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CO2 emissions reduction in road transport sector in Tunisia

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ABSTRACT

This study examines the impact of energy consumption of fuel, intensity energy of road transport, economic growth, urbanization and fuel rate on carbon dioxide (CO2) emissions in Tunisia. The investigation is made using the Vector Autoregressive (VAR) model. It analyses the influencing factors of the changes in CO2 emissions from Tunisian transport sector during the period of 1980–2014. The results show that energy efficiency and fuel rate play a dominant role in reducing CO2 emissions. Our empirical results confirm the hypothesis of Environmental Kuznets Curve (EKC) which suggests that economic development follows an inverted *U*-shaped pattern in relation to CO2 emissions in Tunisia. These findings are important for the relevant authorities in Tunisia in developing appropriate energy policy and planning for the transport sector.

1. Introduction

In Tunisia, transport sector takes the second place in terms of energy consumption with 34% of total energy consumption in 2010 after industrial sector (35%) [1]. Transport energy has been increased from 827.7 kg tone oil equivalent (ktoe) in 1980 to 1.821 ktoe in 2010. Several factors can explain this fact: pricing and taxation of fuel used by road transport vehicles, important road infrastructure investments and vehicle's park structure. The transport sector is considered as the most important consumption of fossil combustibles with 99.5% of petroleum products consumption in 2010. This fact is explained by that road transport activity in Tunisia is closely linked to combustible fossils consumption, especially gasoline (25%) and diesel (60.6%) in 2010. Also, the car park structure is characterized by old gasoline vehicle that contribute more to CO2 emissions. The gasoline car represents more than 76% of total car park in 2010 with an average annual growth rate of 5.5% in the transport sector [2].

Identifying the key driving forces of CO2 emissions is essential for formulating effective environmental protection and emission reduction policies. Aydin [3] analyzed the influencing factors of energy-related CO2 emissions in Turkey from 1971 to 2010, and found that population size, economic growth, clean nuclear energy use, fossil energy consumption, waste energy conversion and renewable energy were the five main factors impacting change in CO2 emissions. Ucak et al. [4] found that there was a positive nexus between economic growth and CO2 emissions, and that the coefficient varied significantly across different low-income and high-income countries. Similar evidence was produced by Begum et al. [5]. They both found that GDP growth, population growth and high-polluting fossil fuels had a significant impact on carbon emissions. Furthermore, Wu et al. [6] pointed out that the relationships between these factors and CO2 emissions were dynamically changing.

Despite this, a few studies have also explored the change in the transport sector's CO2 emissions. He et al. [7] predicted the trend of oil consumption and carbon emissions from China's road transport industry, and proposed related policies to control the excessive increase in oil consumption. Furthermore, Tian et al. [8] studied CO2 emissions from different transport modes and relevant mitigation options for China's transport sector. Kinnear et al. [9] investigated the impact of heavy-duty trucks on the transportation industry's CO2 emissions in Austria. Sanz et al. [10] discussed the effect of bio-fuels consumption on emissions-reduction in Spanish transport sector. Using co-integration method and data from 1960 to 2008, Saboori et al. [11] explored the relationship between the transport sector's energy consumption and GDP growth and CO2 emissions in OECD countries. The results indicated there is a long-term stable nexus between the variables. Specifically, Solis and Sheinbaum [12]calculated the influences of private gasoline car, gasoline light duty freight, diesel interurban buses and diesel heavy duty freight vehicles on road transport sector's CO2 emissions in Mexico, and found the contributions of these vehicles are 32.6%, 25%, 11.3% and 12%, respectively.

In this work, we introduce VAR model to investigate the nonlinear effects of the main influencing factors of Tunisia's transport sector's CO2 emissions and we identify the main driving forces of the transport sector's CO2 emissions and propose appropriate mitigation measures.

The rest of the paper is organised as follows: Section 2 presents econometric methodology. Section 3 reports the empirical results. The last section concludes by some recommendations.

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2. Econometric methodology

2.1. VAR model

The (VAR) model, pioneered by Sims [13] about 25 years ago, have acquired a permanent place in the toolkit of applied macroeconomists both to summarize the information contained in the data and to conduct certain types of policy experiments.

It is commonly used for forecasting systems of interrelated time series and for analyzing the dynamic impact of random disturbances on the system of variables.

The model approach sidesteps the need for structural modelling every endogenous variable in the system as a function of the lagged values of *all* of the endogenous variables in the system. It allows us to consider both long-run restrictions and short-run restrictions justified by economic considerations (Magkonis and Tsopanakis [14]). Consequently, the VAR model is used to capture the dynamic impacts of the influencing factors on CO2 emissions in transport sector in Tunisia.

The mathematical expressions of general VAR (P) model are as follows:

$$y_t = A_1 y_{y-1} + \ldots\ldots + A_p y_{t-p} + Bx_t + \varepsilon_t \tag{1}$$

where y_t is a k vector of endogenous variables, x_t is a d vector of exogenous variables, $A_1, , , , , , , , , A_p$ and B are matrices of coefficients to be estimated, and ε_t is a vector of innovations that may be contemporaneously correlated with each other but are uncorrelated with their own lagged values and uncorrelated with all of the right-hand side variables.

