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Dynamic links between ICT, transport energy, environmental degradation and growth: empirical evidence from Tunisia

Abstract

The transport sector, particularly road transport, is a major factor in the overall emissions balance of the substances involved in air pollution for the majority of developing countries. This paper investigates the dynamic links between information and communication technology (ICT), transport energy, environmental degradation and growth for Tunisia. The authors used a Johansen co-integration analysis to determine this econometric relationship using data during 1990–2015. In order to test the Granger causality links in the short and long run, a panel Vector Error Correction Model is used. The variance decomposition is used to confirm the existing links between the different variables. Different results are found. These findings show the existence of bidirectional in short- and long-run causality between transport energy and CO2 emissions. By cons, ICT does not minimize significantly pollution in Tunisia. These findings are very important for the transport sector and in terms of the choice of government policy decisions in order to minimize the pollution.

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Introduction

Information and communication technologies (ICTs) have long been perceived primarily in terms of their undoubted contribution to the productivity of the economy and the well-being of the population.

According to the European Commission, ICT contributes 2% to global emissions of greenhouse gases. This figure could, however, increase due to the very strong growth of the market and despite technological developments which would make it possible to reduce, in particular, the levels of electricity consumption. Notwithstanding this remark, the first challenge is to allow, through technological innovation, to reduce the remaining 98% of emissions. In fact, ICTs can promote the adoption of more environmentally friendly behavior throughout the economy. They are already playing a decisive role in the systems development to support environmental decision-making and in the possibility that they offer different actors to modulate their behavior according to management and the sustainable use of natural resources. In particular, satellite remote sensing makes it possible to analyze by satellite the evolution of certain phenomena (drought, desertification, pollution of land, air and water, urbanization ...) and to anticipate the consequences for their limiting or neutralization.

Transport considered among the most sector which has the fastest growing energy consumption and consequently carbon dioxide emissions worldwide. In fact, transport sector consumes about 20% of global energy use and it is responsible for nearly one quarter of global energy related greenhouses emissions "carbon dioxide" with 75% of these emissions are due to road transport energy use. These trends and figures are the results and consequences of increasing population and economic development at the cost of the pollutions and environmental degradation.

Due to the development of ICT, we have been able to reduce the ecological footprint of transport and to develop public transport modes (new trams, GPS equipment to optimize journeys, urban bicycle ...). The automotive of 2020, condensed from ICT, will have the means to define and realize the journeys, by communication with the infrastructures, for optimal security and still reduced energy consumption.

It is worth noting that there has not been a study touched the role of ICT development in transport energy use, CO2 emissions and economic growth in the developing economies like Tunisia. In addition, as far as we know, doesn't any of empirical studies that focused on investigating the causal links among ICT, environment-transport-energy and growth via the co-integration and VECM model.

The dynamic links between transport energy use and environmental degradation measured by greenhouse gases (GHG) has long been a subject of constant concern and research. In fact, the transport energy consumption and the CO2 emissions are continuously

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increasing in different countries, whether for developed or developing economies, whose developed economy, trade opening and GDP growth can cause the development of transport sector and therefore the carbon emissions. Whether economic development creates problems for environmental protection or improves environmental degradation may be studied through the use of econometric and statistic methods. In fact, in the field of environmental economics, the literature on transport energy and greenhouse gases (GHG) has attempted to address several and major questions in different lines of research.

Today and despite the benefits that can be associated with public transport, the automobile remains the preferred means of urban.

Le Breton (2001) found that the difficulties facing the public transport from the 60s are behind five leading causes namely, the priority given to land at the expense of a more focused development of cities, preference enhanced by individual modes of housing and transport, the implementation of an urban development model which leads to a dissociation of activities by specific areas favorable to the automobile, lack of foresight among users of the transport networks and the lack of coordination between the local authority and the operators.

In this respect, improving the overall efficiency of public transport networks was a major challenge. The development of infrastructure that meets mobility needs appears to be necessary to make the public transport sector more efficient. It may also be appropriate to use the most advanced techniques as they are developed in so-called intelligent transport systems.

