linkages because our main focus is the nexus of the Internet use and air pollution.

4. Conclusions

This study analyzes the impact of the Internet users on CO_2 emissions for a panel of 32 high-income countries using a panel data framework. In our estimation procedure, we allow for cross-sectional dependence and slope heterogeneity across countries. We first establish that all variables are stationary in their first differences. The panel cointegrations tests developed by Pedroni (1999) and Westerlund (2008) provide evidence of a long-run relationship between the variables of interest. The long-run parameter results indicate that the more Internet users a country has, the lower emissions it will emit. Besides, economic growth and energy consumption, as theoretically expected, appear to raise emissions while financial development does not significantly affect air pollution, and trade openness causes more CO_2 emissions. We also test for the causality relationship between variables of interest and obtain the presence of a mutual relationship between CO_2 emissions and the Internet users. For the remaining pairs of variables, we also find some causality linkages, as well.

The results indicate that substitution effects of the ICTs are greater than their compensation and rebound effects. High-income countries have more sophisticated ICT products and equipments that consume less energy and leads energy efficiency compared to countries with different income groups. Because they are developed and wealth countries, they can easily adapt ICTs to different sectors of their economies in the forms of smart agriculture, smart energy, smart manufacturing, smart buildings, smart logistic, and so on. Therefore, they should continue to benefit these kinds of ICT-enabled technologies because they are able to reduce emissions.

References

Acaravci A, Ozturk I (2010) On the relationship between energy consumption, CO_2 emissions and economic growth in Europe. Energy 35(12):5412–5420.

Al-Mulali U, Ting LS, Ozturk I (2015) The global move toward Internet shopping and its influence on pollution: an empirical analysis. Environ Sci Pollut Res 22(13):9717–9727.

Al-Yousif YK (2002) Financial development and economic growth: another look at the evidence from developing countries. Rev Financ Econ 11(2):131–150.

Breusch TS, Pagan AR (1980) The Lagrange multiplier test and its applications to model specification in econometrics. Rev Econ Stud 47(1):239–253

Cai S, Chen X, Bose I (2013) Exploring the role of IT for environmental sustainability in China: An empirical analysis. Int. J. Prod Econ 146:491–500.

Chavanne X, Schinella S, Marquet D, Frangi JP, Masson SL (2015) Electricity consumption of telecommunication equipment to achieve a telemeeting. Appl Energy 137:273–281.

ChoY, Lee J, Kim TY (2007) The impact of ICT investment and energy price on industrial electricity demand: Dynamic growth model approach. Energ Policy 35:4730–4738

Coroama VC, Hilty LM, Birtel M (2012) Effects of Internet-based multiple-site conferences on greenhouse gas emissions. Telemat Inform 29:362–374.

Dedrick J (2010) Green IS concepts and issues for information systems research. Communications of the Association for Information Systems 27:173–184.

Dumitrescu, E., Hurlin, C (2012) Testing for Granger Non-causality in Heterogeneous Panels. Econ Model 29(4): 1450-1460.

European Commission's Emissions Database for Global Atmospheric Research (EDGAR, 2018) Global per capita CO_2 emissions from fossil fuel use and cement production 1970-2015. http://edgarjrceceuropaeu/

Fichter K (2003) E-commerce: sorting out the environmental consequences. J Ind Ecol 6:25–41.

