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Do information and communication technology and renewable energy use matter for carbon dioxide emissions reduction? Evidence from the Middle East and North Africa region

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ABSTRACT

This study aims to investigate whether information and communication technologies (ICT) and renewable energy consumption can help improve environmental quality for a selected group of the Middle East and North Africa (MENA) region. By using the Panel Vector Autoregressive model over the period 1980–2019, the results show evidence for the first-order effects of ICTs on CO_2 emissions, indicating that the use of ICT in the current economic development context of the MENA region lead to a deterioration of the environmental quality.

The results also show that renewable energy consumption improves environmental quality whatever the sample and the proxy for ICT used. Overall, the results of the impulse responses functions (IRFs) show that the impact of shocks on ICT and renewable energy last between 1 and 7 years. The results of the IRFs are confirmed by the forecast error variance decomposition analysis, which shows that the contributions of ICT and renewable energy to the variability of CO_2 emissions is not zero. Finally, in tests for causality, the results reveal evidence for bidirectional causality in most cases between CO_2 emissions and ICT and renewable energy consumption. To benefit from the potential positive impact of ICT and renewable energy consumption on the quality of the environment, several ICT and renewable energy policies have been developed and discussed.

1. Introduction

Defining and designing suitable energy, economic and environmental policies that can curb the worldwide increase in carbon dioxide (CO_2) emissions continue to be the top agenda of all international, governmental, and non-governmental environmental institutions. The focus on this issue mainly emerges from the adverse effects of CO_2 emissions on human well-being and health, and the preservation of the environment for future generations (Andor et al., 2018; Brown et al., 2017; Lu et al., 2018; Zeng et al., 2017, 2021). However, designing appropriate environmental strategies that can curb CO_2 emissions requires a comprehensive and sound understanding of their causes (Mavromatidis et al., 2016; Ravindra et al., 2019; Sun et al., 2018; Xu et al., 2018; Pandey et al., 2020). According to several studies and environmental experts, if no action is taken to reduce and mitigate the impact of greenhouse gas (GHG) emissions and ensure that the average global temperature does not exceed the pre-industrial level by more than 2 °C, then human life on earth will completely change (Intergovernmental Panel on Climate Change (IPCC), 2007; Lu et al., 2018). A simple illustration is the intensification of extreme weather events and natural disasters such as super-droughts, wildfires, and influential hurricanes over the last few years, both in number and frequency. These natural catastrophes have compelled governments to take real action toward improving environmental quality by reducing CO_2 emissions to avoid a global disaster. In an attempt to curb the increase in CO_2 emissions over the last few decades, several actions and policies aimed at emissions reduction have been proposed by various international institutions (World Bank, 2013; IPCC (Intergovernmental Panel on Climate Change) et al., 2007).

During the last few years, significant policies advocated and recommended to curb GHG and CO_2 emissions have been mostly related to improving energy efficiency, conserving energy, and designing energy strategies. These policies were mainly motivated by the high levels of CO_2 emissions from intense non-renewable energy sources, as well as the

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high share of non-renewable energy in the total energy mix. For instance, non-renewable energy sources represent more than 80% of the total global energy consumption. In particular, two important policies have been largely discussed because of their higher potential to curb the increase in CO_2 emissions: (1) the promotion of renewable energy, and (2) the expansion of information and communication technology (ICT) use.

In the last few decades, renewable energy sources have emerged as an alternative to traditional sources of energy with the added advantage of not only improving the environmental quality but also engendering several other positive economic effects (Charfeddine and Kahia, 2019). One of the important reasons for the expansion of green energy sources is the rapid decrease in their generation cost during the last few years (Capellán-Pérez et al., 2018; Wurster and Hagemann, 2018). Another significant reason is that the promotion of the use of renewable energy has been emphasized and strongly recommended in the 2016 Paris Agreement (COP21; the 21st Conference of the Parties). Several countries around the world have ratified the COP21 agreement with the governments being urged to switch to using new types of energy that are clean, green, and environmentally friendly.[1] Scholars increasingly agree that renewable energy use is negatively associated with CO_2 emissions and that renewable energy can significantly help in improving the environment (Bhattacharya et al., 2017; Zoundi, 2017; Charfeddine and Kahia, 2019; Cheng et al., 2019; Ren et al., 2021).

The second policy is related to the diffusion and development of ICT because of its potential positive impact on the quality of the environment (Zhang and Liu, 2015; Mavromatidis et al., 2016). In the ICT–environment literature, several studies have demonstrated that ICT can significantly reduce CO_2 emissions (e.g., Zhang and Liu, 2015; Asongu et al., 2018; Amri, 2018; Park et al., 2018; Danish et al., 2018; Cheng et al., 2021). For instance, the positive impact on environmental quality can be achieved through dematerialization and digitization, online delivery, intelligent transport systems, transport and travel substitution, smart buildings, and smart grids (Danish et al., 2018; Shabani and Shahnazi, 2019).

Despite the theoretical consensus among scholars, policymakers, and environmental experts on the potential positive impact of ICT use and renewable energy consumption in improving environmental quality (reducing CO_2 emissions), the negative or insignificant impacts cannot be ignored. For instance, several studies have found that renewable energy consumption is insignificant in determining CO_2 emissions (Qi et al., 2014). Furthermore, the ICT literature illustrates that the direct effect, where ICT is positively related to CO_2 emissions, cannot be excluded (Danish et al., 2018). Another important gap in the environmental literature is that only a few studies, to the best of our knowledge, have investigated the simultaneous impact of ICT and renewable energy consumption on environmental degradation in countries in the Middle East and North Africa (MENA). In this study, we attempt to fill the abovementioned gaps by investigating whether ICT and renewable energy consumption can help improve the quality of the environment.

Several reasons motivate us to focus on the MENA region. According to various studies and statistical reports, the environmental situation in MENA has worsened rapidly in the last few decades (OECD, 2013; World Bank, 2016; Kahia et al., 2016, 2017). For instance, statistics show that air pollution and CO_2 emissions are the main contributors to the environmental degradation of the region rather than other types of pollution, such as water or land pollution (Caravaggio et al., 2019; Li et al., 2017). In addition, between 1970 and 2019, MENA registered the second highest average growth (exceeding 500%) in the world in CO_2 emissions, thereby resulting in the region's share in global CO_2 emissions more than trebling during this period. Most previous studies concur that the availability of non-renewable energy at low cost has facilitated the adoption and use of large-scale high-energy equipment and production processes, which, in turn, have increased CO_2 emissions and the carbon footprint of the region more than other regions of the world. According to several international institutions, energy production and consumption are the main sources of CO_2 emissions in MENA. For example, the energy sector (production and consumption) accounts for more than 80% of the MENA region's CO_2 emissions (World Bank, 2017).

Compared with earlier studies, the novelty of this work is threefold. First, to the best of the authors' knowledge, we are among the first to examine the impact of renewable energy consumption on CO_2 emissions for a set of two groups of MENA regions selected based on the share of renewable energy in their total energy mix with the latest data spanning from 1997 to 2019. The examination of the MENA region as a study case is particularly captivating because most of the MENA countries are extremely energy intensive and have considerable potential for the production of renewable energy sources (such as wind and solar). Second, we contribute to environment literature, by exploring which of the three – orders that govern the ICT – environmental degradation nexus holds for the case of the MENA region and whether the impact of ICTs on CO_2 emissions differs significantly between countries with higher share of green energy compared to countries with lower share. Third, we employ the recently developed panel vector autoregressive (PVAR) model, which not only allows us to investigate the effects of ICT use and clean energy on CO_2 emissions in a multivariate panel context but also enables an examination of the impulse response reaction of CO_2 emissions caused by a one standard error shock affecting all the explanatory variables separately. The PVAR model also enables us to assess the contribution of each variable of the system to our variable of interest (CO_2 emissions) and investigate the direction of causality between variables considered as the main outcomes for policy recommendations.

The remainder of this paper proceeds as follows. In Section 2, we undertake an exhaustive review of the theories related to ICT–CO_2 emissions and renewable energy consumption–CO_2 emissions nexus. Section 3 presents the materials and the econometric methods used. In Section 4, we discuss the empirical results while in Section 5, we propose policies designed to improve environmental quality in MENA countries. Finally, Section 6 concludes the paper.

2. Literature review

In this section, we present a review of the literature on two important environmental nexuses, ICT–CO_2 emissions and renewable energy–CO_2 emissions. Our focus on these two nexuses is mainly motivated by the scarcity of theoretical research exploring the impact of ICT and renewable energy consumption on the level of environmental degradation, proxied by CO_2 emissions. In particular, we focus on discussing the different channels through which ICT and renewable energy consumption impact CO_2 emissions. Besides, we highlight the different types of relationships that may exist among ICT, renewable energy consumption, and CO_2 emissions.

2.1. Review of the ICT–CO_2 emissions nexus

The ICT–CO_2 emissions nexus is complex and multifaceted. ICT's potential to reduce CO_2 emissions by improving energy efficiency and energy conservation is very high (Takase and Murota, 2004; Ozcan and Apergis, 2017). The potential benefits also include decoupling the usual

[1] Despite a global concern about the degradation of the quality of the environment and the sustainability of economic development, which provide further impetus for renewable energy, several other reasons explain the development of renewable energy. These include: (1) the high fluctuation in oil prices since the mid-1980s, which have led to the search for new types of energy sources that can avoid the negative impact of oil price increases on economic growth (Baumeister and Hamilton, 2017); (2) the availability of financial resources (petrodollars), which has facilitated the funding of renewable energy research, leading to the flourishing of this field during periods of high oil prices; (3) energy supply security; (4) improving energy access; (5) employment opportunities; and (6) other spillover effects.

positive economic growth–environmental degradation nexus (Salahuddin et al., 2016).

For instance, ICT is well established as a key determinant of the knowledge-based economy, which may affect CO_2 emissions in different ways. Theoretically, three important relationships summarize the ICT–CO_2 emissions nexus: (1) the first-order effects of ICTs on CO_2 emissions, (2) the second-order effects, and (3) the third-order effects, which are known as rebound effects. All these relationships are detailed in the next three subsections.