The use of the intelligent transportation system is a major challenge. It brings a technological benefit to the power of computers and electronics, and a social benefit since public transport by becoming more accessible. Bruglieri et al. (2015) have shown that a real-time transport planning system improves the functioning of the public transport system; it becomes very useful for public transport users. Intelligent transport systems make it possible to boost public transport insofar as they make it possible to improve the conditions of transport use (Stelzer et al., 2016).

Public transport is seen as an attractive alternative to cars. Rising environmental concerns and measures limiting excessive use of automobiles have strengthened the attractiveness of public transport (Boyle, 1990).

Cars are often less efficient than public transport, given their economic, social and environmental costs. The advantage of public transport in relation to cars is indisputable in terms of air pollution and the rational use of energy. Public transport is therefore at the heart of environmental and social issues. It plays an important role in protecting air quality. Air pollution caused by transport causes health problems. Many studies have shown that the use of public transport to the detriment of the automobile can lead to major improvements in health problems (Rojas-Rueda et al., 2013; Wang, 2016).

Beyond the benefits of public transport, several facets of the technology used reinforce its positive impact on the environment. In addition to electrically powered vehicles, there has been no question of making buses less polluting. Nearly 60% of Swedish buses use renewable energies in 2014 compared to 8% in 2007 (Xylia & Silveira, 2017). The emission of CO2 takes an important place since it contributes strongly to the greenhouse effect. Moving to a carbon-free world today is imperative. Public transport is a major player in the fight against climate change, participating in global efforts to save energy resources. The electric bus reduces the use of petroleum by 85 to 87% compared to a diesel bus and leads to a reduction of 32 to 46% in fossil fuel use and 19 to 35% in CO2 emissions (Zhou et al., 2016).

The investigations related to the relationship between growth and transport activity become a very critical topic (Saidi & Hammami, 2017), at both national and international level. In addition, several research studies argue the positive effects of the phenomenon and indicate that the economic development is the mainstay of any country's economic development (Kim, 2002; Fedderke et al., 2006; Pradhan & Bagchi, 2013; Saidi & Hammami, 2017).

Recently, Alshehry and Belloumi (2017) studied the relationship between transport carbon dioxide emissions, energy consumption related to road transport and economic activity for Saudi Arabia. They attempted to check for the environmental Kuznets curve (EKC) hypothesis over the period 1971–2011 for Saudi Arabia by using the autoregressive distributed lag (ARDL), co-integration procedure and Granger causality tests. Their findings confirm the in-exist of inverse U relationship between transport CO2 emissions and economic growth in this country. They found also a bidirectional link between transport CO2 emissions and road transport energy use in the short and long run.

1. Overview on ICT and transport energy sector in Tunisia

The Tunisian economy, among the most competitive economies on the African and Arab scale, offers businesses an adequate environment for the development of their value-added activities. These factors ensure social inclusion and reduce the digital divide through better access to information and knowledge, supporting the creation of added value, guaranteeing the sustainability of organizations and jobs, by supporting entrepreneurship and stimulating innovation, improving the competitiveness of the company, across all sectors, by investing in ICT and positioning in the digital economy, ensuring Tunisia's transition to the digital world through the creation of a suitable regulatory framework, governance and security environment.

According to the annual report of the International Telecommunication Union (ITU) published on Tuesday 22 November 2016, Tunisia ranks 95th out of a total of 175 countries analyzed in the ICT development index. Tunisia, which occupies the same ranking as the year 2015, comes just ahead of its neighbors, Morocco (96th), Egypt (100th) and Algeria (103rd), but lags far behind other Arab countries such as Bahrain (29th), United Arab Emirates (38th), Saudi Arabia (45th), Qatar (46th), Kuwait (53rd), Sultanate of Oman (59th) and Lebanon (66th). At the top of the table are South Korea (1st), Iceland (2nd), Denmark (3rd), Switzerland (4th). The IDI index takes into account more than ten indicators, particularly access to and use of technologies and skills in this area.