Fuchs C (2008) The implications of new information and communication technologies for sustainability. Environ Dev Sustain 10:291–309.
Gelenbe E, Caseau Y (2015) The Impact of Information Technology on Energy Consumption and Carbon Emissions. Ubiquity, an ACM publication, from https://dl.acm.org/citation.cfm?id=2755977
Grossman G, Krueger A (1991) Environmental impacts of a North American free trade agreement. Working Paper 3914, National Bureau of Economics Research, November. http://www.nber.org/papers/w3914.pdf
Hilty LM, Arnfalk P, Erdmann L, Goodman J, Lehmann M, Wager PA (2006) The relevance of information and communication technologies for environmental sustainability: A prospective simulation study. Environ Modell Softw 21:1618-1629.
Hilty LM (2008) Information Technology and Sustainability: Essays on the Relationship between ICT and Sustainable Development. Books on Demand, Norderstedt, Germany.
Ishida H (2015) The effect of ICT development on economic growth and energy consumption in Japan. Telemat Inform 32:79–88.
Lin F (2015) Estimating the effect of the Internet on international trade. J Int Trade Econ Dev 24(3):409–428.
Managi S (2004) Trade Liberalization and the Environment: Carbon Dioxide for 1960−1999. Economics Bulletin 17(1): 1−5.
Matthews HS, Hendrickson CT, Soh D (2001) The net effect: environmental implications of E-commerce and logistics. In: Proceedings of the 2001 I.E. International Symposium on Electronics and Environment, Denver, USA, 9 May 2001
Ozcan B, Apergis N (2018) The impact of internet use on air pollution: Evidence from emerging countries. Environmental Science and Pollution Research 25:4174–4189.
Ozturk I, Acaravci A (2013) The long-run and causal analysis of energy, growth, openness and financial development on carbon emissions in Turkey. Energy Econ 36:262–267.
Pedroni P (1999) Critical values for cointegration tests in heterogeneous panels with multiple regressors. Oxford Bulletin of Economics and Statistics Special Issue 0305-9049: 653-670
Peng GC (2013) Green ICT: A Strategy for Sustainable Development of China's Electronic Information Industry. CIJ 11: 68-86.
Pesaran MH (2004) General diagnostic tests for cross-section dependence in panels. Working Paper 0435. Available via Cambridge Working Papers in Economics. http://www.econ.cam.ac.uk/research/repec/ cam/pdf/cwpe0435.pdf.
Pesaran MH (2006) Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure. Econometrica 74(4):967-1012.
Pesaran MH, Ullah A, Yamagata T (2008) A bias-adjusted LM test of error cross-section independence. The Econometrics Journal 11(1): 105-127.
Reichart I, Hischier R (2003) The environmental impact of getting the news a comparison of on-line, television, and newspaper information delivery. J Ind Ecol 6:185–200.
Røpke I, Christensen T H, Jensen JO (2010). Information and communication technologies - A new round of household electrification. Energ Policy 38:1764-1773.
Sadorsky P (2012) Information communication technology and electricity consumption in emerging economies. Energ Policy 48:130–136.
Salahuddin M, Alam K (2015) Internet usage, electricity consumption and economic growth in Australia: A time series evidence. Telemat Inform 32:862–878.
Salahuddin M, Alam K, Ozturk I (2016) The effects of Internet usage and economic growth on CO_2 emissions in OECD countries: A panel investigation. Renew Sust Energ Rev 62:1226–1235.
Shahbaz M, Lean HH, Shabbir MH (2011) Environmental Kuznets Curve and the Role of Energy Consumption in Pakistan, MPRA Paper 34929, University Library of Munich, Germany
Siikavirta H, Punakivi M, Karkkainen M, Linnanen L (2003) Effects of E-commerce on greenhouse gas emissions: a case study of grocery home delivery in Finland. J Ind Ecol 6:83–97.
Smith V, Leybourne S, Kim TH (2004) More powerful panel unit root tests with an application to the mean reversion in real exchange rates. J Appl Econ 19(2):147–170.
Stern, D. I. (2004) The Rise and Fall of the Environmental Kuznets Curve. World Development, 32(8), 1419–1439.

Sui DZ, Rejeski DW (2002) Environmental Impacts of the Emerging Digital Economy: The E-For-Environment E Commerce? Environ Manage 29:155–163.
Toffel MW, Horvath A (2004) Environmental Implications of Wireless Technologies: News Delivery and Business Meetings. Environ Sci Technol 38:2961-2970.
Westerlund J (2008) Panel cointegration tests of the fisher effect. Journal of Applied Econometrics 23:193–233.
Zadek S, Forstater M, Yu K, Kornik J (2010) The ICT Contribution to Low Carbon Development in China. Prepared For The Digital Energy Solutions Campaign (DESC) China. Discussion Paper
Zhang C, Liu C (2015) The impact of ICT industry on CO2 emissions: A regional analysis in China. Renew Sust Energ Rev 44: 12–19.