2.1.1. First-order effects (positive effect on environmental degradation)

The first-order effects refer to all the environmental impacts related to the lifecycle of ICT products (Higón et al., 2017; Asongu et al., 2018; Danish et al., 2018). These effects are also known as "primary" effects or "direct" effects related to the physical existence and/or creation of ICT products. In other words, these environmental effects correspond to the impacts related to the production, use, recycling, and e-waste of ICT equipment. Based on these first-order effects, the quality of the environment will continue to deteriorate with the increase in energy use during the lifecycle of ICT products. Moreover, the increase in waste originating from ICT products will also lead to an increase in CO_2 emissions.

In a methodological analysis for assessing the impact of ICT on global GHG footprint, Belkhir and Elmeligi (2018) projected that the contribution of ICT to GHG emissions will roughly double from 1 to 1.6% in 2007 to 3–3.6% by 2020 and that smartphones would account for approximately 11% of the total ICT footprint by 2020, which exceeds those of desktops (6%), displays (7%), and laptops (7%).

Several empirical studies have demonstrated that ICT increases the level of air pollution and GHG emissions through equipment production and use (Røpke et al., 2010; Willum, 2008). In a recent study, Salahuddin et al. (2016) investigated the effects of ICT (proxied by Internet usage) per capita real gross domestic product (GDP), financial development, and trade openness on CO_2 emissions in the OECD context over the 1991–2012 period. Their results indicated that Internet usage significantly reduced CO_2 emissions in the long term. However, the authors found that the neutrality hypothesis between Internet usage and CO_2 emissions could not be rejected at conventional levels of significance. Consequently, they concluded that ICT is still not an environmental threat to the OECD region. In the Asian region, Lee and Brahmasrene (2014) investigated the impact of Internet use on CO_2 emissions during the 1991–2009 period and found evidence that Internet use positively impacts CO_2 emissions. In a more recent study, Park et al. (2018) found results similar to those of Lee and Brahmasrene (2014) when investigating the case of selected European Union nations using the pooled mean group method over the 2001–2014 period. In emerging economies, by using interaction terms between ICT, real GDP, and CO_2 emissions, Danish et al. (2018) illustrated that Internet and mobile phone subscriptions threaten the quality of the environment.

2.1.2. Second-order effects (negative effect on environmental degradation)

The second-order effects correspond to "indirect" or "secondary" effects of ICT use on environmental quality (Ozcan and Apergis, 2017; Lu, 2018; Asongu et al., 2018). These ICT effects contribute positively to the environmental quality by improving energy efficiency as they induce a reduction in CO_2 emissions and other types of pollutants (Coroama et al., 2012). These effects are mainly attributed to the positive impacts of using ICT applications, such as intelligent transport systems, smart grids, and smart buildings.

Recent studies have emphasized the importance of ICT in improving environmental quality by making energy use more efficient and conservative (European Commission, 2008; Laitner and Ehrhardt-Martinez, 2008; Malmodin and Bergmark, 2015). Empirically, the positive effects of ICT on environmental quality have been demonstrated in many studies (Ollo-López and Aramendía-Muneta, 2012; Salahuddin et al., 2016). For instance, Ollo-López and Aramendía-Muneta (2012) investigated the impact of ICT on competitiveness, innovation, and environmental quality in 2009 for Germany, Spain, France, Italy, the United Kingdom, and Poland. Using a multivariate analysis technique, they found that the use of ICT improves energy efficiency in both consumption and production, and consequently, reduces GHG emissions. Zhang and Liu (2015) estimated the stochastic impacts by regression on population, affluence, and technology (STIRPAT) model on provincial panel data and found that the ICT industry reduced CO_2 emissions in China. In addition, the impact of the ICT industry on CO_2 emissions in the central region was higher than that in the eastern region and insignificant in the western region.

In another study, Moyer and Hughes (2012) found that advanced ICT can potentially reduce CO_2 emissions; however, rebound effects may occur because of deflation. Asongu et al. (2018) examined the impact of ICT on environmental sustainability in a group of 44 sub-Saharan African countries from 2000 to 2012. By using a generalized method of moments (GMM) model, the authors found that although ICT had an insignificant impact on CO_2 emissions, increasing the use of ICT decreased the level of CO_2 emissions from liquefied fuel consumption, after allowing for interaction among variable. Rivera et al. (2014) investigated the second-order effects in an environmental assessment of ICT using a methodical approach and ethnographic methods. Their empirical findings confirmed that second-order effects can both increase and decrease environmental quality. Finally, by employing a panel data approach, Higón et al. (2017) found evidence of a negative relationship between ICT and CO_2 emissions. Furthermore, the authors encouraged and supported developing countries entering the global ICT market, as they demonstrated that the Environmental Kuznets Curve (EKC) hypothesis holds between ICT and CO_2 emissions.

2.1.3. Third-order effects (rebound effects)

The third type of ICT effect on environmental degradation is the third-order effect, known as the *Jevons paradox* or *rebound effects* (Hilty et al., 2011; Turner, 2013; Hakansson and Finnveden, 2015). According to several studies, these rebound effects can occur when the gains from energy efficiency resulting from the use of ICT are lower than the losses caused by the increase in demand (Plepys, 2002; Hakansson and Finnveden, 2015). In other words, this means that the original positive effects of ICT on the environment are counterbalanced or even surpassed by the negative effects.

The literature on rebound effects has not yet concluded their different typologies (Sorrell and Dimitropoulos, 2008; Druckman et al., 2011; Turner, 2013). However, the literature distinguishes among three important types of rebound effects: direct, indirect, and economy-wide rebound effects (Broberg et al., 2014). The direct rebound effect suggests that the price (cost) decrease resulting from energy efficiency increases the usage demand of ICT goods, which leads to an increase in energy consumption (Hilty and Aebischer, 2015). The indirect rebound effect usually unfolds when the efficiency of a resource leads to a fall in its price, which consequently promotes the consumption of other goods. Finally, economy-wide rebound effects are related to changes in consumption habits (Gossart, 2015). In other words, the decline in energy prices caused by ICT results in a reduction in the price of intermediate and final goods, which in turn lead to changed consumption habits.

Empirically, Houghton (2009) investigated the opportunities offered by ICT and its potentially positive environmental impact in developing countries. The author found that ICT has played a key role in rendering services tradeable and that the globalization of ICT and ICT-enabled services can have a direct, indirect, or rebound effect. In a similar context, Røpke and Christensen (2012) investigated the energy impacts of ICT from a daily life perspective and found that the first-order effect cannot be achieved using an increasing number of devices. The authors highlight that the second- and third-order effects of ICTs have the highest potential to reduce energy intensity by, for example, reducing transportation and dematerializing various practices.

2.2. Review of the renewable energy – CO_2 emissions nexus

Renewable energy resources have emerged in the last few decades as a new type of energy source that can create several opportunities for oil-importing and oil-exporting countries (Charfeddine and Kahia, 2019; Dogan et al., 2021). The possibility of improving energy security and global environmental quality can be considered as the main advantages of promoting and investing in renewable energy. Moreover, the benefits of investing in renewable energy resources are expected to exceed the abovementioned direct impacts, including spillover effects on economic activity (Kahia et al., 2016, 2017), such as the effects on job creation, foreign currency outflow, and exposure to international fluctuations in oil prices. For oil-exporting countries, promoting and investing in renewable energy sources improves their economic diversification as well as their energy mix portfolio (Bhutto et al., 2014; Kahia et al., 2016; Atalay et al., 2016; Al-Maamary et al., 2017; Altinoz and Dogan, 2021).

Several empirical studies have explored the potential role of renewable energy in mitigating environmental degradation (e.g., Saidur et al., 2011; Bhattacharya et al., 2017; Charfeddine and Kahia, 2019; Cheng et al., 2019; Ren et al., 2021). Evidence on the positive impact of renewable energy use in reducing CO_2 emissions has been found in several studies (Zoundi, 2017). For instance, Bhattacharya et al. (2017) used the GMM system and the fully modified ordinary least squares for a panel of 85 heterogeneous countries over the 1991–2012 period and found that renewable energy consumption improved environmental quality by reducing CO_2 emissions. Zoundi (2017) considered some robust tests for panel cointegration to check the validity of the EKC hypothesis and the existence of short- and long-run impacts of renewable energy use on CO_2 emissions for a panel of 25 African countries over a period of 23 years, from 1980 to 2012. The author found that renewable energy use was an efficient way to reduce CO_2 emissions and that renewable energy sources can play an important role as an efficient substitute for non-renewable energy sources.

3. Materials and methods

3.1. Data and preliminary analysis

3.1.1. Data sources and description of variables

The dataset used in this study were sourced from the World Bank (2021), United Nations Statistics Division (United Nations Statistics Division, 2021) and the U.S. Energy Information Administration (2021)[2] for all 12 MENA countries.[3] The data on CO_2 emissions, real GDP, renewable energy consumption, trade openness, Internet usage, mobile phone subscription, and foreign direct investment (FDI) cover the period from 1997 to 2019. A detailed description of the variables, their measures, the expected signs of all the coefficients associated with the explanatory variables, and their economic explanations are reported in Table 1.

The natural logarithm is applied to all the variables in the study to facilitate the interpretation of results and overcome the problem of heteroscedasticity and secure normality (Charfeddine and Khediri, 2016; Charfeddine, 2017).

3.1.2. Descriptive statistics

The descriptive statistics, mean value, standard deviation, and coefficient of variation of all the variables are reported in Table 2. The results indicate that Israel has the highest mean GDP per capita (2480.454 US$), CO_2 emissions in metric tons per capita (8.755 mt), mobile phone subscriptions per 100 people (107.2), and Internet users per 100 people (48.794). Mauritania and Iraq have the highest levels of FDI (8.303) and trade (96.271), respectively. Mauritania has the lowest mean GDP per capita (1237.981) and CO_2 emissions per capita (0.588), while Syria has the lowest mean mobile phone subscriptions per 100 people (41.314) and Internet users per 100 people (15.359). Algeria has the lowest mean renewable energy consumption (0.331), Iraq the lowest mean FDI (0.348), and Egypt the lowest mean trade.

The variability and coefficient of variation exhibit no clear patterns. However, for some variables, the results seem to depend on the geopolitical situation of countries such as Iran, Iraq, Israel, Lebanon, and Syria.