According to the national agency for energy conservation, transport sector takes the second place in Tunisia, in terms of energy consumption; about 34% in 2010 after industrial sector with 35% of total energy consumption. Transport energy has been increased from 827 kg tone oil equivalent (ktoe) in 1980 to 1821 ktoe in 2010. In fact, several factors can explain these data: first, pricing and taxation of fuel used by road transport vehicles, second, the vehicle's park structure and important road infrastructure investments. The transport sector in Tunisia is considered as the most important consumption of energy from fossil combustibles with 99.5% of petroleum products in 2010. This increased consumption is explained by the importance of road transport activity that is closely linked to combustible fossils use, especially diesel (60.6%) and gasoline (25%) in 2010.

Undoubtedly, the rational use of energy constitutes a vector of energy efficiency that plays an important role in the economic and social development of the country. In this regard, Tunisia became aware of the importance of energy control in all sectors at an early stage, by enacting the appropriate legislative texts and creating mechanisms and structures to encourage all parties to renewable energy use, and it was imperative to take the necessary steps to reduce this energy bill and reduce greenhouse gas emissions.

According to the national agency for energy conservation, the transport sector will be the first energy consumer with more than 30% of the final energy balance in 2030. Structural changes and technological improvements are likely to reduce this consumption considerably. This sector is very promising in energy saving. However, in the short term, transport contributes relatively little to cumulative savings.

2. Methodology

The empirical study presented in this article is carried out using the co-integration analyses and Granger causality test. In fact, Granger causality test fits a standard vector autoregressive (VAR) model and vector error correction model (VECM) (Ben Mbarek et al., 2017). The VAR model, which was proposed by Christopher Sims in 1980, is widely used as an econometric tool to detect in a comprehensive and dynamic way several interdependent economic variables in stationary and non-stationary time series (see, for example, Dees et al., 2007 and Gao, 2009, among others). The popularity of autoregressive vector model (VAR) is related to their flexibility of use and their ability to test economic assumptions.

According to the seminal work introduced by Sims (1980), the VAR model was applied to a vast range of empirical topics and especially energy, environmental and economic variables. It is an approach that can be used to achieve comprehensive dynamic links between multiple variables and has the capacity to obtain predictions of relative time series (see Gao et al., 2009). The dynamic causality can be estimated and presented by the regression of lagged terms (AIC and Schwartz are measures of the quality of a proposed statistical model) from each endogenous variable to all studied variables of the model in the short and long term, by which we can detect the impact from itself and the others. The basic expression is as follows:

$$y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + BX_t + U_t, \; t = (1,2,...,T), \quad (1)$$

where y_t is the endogenous variable vector and X_t is the exogenous variable vector; p is the lagged intervals for endogenous variables; T indicates the number of samples; U_t measures the white noise of the time series of vectors.

Following this procedure, we use the Granger causality test (Granger, 1988) based on the vector error correction model (VECM) in order to detect the nexus between ICT, transport energy, environmental degradation and growth. However, this test is conditional on the stationarity of the involved time series variables. In fact, if the subjacent time series are non-stationary, the test statistics of Granger causality (Sims, 1980) based on the vector autoregressive model is invalid. Therefore, we test the order of integration for all variables in the first step. If the variables are stationary at the same difference, the co-integration and VECM is recommended to investigate the dynamic relationship (short- and long-run) between the used variables. Thereafter and in the next step, we employ Johansen co-integration tests in order to examine the long-term links between the studied variables.

We use the Choleski decomposition variance (VDC) to provide an indication of the importance of the causal impact of one selected variable on another variable. A choleski decomposition analysis is used in a VECM, according to Ghali and El-Sakka (2004).