Since only lagged values of the endogenous variables appear on the right-hand side of each equation, there is no issue of simultaneity and OLS is the appropriate estimation technique. Note that the assumption that the disturbances are not serially correlated is not restrictive because any serial correlation could be absorbed by adding more lagged y's.

2.2. Stationary test

The acceptability of a regression result is commonly based on the premise that the series used in the regression model are stationary or co-integrated if the series are non-stationary; otherwise inauthentic regression may occur. Furthermore, multicollinearity among independent variables can cause large variances in estimated coefficients and decrease the accuracy of estimated equations; a multicollinearity test should be performed on independent variables.

The augmented Dickey–Fuller (ADF) unit root test is typically used to examine the stationarity of time series, in which a high-order autoregressive model with an intercept term is established by Maddala and Kim [15]. Taking the ADF test on series lnI as an example, we express the test equation with the constant term, as well as the trend and intercept terms, as follows:

$$\Delta \ln I_t = \alpha + \beta t + \delta \ln I_{t-1} + \sum_{i=1}^{k} \beta_i \Delta \ln I_{t-i} + \varepsilon_t \tag{2}$$

where α, β and δ are coefficients; ε is a residual term; and k is the lag length, which turns the residual term into a stochastic variable.

The null hypothesis $H0$ is $\delta = 0$; i.e., at least one unit root exists, causing the non-stationarity of the series. The test is conducted with three formulations: $(\alpha \neq 0, \beta \neq 0)$, $(\alpha = 0, \beta \neq 0)$ and $(\alpha = 0, \beta = 0)$.

As long as one of the three models rejects the null hypothesis, the series are considered stationary. However, when the results of all the three models do not reject the null hypothesis, the series are regarded as non-stationary.

2.3. Model specification

The IPAT identity (Ehrlish and Holdren [16]) is an equation that is commonly used to analyze the impacts of human behaviour on environmental pressure. The equation is expressed as:

$$I = PAT \tag{3}$$

where I represents environmental impact, P represents population, A stands for affluence, and T denotes technology.

The *IPAT* identity is an accounting model, in which one term is derived from the values of the three other terms. The model requires data on only any three of the four variables for one or a few observational units, and it can only be used to measure the constant proportional impacts of the independent variables on the dependent variable. To overcome this limitation, Dietz and Rosa [17] established the STIRPAT model by reformulating the *IPAT* identity into stochastic form:

$$I_t = aP_t^b A_t{}^c T_t^d e_t \tag{4}$$

where I, P, A and T have the same definitions as in the *IPAT* identity; a, b, c and d are coefficients; and e is a residual term. In this reformulation, data on I, P, A and T can be used to estimate a, b, c, d and e with statistical regression methods. The reformulated version can convert the *IPAT* accounting model into a general linear model, in which statistical methods can be applied to test hypotheses and assess the non proportionate importance of each influencing factor. As a special case, the stochastic version can be converted back to the original model given that$a = b = c = d = e = 1$.

In order to eliminate the possible existing heteroskedasticity in the model and to facilitate hypothesis testing, all the factors take logarithmic form Zhao et al. [18]. Owing to e_t is the disturbance term, we do not need to distinguish between e_t and Logarithmic Le_t. Then Eq. (4) can be written as:

$$LI_t = La + b(LP_t) + c(LA_t) + d(LT_t) + e_t \tag{5}$$

where P represents population size, A is measured by the per capita GDP, T is a technology index and measured by total energy consumption divided by total outputs (energy intensity-EI). In order to investigate the impacts of the driving forces of the transport sector's CO2 emissions, Eq. (5) can be rewritten as follows:

$$LCO2 = La + b(LPOP_t) + c(LGDP_t) + d(LEI_t) + e_t \tag{6}$$

where CO2 represents total CO2 emissions of the transport sector, POP is population size, GDP denotes economic development level measured in real per capita GDP, EI is proxied by energy use in the transport sector divided by its total outputs, which has been used to investigate the changes in CO2 emissions (Zhang and Da [19]). b, c and d represent the elasticities of the transport sector's CO2 emissions in response to changes in total population, GDP growth and energy intensity respectively. It refers to the percentage change in carbon emissions in response to a 1% change in the influencing factors with the other variables unchanged. a and e_t denote the constant term and random disturbance term.

To further analyze the driving forces of the CO2 emissions in road transport sector, and considering the specific situation in road transport sector in Tunisia, we expand the STIRPAT model by incorporating urbanization level (URB), EC (Energy consumption of fuel), IT (Intensity energy of road Transport) and FR (Fuel Rate) obtained by dividing fuel consumption by mileage of motor vehicle and used a proxy for technology progress into the model for some reasons.

The transport in Tunisia is one of the major economic activities which consume a big part of energy.

In 2010, the road transport has the highest energetic consumption (76%) compared to the railway transport (3%). Public passenger transport energy consumption was about 38.78 ktoe in 2010. Road transport energy use has increased from 514 ktoe in 1980 to 1689 ktoe