The next three subsections provide a detailed analysis of the evolution of the main variables of interest (CO_2 emissions per capita, mobile phone subscriptions, Internet users, and renewable energy consumption).

3.1.3. CO_2 emissions in the MENA region

Fig. 1 depicts the evolution of CO_2 emissions per capita in the sample of the 12 MENA countries, along with the world average. In our sample of the MENA region, most countries with high CO_2 emissions per capita are not selected because of the zero shares of renewable energy in their total energy mix. These countries include mainly the six Gulf Cooperation Council (GCC) countries, which are usually ranked among the top 10 most polluted countries in terms of CO_2 emissions per capita.

Fig. 1 illustrates that three countries at the beginning of our sample period and four countries at the end of the sample period show values of CO_2 emissions per capita exceeding the world average. Further, two countries, Iran and Israel, always display greater per capita emissions than the world average. The remaining countries show a small positive trend over the period of analysis. We also find that the year 2015 was characterized by a strong positive shock, where the level of CO_2 emissions per capita decreased in all countries except Israel.

3.1.4. ICT in the MENA region

In this subsection, we analyze the evolution of the two ICT measures in MENA. Constrained by data availability, we use only cellular (mobile) phone subscriptions and the Internet usage measures in this study.[4]

i. Mobile phone subscriptions

Fig. 2 depicts the trend in the number of mobile phone subscriptions per 100 people for the 12 MENA countries from 1997 to 2019.[5] Three important periods characterize the evolution of mobile phone subscriptions. During the first period, between 1997 and 2003, only Israel (104.23) and Turkey (42.2) had high levels of registered mobile phone subscriptions per 100 people. For the remaining MENA countries, the number of subscriptions varied between 0.3 and 24.66 per 100 people. The second period, between 2004 and 2009, was characterized by a rapid improvement in the number of mobile phone subscriptions in all the countries. For instance, by 2009, the minimum number of mobile phone subscriptions was found in Syria (48) and the maximum in Israel (124). Finally, between 2010 and 2019, almost all the MENA countries recorded an increasing trend except for Jordan and Lebanon since 2015. During this period, Lebanon (62.8) and Iran (142.4) had the minimum and maximum average number of mobile phone subscriptions per 100 people, respectively. Moreover, the data show that 6 out of the 12 MENA countries reported values of mobile phone subscriptions greater than 100%.

ii. Internet users per 100 people

[2] Only the renewable energy data have been collected from EIA (2021) and World Bank (2021).

[3] The 12 MENA countries include: Algeria, Egypt, Iran, Iraq, Israel, Jordan, Lebanon, Morocco, Mauritania, Syria, Tunisia, and Turkey.

[4] Some of the ICT proxies used in developed countries, such as the amount of investment in ICT, are not available for emerging and developing countries.

[5] Before 1997, due to the delay in the diffusion of mobile phones in developing and emerging countries.

Table 1
Variable description, measures, expected sign and economic explanation.

Variable	Symbol	measure	Expected sign	Economic explanation	Data source
CO_2 emissions per capita	CO_2	In metric tons, mt	NA	Dependent variable	WDI (2021)/ UNdata (2021)
Real GDP per capita	RGDP	In constant 2010US$	+	+	WDI (2021)
Renewable energy consumption	REC	% of total energy mix.	–	Expected to have a negative effect on CO_2 emissions since increasing the share of renewable energy in the total mix is expected to emit less CO_2.	U.S. EIA(2021)/ WDI(2021)
Trade openness	TR	Total real export and total imports as share of GDP	+/−	Expected to be a contributor to emissions since international trade boosts embodied emissions	WDI (2021)
Foreign direct investment	FDI	FDI inflow	+/−	Positive if Foreign direct investment causes CO2 emissions, negative otherwise.	WDI (2021)
Mobile cellular subscription	MB	Number of mobile cellular subscription as percentage of 100 people	+/−	Positive if direct if the effects of energy efficiency gained from the use of ICTs exceed its direct and rebound effects, negative otherwise.	WDI (2021)
Internet users	INT	Number of internet use as percentage of 100 people	+/−	Positive if direct if the effects of energy efficiency gained from the use of ICTs exceed its direct and rebound effects, negative otherwise.	WDI (2021)

Table 2
Descriptive statistics.

		INT per 100 people	MB per 100 people	REC (% of Total energy)	CO_2 emission per capita	TR (in % GDP)	FDI (in % of GDP)	GDP per capita (constant U.S dollar)
Algeria	Mean	17.368	62.726	0.331	3.258	39.902	1.056	3422.280
	Std. Dev	19.379	48.166	0.157	0.384	12.995	0.543	920.204
	CV	1.115	0.767	0.473	0.117	0.325	0.514	0.268
Egypt	Mean	20.272	53.684	6.256	2.188	29.560	2.703	1738.308
	Std. Dev	17.206	45.394	1.448	0.323	8.892	2.553	716.855
	CV	0.849	0.846	0.231	0.148	0.301	0.944	0.412
Iran	Mean	21.899	51.118	0.976	7.000	32.411	0.843	3803.692
	Std. Dev	23.386	45.193	0.375	1.451	13.254	0.719	1755.088
	CV	1.068	0.884	0.384	0.207	0.409	0.853	0.461
Iraq	Mean	11.794	48.245	1.330	3.991	96.271	0.348	4509.454
	Std. Dev	19.390	41.587	1.063	0.942	26.445	1.505	866.870
	CV	1.644	0.862	0.799	0.236	0.275	4.322	0.192
Israel	Mean	48.245	107.200	5.819	8.755	67.703	3.706	24802.764
	Std. Dev	28.615	30.637	1.975	0.731	8.251	2.017	6226.958
	CV	0.593	0.286	0.339	0.083	0.122	0.544	0.251
Jordan	Mean	27.965	67.412	2.633	3.049	72.412	0.843	3280.965
	Std. Dev	23.657	45.263	0.765	0.328	18.760	0.719	339.573
	CV	0.846	0.671	0.291	0.107	0.259	0.853	0.103
Lebanon	Mean	36.074	45.175	4.924	4.421	51.994	7.043	6126.682
	Std. Dev	30.728	24.427	1.920	0.507	21.594	4.998	835.653
	CV	0.852	0.541	0.390	0.115	0.415	0.709	0.136
Mauritania	Mean	5.874	52.464	36.053	0.588	95.050	8.303	1237.981
	Std. Dev	7.646	41.427	6.824	0.146	19.133	10.191	255.794
	CV	1.301	0.789	0.189	0.249	0.201	1.227	0.206
Morocco	Mean	31.874	69.975	14.441	1.529	71.644	2.079	2644.950
	Std. Dev	26.226	49.557	3.900	0.274	12.443	1.379	513.339
	CV	0.823	0.708	0.270	0.179	0.174	0.663	0.194
Syria	Mean	15.359	41.314	1.777	2.577	67.649	0.937	1556.771
	Std. Dev	13.082	36.238	0.548	0.648	5.462	0.641	333.926
	CV	0.852	0.877	0.308	0.251	0.081	0.684	0.214
Tunisia	Mean	27.343	72.398	14.030	2.294	95.301	2.870	3723.765
	Std. Dev	22.773	51.980	0.767	0.266	11.239	1.765	584.197
	CV	0.833	0.718	0.055	0.116	0.118	0.615	0.157
Turkey	Mean	31.779	67.264	15.381	3.929	49.267	1.435	10894.520
	Std. Dev	23.769	33.175	2.983	0.697	6.005	0.902	2585.836
	CV	0.748	0.493	0.194	0.177	0.122	0.628	0.237

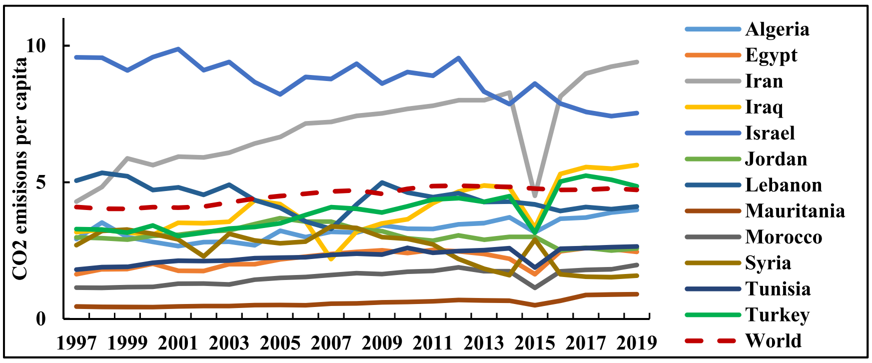

Fig. 1. CO_2 emissions per capita in the MENA selected countries.
Source: Authors' calculation

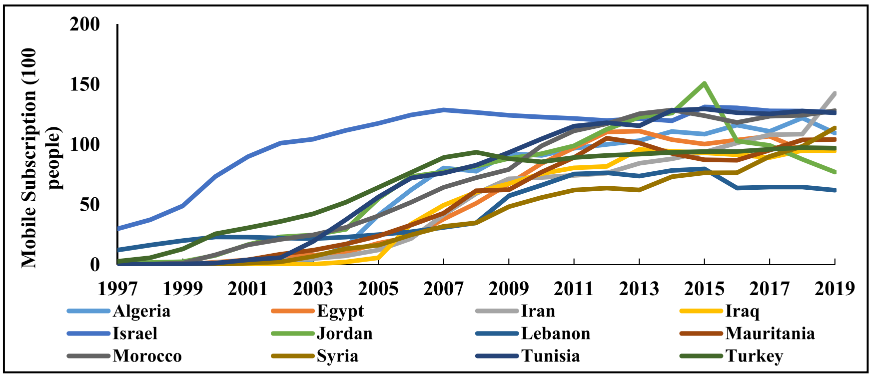

Fig. 2. Evolution of the number of cellular mobile phone subscriptions by 100 people for the 12 MENA countries.
Source: Authors' calculation