3. Empirical findings

3.1. Data and descriptive statistic. Table 1 summarizes the description associated with the four used variables. The empirical study is based on 26 annual observations. As a summary, the Mean of FFEC is highest and that of LICT is the lowest. It is evident from this table also that standard deviation (Std. Dev.) of CO2 is highest and that of GDP is the lowest. All variables have negative value of skewness by except the GDP indicating that the distribution is skewed to the left, with more observations on the right. All variables have low values of Skewness. The statistic of Jarque-Bera shows that all variables used in the analysis have a normal distribution. Finally, all variables are downloaded from the World Bank's Development Indicators.

Table 1. Data and descriptive statistic of variables

	LICT	LGDP	CO2	FFEC
Mean	19.32843	24.16698	23.55844	87.17610
Median	19.18300	24.16883	22.83352	87.03364
Maximum	20.14039	24.59614	29.45470	88.43208
Minimum	18.67603	23.63226	19.87952	85.96209
Std. Dev.	0.472073	0.312659	2.402970	0.666859
Skewness	0.518245	-0.187791	0.932855	0.516630
Kurtosis	1.853965	1.698526	3.342359	2.424444
Jarque-Bera	2.586682	1.987803	3.897920	1.515465
Probability	0.274353	0.370130	0.142422	0.468728
Sum	502.5391	628.3414	612.5195	2266.579
Sum Sq. Dev.	5.571329	2.443891	144.3566	11.11752
Observations	26	26	26	26

3.2. Unit root tests. In the early 1980s, many studies revealed that most macroeconomic series are non-stationary. In fact, the results of econometric regressions may be misleading if preliminary statistical tests are not performed on the time series used. To this end, the unit root tests of Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) are performed. Therefore, to check the stationarity of all variables, we test the existence of the "unit root" in the complete sample, through two tests that are used: ADF and PP, the results are presented in Table 2, which shows the values of the Student statistic (t) for the variables at level and at first difference. Thus, the unit root test indicates that all series are integrated of order one (I (1)) and therefore stationary in first difference. Table 3 below also shows the results of the unit root tests.

Table 2. Unit root test (Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP))

Variables	Level			1st difference		
	(i)	(ii)	(iii)	(i)	(ii)	(iii)
ADF test						
LGDP	5.286767	-1.996159	-0.387882	-3.825507**	-4.085698*	-4.750207*
FFEC	0.491874	-1.785280	-2.367795	-7.596853*	-7.665037*	-7.605455*
LICT	1.114645	-0.623396	-2.254948	-5.291907*	-5.560317*	-5.493509*
CO2	0.517082	-1.660872	-3.268570***	-3.878107	-3.854931*	-3.804509*
Phillips-Perron test						
LGDP	8.858244	-1.996159	-0.387882	-3.420561**	-4.083515*	-4.754470*
FFEC	0.718547	-1.650565	-2.229908	-7.596853*	-7.563362*	-7.703566*
LICT	1.717696	-0.269405	-2.258951	-5.318338*	-5.894190*	-6.415034*
CO2	0.517082	-1.660872	-2.183726	-3.894111*	-3.870713**	-3.817689**

Note: (i): without intercept, (ii): with an intercept, and (iii): with an intercept and trend. ***, ** and *: asterisks mean a p-value less than 1%, 5% and 10%. Critical levels in the model: (i) −2.60 (1%), −1.95 (5%) and −1.61 (10%). Critical levels in: (ii) −3.51, −2.89 and −2.58. Critical levels in: (iii) −4.04, −3.40 and −3.15.

3.3. Cointegration analysis. The study of co-integration makes it possible to test the existence of a stable long-term relationship between two non-stationary variables, including delays and exogenous variables. There are several tests of co-integration, the most general being that of Johansen. Since all the series are integrated of order one, the co-integration relationship between them are established by using Johansen co-integration test. Two series (x and y) are said to be co-integrated if the two following conditions are satisfied: they are affected by a stochastic trend of the same order of integration and a linear combination of these series makes it possible to reduce to a series of order of lower integration. We use the maximum likelihood estimation (MLE) method of Johansen and Juselius (1990). The Johansen's co-integration test is based on two different likelihood ratio statistics (LR): the trace statistic and the maximum eigenvalue statistics. The co-integration test implies the existence of causality links between the series, but it does not indicate the direction of causality. The results of co-integration tests reported in Table 3 indicate the existence of a long-run relationship between ICT, transport energy, environmental degradation and growth.

Both the maximum eigenvalue and the trace statistic reject the null hypothesis of no cointegration.

Table 3. Results of Johansen cointegration test

Unrestricted cointegration rank test (Trace)				
Hypothesized		Trace	0.05	
No. of CE(s)	Eigenvalue	Statistic	Critical value	Prob.**
None *	0.781544	83.28428	54.07904	0.0000
At most 1 *	0.708025	48.29736	35.19275	0.0012
At most 2	0.372729	19.98237	20.26184	0.0546
At most 3 *	0.331302	9.255722	9.164546	0.0480

Note: trace test indicates 2 cointegrating(s) at the 0.05 level * denotes rejection the hypothesis at the 0.05 level ** P-values of MacKinnon-Haug-Michelis (1999).

3.4. Granger causality tests. After examining the long run links between the variables and the existing of co-integration, a causality test is designed to detect the dynamic causal direction between the two time series. In fact, the approach of Granger (1968) for the formalization of the causality concept has certainly had big echoes among researchers in economics. The basis of Granger causality test is the dynamic relationship between the variables in the short- and long-run. According to Granger's theorem of representation, any co-integrated system implies the existence of an error correction mechanism that prevents the variables from deviating too much from their long-term equilibrium. To ascertain the direction of causality between the studied variables, we estimate the error-correction model (ECM). The vector error-correction model VECM with our variables can be written as follows:

$$\Delta LGDP_t = \alpha_1 + \sum_{i=1}^{k}\beta_{1i}\Delta LGDP_{t-i} + \sum_{i=0}^{k}\delta_{1i}\Delta LICT_{t-i} + \sum_{i=0}^{k}\lambda_{1i}\Delta CO2_{t-i} + \sum_{i=1}^{k}\gamma_{1i}\Delta FFEC_{t-i} + \psi_1\varepsilon_{T\text{-}1} + \xi_{1t} \quad (2)$$

$$\Delta LICT_t = \alpha_2 + \sum_{i=1}^{k}\beta_{2i}\Delta LGDP_{t-i} + \sum_{i=0}^{k}\delta_{2i}\Delta LICT_{t-i} + \sum_{i=0}^{k}\lambda_{2i}\Delta CO2_{t-i} + \sum_{i=1}^{k}\gamma_{2i}\Delta FFEC_{t-i} + \psi_2\varepsilon_{T\text{-}1} + \xi_{2t} \quad (3)$$

$$\Delta CO2_t = \alpha_3 + \sum_{i=1}^{k}\beta_{3i}\Delta LGDP_{t-i} + \sum_{i=0}^{k}\delta_{3i}\Delta LICT_{t-i} + \sum_{i=0}^{k}\lambda_{3i}\Delta CO2_{t-i} + \sum_{i=1}^{k}\gamma_{3i}\Delta FFEC_{t-i} + \psi_3\varepsilon_{T\text{-}1} + \xi_{3t} \quad (4)$$

$$\Delta FFEC_t = \alpha_4 + \sum_{i=1}^{k}\beta_{4i}\Delta LGDP_{t-i} + \sum_{i=0}^{k}\delta_{4i}\Delta LICT_{t-i} + \sum_{i=0}^{k}\lambda_{4i}\Delta CO2_{t-i} + \sum_{i=1}^{k}\gamma_{4i}\Delta FFEC_{t-i} + \psi_4\varepsilon_{T\text{-}1} + \xi_{4t} \quad (5)$$

where Δ is the difference operator, $\alpha, \beta, \delta, \lambda, \gamma$ *and* ψ are parameters for estimation, *t* is the lag order, ε_{t-p} is an error term. To test whether the Granger causality runs from *LICT* to *GDP*, the null (H_0) hypothesis is: H_0 : $\delta_{1i} = 0$, i = 1,2,………*p*; If H_0 is rejected, i.e., at least one of δ_{1i} is not equal to zero, then it suggests that the past value of *LICT* has a significant linear predicative power on the current value of *GDP*. It normally denotes that *LICT* Granger causes *GDP*, and vice versa.