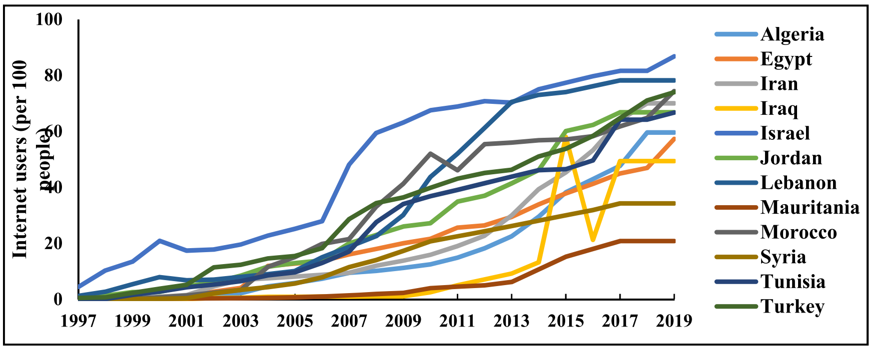

Fig. 3. Number of internet users by 100 people for all the 12 selected MENA countries.
Source: Authors' calculation

The second proxy for ICT used in this study is the number of Internet users. The evolution of this proxy over the 1997–2019 period for MENA is illustrated in Fig. 3. Although the overall trend in the number of Internet users is similar to that of the mobile phone subscription proxy, the two ICT proxies have some important differences. Firstly, for mobile phone subscriptions during the first period, the number of Internet users did not exceed 20 persons per 100 people. This can be attributed mainly to the very low number of computers connected to the Internet globally. As an illustration, only 3.6 million computers in 1996 were connected to the Internet worldwide, most of which were in developed countries. Secondly, Fig. 2 shows that the number of Internet users has steadily increased since 2005, except for Iraq between 2015 and 2016. Finally, we find that Syria and Israel have the lowest and highest number of Internet users, respectively, over the entire analysis period.

3.1.5. *Renewable energy consumption in the MENA region*

The trend in the share of total renewable energy consumption in the total energy mix from 1997 to 2019 is depicted in Fig. 4.

Based on Fig. 4, the 12 MENA countries can be divided into two main groups. The first group is characterized by a high share of renewable energy consumption (on average, above 10%). This group includes four countries: Mauritania, Morocco, Tunisia, and Turkey, with Mauritania having the highest share of renewable energy consumption over the entire period of analysis. For the remaining MENA countries, the share

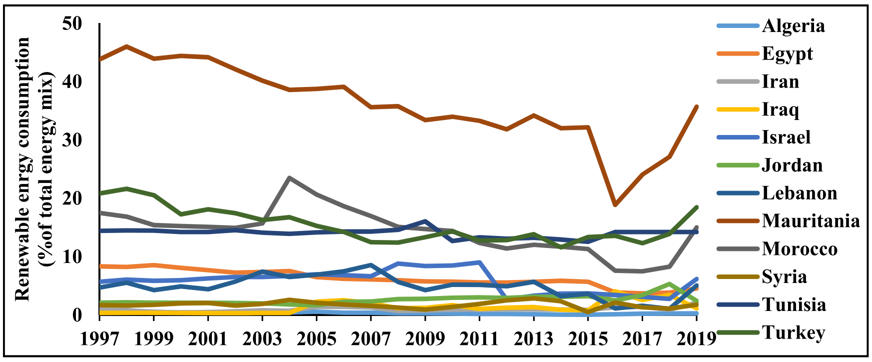

Fig. 4. Evolution of renewable energy share on the total energy mix for the 12 selected countries.
Source: Authors' calculation

was low, and on average, did not exceed 5%. For the latter group, the data show evidence of improvement in the share of renewable energy over the end of our analysis period. For example, by the end of 2015, all the countries except Algeria and Iraq, both of which are oil and gas producing countries, had a share that exceeded 2%.

3.2. Model specification

In this study, as a starting point to analyze the relationship between environmental degradation, ICT, renewable energy consumption, and macroeconomic variables, we use the STIRPAT model of Dietz and Rosa (1997) to formulate our model and select the key variables.

The STIRPAT model is a reformulation of the influence, population, affluence, and technology (IPAT) mathematical identity developed by Ehrlich and Holdren (1971), given by $I = P \times A \times T$. By developing the STIRPAT model, Dietz and Rosa (1997) attempted to overcome the two important shortcomings of the IPAT model. First, Dietz and Rosa (1997) added a stochastic disturbance term to allow for the possible estimation and testing of hypotheses. Second, in contrast to the IPAT model, which assumes rigid proportionality between the P, A, and T variables and the I variables, the STIRPAT formulation allows for more flexibility in the relationship between variables.

The STIRPAT model proposed by Dietz and Rosa (1997) is given by:

$$I_{it} = a\, P_{it}^{b} \times A_{it}^{c} \times T_{it}^{d} \times u_{it} \tag{1}$$

In this specification, the subscript i $(i = 1, \ldots, N)$ denotes the countries, and the subscript t $(t = 1, \ldots, T)$ represents the time period. The terms a and u_{it} are the country-specific effects and error disturbances, respectively. By taking the natural logarithm of the previous equation, we can write the model as:

$$\log I_{it} = \beta_0 + \beta_1 \ \log P_{it} + \beta_2 \ \log A_{it} + \beta_3 \ \log T_{it} + \varepsilon_{it} \tag{2}$$

In this model, β_0 represents the country-specific coefficients, and β_1, β_2, and β_3 are the coefficients to be estimated. ε_{it} is the new error term assumed to be independent and identically distributed. In our analysis, variable I refers to the CO_2 emissions per capita variable, A is the real GDP per capita variable, and T is the ICT variable. In our analysis, we ignore the P variable as its proxy (urbanization) was not found to be significant.

However, to allow for more flexibility in the analysis, we revise equation (2) to include additional explanatory variables (renewable energy and trade variables). We also extend model 2 to the multivariate case and assume that it follows a PVAR model (Abrigo and Love, 2015), which takes the following form:

$$Y_{it} = A_0 + \sum_{J=1}^{p} Y_{it-j} A_j + X_{it} B + u_i + \lambda_t + e_{it} \tag{3}$$

$$i \in \{1, 2, \ldots, N\}, t \in \{1, 2, \ldots, T\}$$

where $Y_{it} = (CO_{2it},\ GDP_{it},\ REC_{it},\ TR_{it}, ICT_{it})$ is the vector of the endogenous variables. X_{it} is the vector of exogenous variables, which, in our case, includes the FDI variable FDI_{it}. Matrices A_0, A_j, and B include the parameter matrices to be estimated. The specific panel fixed effects, time fixed effects, and idiosyncratic errors are denoted by u_i, λ_t, and e_{it}, respectively.

Several reasons motivate us to use the PVAR model in this study, including: (1) the possibility of assessing the reaction of our main variable, CO_2 emissions, to a one standard deviation shock on all the explanatory variables, particularly our two variables of interest, ICT and renewable energy consumption; (2) the PVAR model allows the assessment of the contribution of all the variables of the system to the variability in CO_2 emissions by using forecast error variance decomposition (FEVD); and (3) the PVAR model allows the analysis of the causality direction between all the models under the study framework.

Technically, the PVAR model has some interesting advantages over other econometric models used in the energy and environment literature. The most important advantage is its ability to mix different econometric characteristics as it links features of the traditional panel model with those of the vector autoregressive model. Another important benefit of the PVAR methodology is that it allows unobserved individual heterogeneity in a multivariate context as it assumes fixed effects (Abrigo and Love, 2015).

The estimation process of the PVAR model is summarized in the following three main steps. The first step corresponds to the pre-estimation step, where we verify the stationarity of all the variables included in the model and determine the optimal lag of the PVAR order.[6] The second step corresponds to the estimation step, where the PVAR model with the appropriate optimal lag is estimated, and the stability condition of the estimated PVAR model is checked. Finally, the last step corresponds to the post-estimation step, where the impulse response functions (IRFs), the FEVD, and the causal direction results are calculated.

4. Results and discussion

4.1. Pre-PVAR estimation model analysis

4.1.1. Panel unit root tests results

An important step before estimating the PVAR model is the examination of the order of integration of all the variables under

[6] We use the usual information criteria including the Bayesian, Akaike, and Hannan–Quinn information criteria to select the optimal order of the PVAR model.

consideration. The stationarity of all the series is an important precondition for using the PVAR model. In this study, various panel unit root tests were conducted to investigate the statistical property of stationarity. Specifically, we propose the use of both first- and second generation panel unit root tests. The main difference between these two panel unit root test generations is that the former assumes independence in cross-sections, whereas the latter assumes dependence across sections.

In this study, two first-generation tests were used, namely those employed by Levin et al. (2002) and Im et al. (2003). For the second generation, we propose the use of the cross-sectionally augmented IPS (CIPS) test, which is the average of the cross-sectional augmented Dickey-Fuller test (see Pesaran, 2007). All three tests have the unit root assumption under the null hypothesis and the stationarity assumption under the alternative hypothesis (see Pesaran, 2007 for the tabulated critical values).

Table 3 reports the calculated values of the three-panel unit root tests used in our study. We report the results of the variables in levels and first differences. Overall, we found that all variables were first-order integrated. Consequently, in the PVAR estimation, all variables are introduced in their first differences.

4.1.2. Optimal lag selection

The results of computing all the tests and information criteria for different lags up to $k = 2$ are reported in Table 4. The results demonstrate clear evidence that the optimal lag is obtained when $k = 1$, which corresponds to the lowest values obtained for all the tests and criteria. Therefore, in the rest of our analysis, we consider the optimal lag to be $k^* = 1$.

4.2. PVAR estimation results

The estimation results of the PVAR model with this optimal lag, $k^* = 1$, for the two groups of countries (all and selected MENA countries), are reported in Tables 5 and 6, respectively. However, before starting the analysis and interpreting the PVAR results, checking and validating the hypothesis of stability in the estimated models is important. Similar to the standard vector autoregressive model context, the modulus of each eigenvalue is computed to check the stability of the PVAR model. The results depicted in Figures A1 and A2, as well as in Table A1 in the supplementary document, illustrate that the PVAR estimates satisfy the condition of model stability since all the roots lie inside the unit root circle (Lütkepohl, 2005).

We focus our analysis on the CO_2 emissions equation, which will enable us to assess the impact of both ICT and renewable energy consumption. Therefore, we divide this section into two subsections, covering the impact of (1) ICT (mobile phone subscriptions and Internet users) and (2) renewable energy, respectively, on CO_2 emissions. Note that the results will be discussed based on two groups (the whole sample and a group of selected countries with a high share of renewable energy consumption, referred to as the group of eight).

4.2.1. Impact of ICT on CO_2 emissions

The estimation results of the CO_2 emissions equation when the variable mobile phone subscriptions are used as a proxy for ICT are reported in Tables 5 and 6 for the groups of 12 and 8 countries, respectively. For the group of 12 countries, column 6 of Table 5 shows that all the coefficients associated with the first lag of Internet users, renewable energy, trade, economic growth, and CO_2 emission variables are significant at the 1% level of significance (p-value$>$ 0.01), except for renewable energy and FDI variables at the 5% level. The results for the group of 8 countries for the CO_2 emissions equation reported in column 6 of Table 6 are similar in terms of sign to those of the group of 12 countries. The only exception is the FDI coefficient, which has a negative sign in the case of the group of eight. In terms of significance, the results show that all the coefficients are highly significant at the 1% level of significance, except GDP, which is only significant at the 5% level.

Economically, the sign of the coefficient associated with our variable of interest, $D(INT_{t-1})$, is positive and highly significant in the two groups of countries, indicating that ICT, proxied by Internet users per 100 people, degrades the environmental quality as it increases the level of CO_2 emissions. These results are valid regardless of the sample used (12 or 8 countries). In terms of magnitude, we find that the Internet users proxy lowers the environmental quality more in the group of 8 than in the group of 12, with coefficients equal to 0.080 and 0.049, respectively.

The results of the CO_2 emissions equation (Equation (5) in the estimated PVAR model) when mobile phone subscriptions per 100 people are used are reported in column 12 of Tables 5 and 6 for the groups of 12 and 8 countries, respectively. The empirical findings show that the coefficients associated with the first lag of mobile phone subscriptions as a proxy for ICT are positive and highly significant for the two groups at the 1% level. The only coefficient that is not significant is the coefficient associated with the FDI variable for only the group of eight countries, which is considered to be an exogenous variable in our study.

Moreover, compared with the case of Internet users, the coefficients associated with mobile phone subscriptions are found to have a higher impact on deteriorating environmental quality. This confirms that ICT worsened the environmental quality rather than improving it. This finding can be explained by the first-order effect (see Section 2), where environmental degradation is caused by the impact of the production, use, recycling, and e-waste of ICT equipment.

4.2.2. Impact of renewable energy on CO_2 emissions

The impact of the renewable energy consumption variable on CO_2 emissions is reflected by the coefficients related to the first lag of the renewable energy consumption variable (see columns 6 and 12 of Tables 5 and 6 for the two groups of countries, respectively). In contrast to the ICT proxies, we find that the use of renewable energy significantly reduces CO_2 emissions, regardless of the group of countries considered and the ICT proxy used. The coefficient associated with renewable energy consumption is significant in the four cases (twice at 1% and once each at 5%, and 10%). This result indicates that renewable energy consumption improves environmental quality by reducing the level of CO_2 emissions. Consequently, policymakers and MENA governments should promote the production and use of renewable energy to reduce GHG and CO_2 emissions. Regarding the extent of the impact, the coefficients associated with the renewable energy consumption variable are higher (in absolute values) for the Internet user proxy than for the mobile phone subscription proxy.

For the remaining variables, the results show that the trade growth and economic growth variables positively affect the level of environmental degradation as all the coefficients associated with trade and economic growth are positive, except for the group of 12 MENA countries for which the trade variable was found to negatively affect the environmental degradation level. We also find that the first lag of the coefficients of CO_2 emissions is negatively associated with current CO_2 emissions and highly significant at the 1% level in the four cases.

4.3. Post-PVAR estimation model analysis

4.3.1. IRFs analysis

This section is devoted to the analysis of the IRFs of the CO_2 emissions following a one standard innovation shock affecting the two variables of interest (ICT and renewable energy consumption) separately. We follow Sims (1980) by decomposing the variance-covariance matrix of residuals via Cholesky decomposition to ensure the orthogonalization of shocks. The following order of variables is used: *ICT* proxy, *REC*, *TR*, *RGDP*, and CO_2 (FDI is an exogenous variable). This order is based on previous studies in the field and economic theories. Specifically, we follow the suggestion of Sims (1980) that the more exogenous variables should appear earlier in the order of variables followed by more

Table 3
Results of panel unit root tests.

	All MENA countries			Selected MENA countries		
Variables	LLC(2002)	IPS(2003)	CIPS(2007)	LLC(2002)	IPS(2003)	CIPS(2007)
CO_2	3.22	0.19	−0.62	−0.39	−0.50	−0.41
	(0.99)	(0.57)	(0.26)	(0.34)	(0.30)	(0.33)
$D(CO_2)$	−7.04***	−7.77***	−10.86***	−7.58***	−6.14**	−9.36***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RGDP	−0.72	0.96	1.97	−0.75	1.42	2.29
	(0.23)	(0.83)	(0.97)	(0.22)	(0.92)	(0.98)
D(*RGDP*)	−2.91***	−2.94***	−4.96***	−6.18***	−5.98***	−3.58***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
REC	1.21	−1.06	−0.84	7.81	0.89	−0.94
	(0.88)	(0.14)	(0.19)	(1.00)	(0.81)	(0.17)
D(*REC*)	−3.98***	−8.82***	−6.92***	−5.80***	−7.60***	−6.39***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
TR	1.07	−0.38	0.32	2.66	−0.01	−0.05
	(0.85)	(0.34)	(0.62)	(0.99)	(0.49)	(0.47)
D(*TR*)	−8.46***	−7.23***	−8.55***	−10.20***	−8.14***	−6.17***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FDI	−0.09	−0.72	1.80	0.35	−0.06	1.16
	(0.46)	(0.23)	(0.94)	(0.63)	(0.47)	(0.87)
D(*FDI*)	−6.02***	−6.98***	−9.88***	−4.60***	−6.22***	−8.90***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
INT	9.01	−0.75	−0.96	2.98	0.81	0.16
	(1.00)	(0.22)	(0.16)	(0.99)	(0.79)	(0.56)
D(*INT*)	−11.01***	−8.44***	−8.95***	−6.13***	−6.85***	−7.22***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MB	0.73	−0.18	−1.12	0.06	−1.24	−1.10
	(0.76)	(0.40)	(0.13)	(0.52)	(0.10)	(0.13)
D(*MB*)	−4.80***	−3.98***	−5.96***	−7.99***	−6.69***	−6.56***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Notes: Probability values are reported in parentheses. Panel root test includes intercept and trend.***and ** denotes the significance at 1% and 5% level, respectively. *D*(.) denotes the first differences.

Table 4
Results of selection order criteria.

	All MENA countries				**Selected MENA countries**			
	Model 1		**Model 2**		**Model 1**		**Model 2**	
	$k=1$	$k=2$	$k=1$	$k=2$	$k=1$	$k=2$	$k=1$	$k=2$
MBIC	−519.19***	−415.80	−538.96***	−449.61	−379.77***	−280.77	−315.78***	−214.78
MAIC	−131.71***	−105.82	−131.63***	−118.85	−94.57***	−72.57	−89.70***	−69.45
MQIC	−289.01***	−231.66	−297.05***	−253.17	−210.45***	−157.16	−181.38***	−128.39

Notes: *k* denotes the length of lags. MAIC, MBIC and MQIC refer to the Akaike information criteria, the Bayesian information criteria, and the Hannan-Quinn information criteria, respectively. *** denotes the significance at 1%.

endogenous variables (Love and Zicchino, 2006; Charfeddine and Kahia, 2019). In this study, IRFs were obtained via Monte Carlo simulations. In each figure, we report the results of the reaction of CO_2 emissions with 5% error bands. It is important to remember that the reaction of CO_2 emissions is significant if the zero horizontal line does not fall into the 5% error band. The results of the reaction of CO_2 emissions following a one standard deviation shock on mobile phone subscriptions and Internet users for the group of 12 and 8 countries are illustrated in Fig. 5 (a)–(d) and Fig. 6(a)–(d), respectively.

We begin our analysis of the IRFs by first focusing on the reaction of CO_2 emissions following a one standard deviation shock on the ICT proxies. The results reported in Fig. 5 (a) and (c) for the group of 12 countries show that the response of CO_2 emissions to a one standard deviation shock affecting Internet users and mobile phone subscriptions is positive and remains significant for 7 and 4 years, respectively. For the group of 8 countries, the response of CO_2 emissions is weaker than that for the group of 12 countries when using Internet users as a proxy for ICT. For instance, the response of CO_2 emissions is positive and remains significant between years 1 and 5 for Internet users. For mobile phone subscriptions, the reaction of $\mathrm{CO_2}$ emissions is only significant for year 2 alone.

Regarding the responses of CO_2 emissions to a shock on renewable energy consumption, as expected, the results seem to depend on the group of countries used because the categorization of our two groups of countries was based on the share of renewable energy consumption. For the group of 12 countries, the results show that a shock on renewable energy consumption has only an immediate significant negative impact on CO_2 emissions when Internet users are used as a proxy for ICT. In the second case, when the number of mobile phone subscriptions is used as a proxy for ICT, the IRF results show that the response of CO_2 emissions is significant to a one standard deviation shock on renewable energy consumption. For the group of eight countries, the response of CO_2 emissions is completely different. The results demonstrate that for both ICT proxies, the response of CO_2 emissions is significantly negative for up to two years for the Internet user proxy and four years for the number of mobile phone subscription proxy.

4.3.2. *Variance decomposition analysis*

The FEVD results for the Internet user proxy for ICT are reported in Table 7. We find that for the whole sample of 12 MENA countries, Internet users, renewable energy consumption, trade, and economic growth explain approximately 20.5%, 10.2%, 2.8%, and 10.6% of the fluctuations in $\mathrm{CO_2}$ emissions, respectively. Regarding the group of eight countries, we find that Internet users explain only 3.3% of the variation

Table 5
Results of panel vector autoregressive estimation for all MENA sample.