After validating the stationarity of the data, we can test a causal relationship between the time series. At this step of the study, we can empirically apply the Granger causality test to our variables and analyze the results. The test was performed on all the variables and intersections between the pairs of variables taken into account. Crossing couples which have not yielded significant results will not be discussed in this section. We perform a VECM model based on Granger causality test to identify the direction of causality (running from x to y...) between ICT, transport energy, environmental degradation and growth measured by GDP. The long-run causality is captured by a significant t-test on a negative coefficient of the lagged error-correction term ECM_{t-1}.

Based on co-integration analysis, the VECM presented in equations (2), (3), (4) and (5) is employed to determine the direction of causality in the short and long run using Granger causality tests. These results are shown in Table 5. Results show that there is a unidirectional links running from transport energy consumption to economic growth measured by LGDP at 1% level of significance in the short and long run. Unidirectional relationship running from CO2 emissions to economic growth also is found at 1% level of significance in the short and long run. In fact, the Tunisian economy is based in the non-renewable energy use that considered as a principal factor of the greenhouse emissions. On the other hand, there is a big interdependence between CO2 emissions and transport energy consumption explained by the bi-directional relationship at the 5% level of significance in the short run.

Table 4. The VECM Granger causality analysis

	Short run				Long run
Dependent variables	D(LGDP)	D(FFEC)	D(LICT)	D(CO2)	ECM_{t-1}
D(LGDP)		7.667876* (0.0056)	0.000472 (0.9827)	19.61362* (0.0000)	-0.033396* [-6.47515]
D(FFEC)	0.511289 (0.4746)		0.210911 (0.6461)	6.119163** (0.0134)	-0.149319* [-0.94429]
D(LICT)	0.011497 (0.9146)	0.174408 (0.6762)		0.023234 (0.8788)	-0.041334 [-0.46898]
D(CO2)	1.639424 (0.2004)	4.660298** (0.0309)	0.045703 (0.8307)		0.547165 [1.02228]

Notes: ECT represents the coefficient of the error correction term. *, ** and *** significant at 1%, 5% and 10% level

3.5. Variance decomposition. The VAR models are often analyzed through their dynamics and this via the simulation of random shocks and the analysis of the decomposition of their variance. The variance decomposition (VD) indicates the proportion of the movements in the dependent variables which are due to their "own" impacts and against shocks to the other variables. In fact, after estimating these regressions, we can use the residuals to decompose the variance. This will allow us to determine the contribution of past values of each model variable to the variance prediction of one or other of the model variables in the future. This method does not allow assessing the percentage of the variance of the forecast error that explained by each variable in absolute terms, but only in relative terms. The VD measures the quantitative effect that the shocks have on the variables (see Enders, 2004). On the other hand, Diebold and Yilmaz (2009) introduce a volatility spillover (VS) measure based on forecast error variance decompositions (FEVD) from vector autoregressions (VAR (p)). Considering N stationary variables VAR (p),

$$y_i = A \sum_{i=1}^{p} \Phi_i y_{t\text{-}1} + \varepsilon_i,$$

in which where y_i is a (4 × 1) vector of jointly determined endogenous variables, $\varepsilon \to (0, \theta)$ is the vector of IID disturbances, ϕ_1 through ϕ_p are (4 × 4) coefficient matrices, A is a vector of constants. In addition, Diebold and Yilmaz (2012) used the generalized VAR framework proposed by Pesaran and Shin (1998); they constructed a variance decomposition invariant to commanding. Let us denote the generalized forecast error variance decompositions by:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{ij}^{-1} \sum_{h=0}^{H\text{-}1} (e_i' A_h \sum e_j)^2}{\sum_{h=0}^{H\text{-}1} (e_i' A_h \sum A_h' e_i)},$$

where Σ is the variance matrix for the error vector ε, σ_{ij} is the standard deviation of the error term for the j^{th} equation, and e_i is the selection vector, with one as the i^{th} element and zero otherwise.