Response to	All MENA countries										
	Model 1					**Model 2**					
	Response of					Response of					
	$D(INT)$	$D(REC)$	$D(TR)$	$D(GDP)$	$D(CO_2)$	Response to	$D(MB)$	$D(REC)$	$D(TR)$	$D(GDP)$	$D(CO_2)$
$D(INT_{t-1})$	0.533***	−0.139*	−0.035**	0.074***	0.049***	$D(MB_{t-1})$	0.658***	−0.101***	−0.021*	0.027***	0.072***
	(0.000)	(0.062)	(0.019)	(0.000)	(0.004)		(0.000)	(0.002)	(0.066)	(0.000)	(0.000)
$D(REC_{t-1})$	0.310***	−0.767***	−0.090***	0.023**	−0.053**	$D(REC_{t-1})$	−0.036***	−0.129***	0.017***	−0.040***	−0.033*
	(0.000)	(0.000)	(0.000)	(0.039)	(0.023)		(0.000)	(0.000)	(0.000)	(0.000)	(0.069)
$D(TR_{t-1})$	−0.222***	−0.093	0.068	−0.161***	−0.271***	$D(TR_{t-1})$	0.026	−0.118*	0.022	0.145***	−0.099***
	(0.007)	(0.450)	(0.118)	(0.000)	(0.000)		(0.129)	(0.067)	(0.318)	(0.000)	(0.000)
$D(RGDP_{t-1})$	0.555***	−0.403	−0.224***	0.450***	0.578***	$D(RGDP_{t-1})$	−0.089***	−1.369***	−0.154***	0.440***	0.246***
	(0.000)	(0.200)	(0.003)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$D(CO_{2(t-1)})$	0.636***	−0.708***	−0.096***	−0.048***	−0.123***	$D(CO_{2(t-1)})$	−0.060***	0.037	0.120***	−0.092***	−0.344***
	(0.000)	(0.000)	(0.005)	(0.000)	(0.005)		(0.000)	(0.566)	(0.000)	(0.000)	(0.000)
$D(FDI)$	0.026**	−0.019	0.048***	0.001	0.009**	$D(FDI)$	0.057***	−0.095***	0.042***	0.002	−0.004**
	(0.047)	(0.157)	(0.000)	(0.960)	(0.036)		(0.000)	(0.000)	(0.000)	(0.145)	(0.049)
Hansen-J-test (p-value)			118.134 (0.655)			Hansen-J-test (p-value)			124.734 (0.565)		
AR(2) test (p-value)			0.95 (0.343)			AR(2) test (p-value)			1.44 (0.149)		

Notes: ***, ** and* denote the significance at 1%, 5% and 10% level, respectively. $D(.)$ denotes the first differences. Hansen J-test refers to overidentification test of restrictions in GMM estimation and the null hypothesis is that all instruments as a group are exogenous. AR(2) test – Arellano–Bond's test to analyze the existence of 2nd order autocorrelation in first differences and the null hypothesis that error term of the differenced equation is not serially correlated.

Table 6
Results of panel vector autoregression estimation for selected MENA sample.

Response to	Selected MENA countries										
	Model 1						**Model 2**				
	Response of						Response of				
	$D(INT)$	$D(REC)$	$D(TR)$	$D(GDP)$	$D(CO_2)$	Response to	$D(MB)$	$D(REC)$	$D(TR)$	$D(GDP)$	$D(CO_2)$
$D(INT_{t-1})$	0.674***	−0.109***	−0.007	0.045***	0.080***	$D(MB_{t-1})$	0.729***	0.333***	−0.056	−0.024	0.106***
	(0.000)	(0.000)	(0.688)	(0.000)	(0.000)		(0.000)	(0.000)	(0.207)	(0.422)	(0.000)
$D(REC_{t-1})$	0.024	−0.189***	0.041**	−0.069***	−0.336***	$D(REC_{t-1})$	0.002	0.114	−0.223***	0.108***	−0.035***
	(0.247)	(0.000)	(0.018)	(0.000)	(0.000)		(0.968)	(0.215)	(0.001)	(0.000)	(0.000)
$D(TR_{t-1})$	−0.238***	0.285***	0.062***	0.011	0.103***	$D(TR_{t-1})$	0.085	0.869***	0.371***	0.142***	0.222***
	(0.000)	(0.000)	(0.004)	(0.211)	(0.000)		(0.268)	(0.000)	(0.000)	(0.005)	(0.002)
$D(RGDP_{t-1})$	0.455***	−1.444***	−0.456***	0.019	0.091**	$D(RGDP_{t-1})$	−0.300	−0.453	0.566**	−0.649***	0.265*
	(0.000)	(0.000)	(0.000)	(0.383)	(0.024)		(0.142)	(0.326)	(0.034)	(0.000)	(0.083)
$D(CO_{2(t-1)})$	0.198***	0.078	0.295***	−0.020	−0.271***	$D(CO_{2(t-1)})$	0.050	−0.065	0.079	0.157***	−0.380***
	(0.000)	(0.306)	(0.000)	(0.219)	(0.000)		(0.565)	(0.756)	(0.253)	(0.005)	(0.000)
$D(FDI)$	−0.036***	−0.025***	0.042***	−0.001	−0.001***	$D(FDI)$	0.067	0.005	0.052***	0.010	0.001
	(0.000)	(0.000)	(0.000)	(0.702)	(0.000)		(0.000)	(0.715)	(0.000)	(0.149)	(0.808)
Hansen-J-test (p-value)			111.471 (0.166)			Hansen-J-test (p-value)			79.296 (0.469)		
AR(2) test (p-value)			1.55 (0.121)			AR(2) test (p-value)			1.61 (0.107)		

Notes: ***, ** and* denote the significance at 1%, 5% and 10% level, respectively. $D(.)$ denotes the first differences. . Hansen J-test refers to overidentification test of restrictions in GMM estimation and the null hypothesis is that all instruments as a group are exogenous. AR(2) test – Arellano–Bond's test to analyze the existence of 2nd order autocorrelation in first differences and the null hypothesis that error term of the differenced equation is not serially correlated.

in CO_2 emissions. The results differ by as much as 17%, which demonstrates the importance of selecting homogenous countries in this type of study. We also note that the percentage explained by renewable energy consumption, trade, and economic growth increases remarkably to more than 15%, 13%, and 20%, respectively.

In addition, in Table 8, we report the estimates of the FEVD for the second ICT proxy, namely mobile phone subscriptions, for the two MENA samples. The findings show that mobile phone subscriptions and trade explain approximately 10.4% and 11.2% of the changes in CO_2 emissions, respectively, whereas the proportion of both renewable energy consumption and economic growth have smaller explanatory power, approximately 3.7% and 5.5%, respectively. For the group of eight countries, the results demonstrate that the contribution of mobile phone subscriptions and trade in explaining the fluctuations in CO_2 emissions decreased to approximately 7.8% and 5.1%, respectively. Furthermore, renewable energy consumption and economic growth were the highest contributors to the variations in CO_2 emissions: 24.9% and 13.3%, respectively.

4.3.3. *Causality analysis*

Table 9 reports the results of the causality test among all the variables and for both samples of MENA economies. We summarize the results in Figs. 7 and 8 for the whole sample and the selected eight countries, respectively. Regarding the group of 12 countries, the results

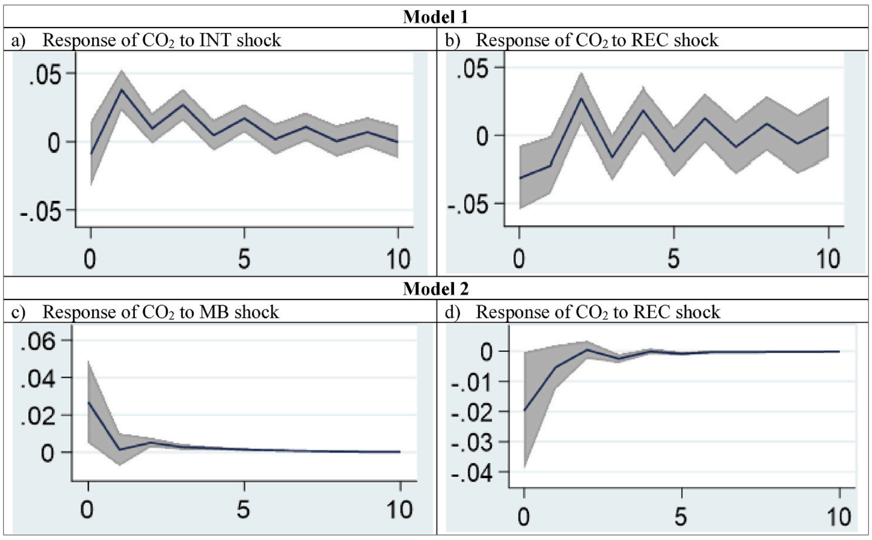

Fig. 5. Reaction of CO_2 emissions to one standard deviation shock on INT, MB and REC for whole MENA sample.

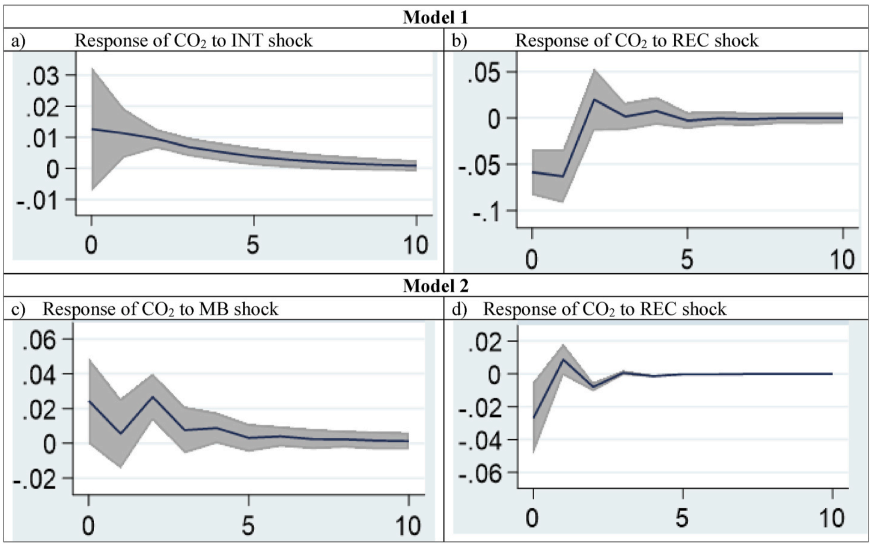

Fig. 6. Reaction of CO2 emissions to one standard deviation shock on INT, MB and REC for selected MENA sample.

Table 7
Results of Forecast-error variance decomposition for Model 1.

Response variable	All MENA countries						Response variable	Selected MENA countries					
	Impulse variable							Impulse variable					
	INT		*REC*	*TR*	*RGDP*	CO_2		*INT*		*REC*	*TR*	*RGDP*	CO_2
INT	10	0.683	0.100	0.008	0.124	0.083	*INT*	10	0.948	0.004	0.013	0.026	0.006
REC	10	0.169	0.706	0.023	0.008	0.092	*REC*	10	0.031	0.847	0.004	0.113	0.002
TR	10	0.057	0.125	0.766	0.024	0.025	*TR*	10	0.010	0.030	0.865	0.038	0.055
RGDP	10	0.164	0.009	0.080	0.736	0.008	*RGDP*	10	0.068	0.058	0.055	0.815	0.002
CO_2	10	0.205	0.102	0.028	0.106	0.559	CO_2	10	0.033	0.156	0.131	0.201	0.479

Notes: FEVD (Forecast-Error Variance Decomposition) standard errors and confidence intervals are based on 1000 Monte Carlo simulations.

of Model 1 indicate strong evidence for bidirectional causality among internet users, renewable energy consumption and economic growth. This bidirectional effect implies that extensive use of renewable energy can play a strategic role in promoting economic growth by reducing the use of electricity generated from non-renewable energy sources and improving energy efficiency overall. Similar results of bidirectional

Table 8
Results of Forecast-error variance decomposition for Model 2.

Response variable	All MENA countries						Response variable	Selected MENA countries					
	Impulse variable							Impulse variable					
		MB	*REC*	*TR*	*RGDP*	CO_2			*MB*	*REC*	*TR*	*RGDP*	CO_2
MB	10	0.985	0.005	0.001	0.005	0.003	*MB*	10	0.949	0.012	0.009	0.025	0.002
REC	10	0.017	0.867	0.008	0.103	0.002	*REC*	10	0.061	0.683	0.192	0.056	0.005
TR	10	0.004	0.005	0.964	0.010	0.016	*TR*	10	0.017	0.093	0.821	0.059	0.007
RGDP	10	0.008	0.036	0.122	0.813	0.019	*RGDP*	10	0.014	0.066	0.060	0.775	0.083
CO_2	10	0.104	0.037	0.112	0.055	0.692	CO_2	10	0.078	0.249	0.051	0.133	0.489

Notes: FEVD (Forecast-Error Variance Decomposition) standard errors and confidence intervals are based on 1000 Monte/Carlo simulations.

causality occur among internet users, economic growth, and CO_2 emissions. The empirical findings demonstrate that a one-way causality stemming from renewable energy consumption and economic growth to trade openness, as well as from CO_2 emissions to renewable energy use and from trade openness to CO_2 emissions. However, the neutrality assumption is confirmed between internet users and trade openness, indicating no established linkage between these series. Concerning Model 2, the same results are found when using mobile phone subscriptions as a proxy for measuring ICT. The only two exceptions are found for economic growth, which unilaterally causes renewable energy consumption, and bilateral causality between CO_2 emissions and economic growth, as well as between renewable energy consumption and CO_2 emissions.

Regarding the eight selected MENA countries, the causality outcomes of Model 1 reveal strong evidence for a mutual association between internet users and CO_2 emissions. This result means that a permanent increase in internet users may lead to an alarming environmental effect if sustainability is neglected and vice versa. In addition, the empirical findings provide proof of a one-way causality stemming from renewable energy consumption, trade, and economic growth to internet users. These unilateral effects suggest that the promotion of energy from renewables, increasing trade and a well-developed economy certainly will boost growth in internet users. Moreover, we found evidence for unilateral causality running from trade to renewable energy consumption and economic growth, as well as from renewable energy consumption to CO_2 emissions.

Compared with Model 1, the estimation results of Model 2 strongly support the same outcome, except that no causal linkage was seen between trade and mobile phone subscriptions. In addition, a one-way association from economic growth to CO_2 emissions is supported.

4.4. Results discussion

4.4.1. Impact of ICT on CO_2 emissions

In both groups of countries, the sign of the coefficient associated with our variable of interest, D(MB $_{(t-1)}$), is positive and highly significant, showing that ICT, as measured by mobile phone subscriptions per 100 people, affects environmental quality by increasing CO_2 emissions. These findings are valid independently of the sample being used (12 countries or 8 countries). Moreover, the empirical findings, for the case of internet users, show also that for the two groups of countries, the coefficients associated to the first lag of internet users are positive and highly important at a 1% level. This finding confirms that ICT has deteriorated rather than improved environmental quality. Our outcomes are consistent with the results of Danish et al. (2018) for the case of emerging economies who confirmed that ICTs have been found to have a positive impact on CO_2 emissions. Similar results are found by Park et al. (2018) for the case of 23 European Union (EU) countries, who showed that in EU countries, the usage of the internet has a long-term association with CO_2 emissions and reduces the environmental quality. Besides, our findings are online with that of Arshad et al. (2020) who approved that ICT harmed the environment in the SSEA (South and Southeast Asian) region, implying that ICT goods and services are inefficient in terms of energy use in both developing and developed countries. On the other hand, our results are in contrast with that of Asongu et al. (2018) for the case of 44 Sub-Saharan African countries who found that ICT can be used to mitigate the possible detrimental impact of globalization on environmental degradation proxied by CO_2 emissions. In addition, our outcomes are different from that of Khan et al., (2020) who concluded that for the entire sample of 91 countries, ICT was found to lower CO_2 emissions. However, a comparison of developed and developing countries reveals that ICT promotes environmental sustainability in developed countries, whilst developing economies show the contrary.

4.4.2. Impact of renewable energy on CO_2 emissions

As discussed above the impact of the renewable energy consumption variable on CO_2 emissions is reflected by the coefficients related to the first lag of the renewable energy consumption variable. We find that the increase in the use of renewable energy lessens CO_2 emissions significantly, regardless of the group of countries analyzed or the ICT proxy utilized. For four cases, the coefficient linked with renewable energy use is negative and significant. Our findings are in line with that of Zoundi (2017) for a panel of 25 African countries over a period of 23 years who found that renewable energy use was a cost-effective strategy to minimize CO_2 emissions, and renewable energy sources can serve as a viable substitute for non-renewable energy sources. A similar result is confirmed by Bhattacharya et al. (2017) for a panel of 85 heterogeneous countries who revealed that using renewable energy benefitted the environment by lowering CO_2 emissions. Further, our outcomes are consistent with those of Charfeddine and Kahia (2019) as well as Namahoro et al. (2021) for the case of the Middle East North Africa region, and 50 African countries, respectively. Their studies demonstrated that using renewable energy reduced CO_2 emissions. However, our findings are not in line with those of Apergis et al. (2010) and Adams and Nsiah (2019) for the groups of 19 developed and developing economies and 28 Sub-Sahara African countries, respectively. The authors revealed that renewable energy does not help to reduce CO_2 emissions. According to Adams and Nsiah (2019), the findings are linked to insufficient storage technology and regular power disruptions, prompting some people to turn to emission-generating renewable energy sources such as open firewood burning.

5. Policy implications

5.1. ICT policies

Our empirical results show that the first-order effect (the negative impact of ICT on environmental quality) holds for our two MENA samples. This result seems to be logical and expected because of the economic structure and the level of economic development of the countries forming our samples. However, in order to fully benefit from the potential positive effects of ICT on environmental quality, policymakers and governments must propose and design different ICT policies that ensure a rapid transition to the second-order effects without the risk

Table 9
Results of PVAR Granger causality test.

Equation \ Excluded	All MENA countries				Selected MENA countries			
	Model 1		Model 2		Model 1		Model 2	
	chi2	*Prob*	*chi2*	*Prob*	*chi2*	*Prob*	*chi2*	*Prob*
*INT*rowhead								
MB	–	–	–	–	–	–	–	–
REC	66.829***	0.000	–	–	6.587 **	0.010	–	–
TR	2.305	0.112	–	–	26.536***	0.000	–	–
RGDP	12.471***	0.000	–	–	61.773***	0.000	–	–
CO_2	71.685***	0.000	–	–	36.887***	0.000	–	–
ALL	117.27 ***	0.000	–	–	89.543***	0.000	–	–
*MB*rowhead								
INT	–	–	–	–	–	–	–	–
REC	–	–	48.868 ***	0.000	–	–	25.395***	0.000
TR	–	–	2.309	0.129	–	–	1.068	0.301
RGDP	–	–	32.073***	0.000	–	–	4.156**	0.041
CO_2	–	–	34.513***	0.000	–	–	8.521***	0.004
ALL	–	–	266.725***	0.000	–	–	139.335***	0.000
*REC*rowhead								
MB	–	–	9.914 ***	0.002	–	–	0.965	0.326
INT	3.475*	0.062	–	–	1.047	0.306	–	–
TR	0.570	0.450	0.329	0.566	31.336***	0.000	69.870***	0.000
RGDP	12.400***	0.000	92.834***	0.000	17.060***	0.000	20.333***	0.000
CO_2	25.930***	0.000	3.346*	0.067	1.569	0.210	0.096	0.756
ALL	44.18 ***	0.000	166.884***	0.000	43.855***	0.000	109.895***	0.000
*TR*rowhead								
MB	–	–	0.263	0.608	–	–	0.268	0.605
INT	1.492	0.210	–	–	0.161	0.688	–	–
REC	14.067***	0.000	11.229***	0.000	0.138	0.710	1.231	0.267
RGDP	8.850***	0.003	44.541***	0.000	0.153	0.696	1.559	0.212
CO_2	0.800	0.480	0.299	0.585	96.178***	0.000	23.867***	0.000
ALL	37.422***	0.000	115.198***	0.000	75.301***	0.000	35.950***	0.000
*RGDP*rowhead								
MB	–	–	17.428***	0.000	–	–	0.646	0.422
INT	42.299***	0.000	–	–	1.565	0.211	–	–
REC	4.276**	0.039	0.092	0.762	83.544***	0.000	26.500 ***	0.000
TR	0.656	0.429	0.990	0.320	6.537**	0.011	7.714***	0.005
CO_2	15.409***	0.000	77.195***	0.000	14.836***	0.000	1.308	0.647
ALL	222.78***	0.000	170.908***	0.000	107.272***	0.000	42.942***	42.942
*CO_2*rowhead								
MB	–	–	106.308***	0.000	–	–	28.729***	0.000
INT	8.289***	0.004	–	–	35.163***	0.000	–	–
REC	0.710	0.650	14.210***	0.000	16.720***	0.000	60.044***	0.000
TR	32.566***	0.000	16.578***	0.000	31.582***	0.001	9.192***	0.002
RGDP	26.493***	0.000	12.571***	0.000	5.114**	0.024	2.998*	0.083
ALL	137.285***	0.000	189.739***	0.000	64.071***	0.000	103.536***	0.000