Table 5 shows the results of the estimate forecast error of variance decomposition for each variable. The decomposition variance is taken temporally with respect to the source of disturbance. In fact, median forecast error of variance decompositions are computed to a horizon of two, four, six and eight years. The impact of FFEC on GDP is 24.29 percent by the first two years; this effect increases for the remaining periods and up to 83.55 in the eight periods. This result shows that the economic growth measured by GDP is more dependent by transport energy compared to the other variables. Our results show that the most of the variation in the forecast error for CO2 emissions comes from shocks to transport energy consumption which exceeds 29.18% after 8 periods. In fact, transport sector is responsible for more than a quarter of national emissions of greenhouse gases in Tunisia. The CO2 emissions are less explained by the ICT. Result shows that for a time horizon of 4 years, almost 2.01% of the variation CO2 is explained by the ICT. This variation decreases less than 2% at the 6th period and up 1.81% in the 8^{th} period (8 years). The influence of the transport energy consumption on CO2 emissions is taken into account, while the direct effect of GDP on ICT is almost stable during 8 years, 2.36% of the effects on GDP in 2 years, and this cross until 2.09% in 8 years.

Table 5. Variance decomposition: Cholesky ordering: LNGDP FFEC LNICT CO2

Period	S.E.	LNGDP	FFEC	LNICT	CO2
Variance decomposition of LNGDP					
2	0.021636	63.29042	24.29938	2.904420	9.505782
4	0.037580	29.75749	48.00625	6.798376	15.43789
6	0.059070	13.71315	72.74176	6.851895	6.693188
8	0.085552	6.993442	83.55777	6.200802	3.247984
Variance decomposition of FFEC					
2	0.517704	3.568371	67.34309	0.310023	28.77852
4	0.704650	4.413621	44.51950	0.309342	50.75754
6	0.819301	4.782577	37.90308	0.237382	57.07696
8	0.920565	4.745090	32.76622	0.188516	62.30018
Variance decomposition of LNICT					
2	0.305377	2.364488	0.101633	97.19618	0.337698
4	0.420565	2.341398	1.368388	95.08058	1.209636
6	0.510216	2.242186	2.926046	93.22668	1.605088
8	0.588169	2.093655	4.832679	91.05330	2.020371
Variance decomposition of CO2					
2	2.267525	0.842878	22.41637	1.764821	74.97593
4	3.198119	1.445495	25.58898	2.010333	70.95519
6	3.855313	1.395904	27.61469	1.922053	69.06735
8	4.477910	1.319308	29.18501	1.813856	67.68183

Conclusion and implications

This study aims to investigate the dynamic relationship between transport energy consumption, economic growth, ICT's and carbon emissions in Tunisia during the period 1990–2015. The main results show that transport energy increases the CO2 emissions in Tunisia. Otherwise, there is not a significant effect of ICT in CO2 emissions. These results are confirmed by the Granger causality test and the variance decomposition.

Thus, such an in-depth knowledge of the transport sector will make it possible to evaluate the potential of rational energy use, reduction of pollution and greenhouse gas emissions and to establish programs of action for rational energy use in this sector. However, it should be noted that Tunisia's energy policy is focused on controlling energy demand, diversifying sources of technical production and supply, developing research in the energy sector, ensuring the existence transport infrastructure and energy storage adapted to consumer needs. It is within this framework that the National Agency for Energy Management, which promotes energy savings, particularly in the sectors of everyday use (housing, offices, shops, transport), where consumption is high, as well as the promotion of renewable energies. In the same context, these findings recommend, to encourage and support the creation of freight plants, in particular by setting up specific financing mechanisms. In addition, the strategy must include a real encouragement of rail for the transport of goods. In this context, the Tunisian National Railway Company will be able to promote this service technically and commercially.

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