Notes: Ho: Excluded variable does not Granger-cause Equation variable versus Ha: Excluded variable Granger-causes Equation variable. ***, ** and * denotes the significance at 1%, 5% and 10% level, respectively.

of reaching the stage of rebound effects. The proposed policies are based on the recent development of ICT tools and applications such as smart meters, smart sensors, the internet of things (IoT), artificial intelligence, and Blockchain technology. Policymakers can focus on developing new or expanding existing ICT initiatives. These policies include the following:

i. Extending and promoting the use of smart meters[7] to help conserve and reduce energy consumption by the different industry sectors and residential areas. In fact, this transformation

[7] The smart meters market in the MENA region was estimated at 0.68 million units in 2019 and is expected to reach 3.75 million units by 2025, at a compound annual growth rate of 42% during the projected period 2020–2025 (Mordor Intelligence, 2020).

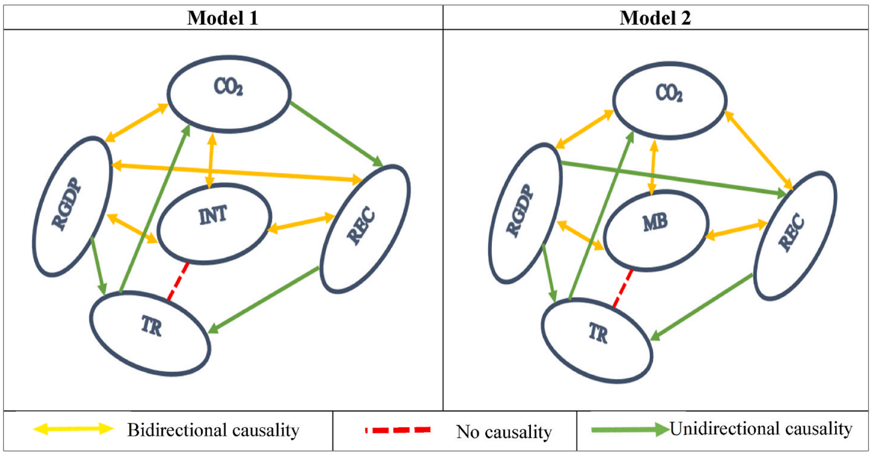

Fig. 7. Short-term causalities between ICT proxies, RGDP, CO_2 emissions, REC and TR for all MENA sample.

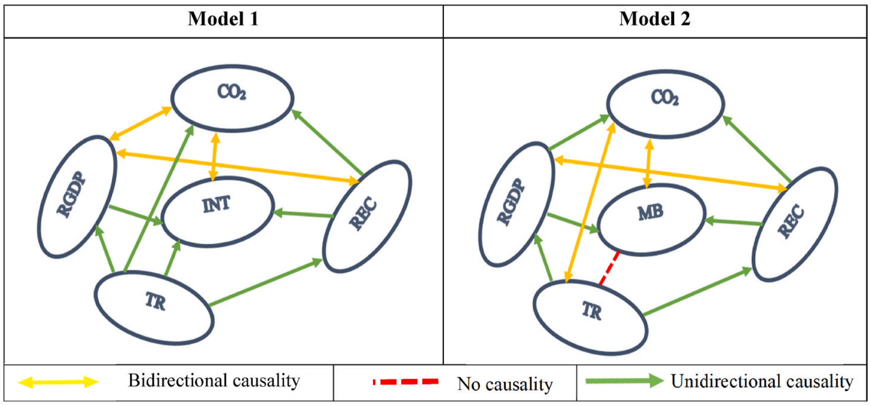

Fig. 8. Short-term causalities between ICT proxies, RGDP, CO2 emissions, REC and TR for selected MENA sample.

requires relevant and general strategies as follows: first, an organization structure needs to be in place to control the design, development, and implementation; determine priorities and requirements; and guarantee the availability of resources. This could be achieved through establishing an operational efficiency design for the different facilities and services involved. Second, the necessity to produce accurate data on how a forecast or a decision positively affects the management and operation of the smart services and resources. Finally, there is a strong need to put contingency procedures in place to respond to disaster control and unexpected failures (Aslam et al., 2015; Mordor Intelligence, 2020).

ii. Use of the internet of things and digitalization: these can play a fundamental role in the upcoming years to address the problem of reducing CO_2 emissions. This can be achieved in various ways, such as through better asset management (since fixed assets represent a large part of operating costs), making remote maintenance possible via environmental scans to achieve better logistics control through accurate and timely weather forecasting and precise planning (Maksimovic, 2017; Shaikh et al., 2017).

iii. Use of Blockchain, which is considered to be a powerful implement serving to considerably improve the accountability, transparency, and traceability of CO_2 emissions (Wang et al., 2019; Zhang et al., 2020). Blockchain technology works as a decentralized network of released nodes. It assists companies to make more precise, authenticated, consistent, and real-time data available on CO_2 emissions, catalyzed by the use of smart contracts to better compute, monitor, and report on the mitigation of CO_2 emissions across the entire value chain. Decentralized blockchain technology provides both depth and extensiveness, as it allows everyone to contribute to the computing, monitoring, and reporting of decreases in CO_2 emissions throughout the supply chain (including distributors, suppliers, consumers, and manufacturers) and to fight climate change collectively (Pan et al., 2019).

iv. Develop innovative technologies that should be characterized by higher levels of energy efficiency and energy conservation (Chen and Lei, 2018; Shahbaz et al., 2020).

5.2. Renewable energy policies

There is no doubt that renewable energy has a crucial role to play in reducing CO_2 emissions. In fact, the priorities of the MENA governments should focus on supporting policies and incentives to encourage investments in green technologies aimed at improving environmental quality (Charfeddine and Kahia, 2019; REN21, 2019). Although the provision of investment incentives is needed for the deployment of renewables, these incentives are not enough in themselves, as barriers to deployment must also be removed. Furthermore, resource-rich MENA countries need to guarantee the required institutional capacity to be present in the country to provide energy from renewables. For example, generators need to have access to a flexible and consistent grid and suitable risk mitigation mechanisms must also be available to handle uncertainties and the inherent risks. These obstacles can result in underinvestment not only in renewable energy sectors but also in conventional production that is indispensable to safeguarding renewable sources. Moreover, the development of a suitable market structure is strongly required in an attempt to avoid any perverse incentives, especially those seen in 'integrated monopolies', and to reduce the default risk and credit posed by having only one power provider (Poudineh et al., 2018). MENA countries may draw on years of existing international experience (e.g. from Europe) to eliminate all design errors and build a maintainable solution suited to their own context.

6. Conclusion

In this study, we investigated the impact of ICT and renewable energy consumption on CO_2 emissions for two groups of MENA countries. For a better understanding of the relationships among all the variables of the system, we used the PVAR technique over the 1997–2019 period. First, we examined the order of integration of all the variables under study. The results showed that all the series in level are first-order integrated. Once the order of the PVAR model was selected using information criteria, we estimated the PVAR model via the GMM technique.

The estimation results of the PVAR model illustrated that all the coefficients, except for FDI in some cases, were highly significant. Furthermore, the ICT proxies were found to have an adverse effect on the environmental quality for both samples. Concerning renewable energy consumption, the results indicated that using more renewable sources reduced the level of CO_2 emissions, and therefore, improved the environmental quality. For the remaining variables, the results showed that trade growth, especially in some cases, and economic growth for the four cases, positively affected the level of environmental degradation as the coefficients associated with trade and economic growth were positive.

Moreover, the analysis of the IRFs of the CO_2 emissions following a one standard deviation shock separately affecting the two variables of interest (ICT and renewable energy consumption) displayed mixed results. First, the response of CO_2 emissions to a one standard deviation shock affecting Internet users and mobile phone subscriptions was positive and remained significant for both samples. Second, the response of CO_2 emissions to a shock on renewable energy consumption produced different results depending on the group of countries. The FEVD estimations of the whole sample indicated that mobile phone subscriptions, Internet users, and renewable energy consumption explained approximately 10.4%, 20.5%, and 3.7%–10.2% of the fluctuations in CO_2 emissions, respectively. Regarding the group of eight MENA economies, the findings indicated that mobile phone subscriptions, Internet users, and renewable energy consumption explained 7.8%, 3.3%, and 15.6%–24.9% of the changes in CO_2 emissions, respectively. The results derived from the PVAR Granger causality tests for our variables of interest provided evidence for the presence of a mutual association between ICT variables and CO_2 emissions for both groups of MENA countries. Furthermore, the same result was found between renewable energy and CO_2 emissions when ICT was proxied by mobile phone subscriptions for the group of 12 countries. Moreover, unilateral causality running from CO_2 emissions to renewable energy was demonstrated for the group of 12, whereas the path ran from renewable energy to CO_2 emissions for the subsample of 8 MENA countries.

The main limitation of this investigation is ignoring the comparison between MENA countries and other developing economies. Thus, a possible extension may focus on a comparison between MENA countries and some select developing countries without neglecting the heterogeneity between the two samples to evaluate the main determinants of environmental quality for each subcategory. Future studies may incorporate other indicators of environmental degradation as possible extensions.

CRediT authorship contribution statement

Lanouar Charfeddine: Conceptualization, Methodology, and, Software, Writing – original draft, Visualization, and, Investigation, Validation, Writing – review & editing. **Montassar Kahia:** Data curation, Methodology, and, Software, Writing – original draft, Visualization, and, Investigation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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