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Abstract

The World is confronted with a slew of environmental issues, one of which is how to attenuate the detrimental impacts of CO_2 emissions-induced climate change. The ever-increasing use of energy is eroding natural resources to the point that our economic future may be jeopardized. The Tunisian economic growth indicates the excellent performance in the industrial sector as the minimum required input for these developments necessitates additional energy consumption, resulting in increased CO_2 emissions and environmental degradation. This study explores the role of energy efficiency, urbanization, economic growth, and natural gas energy usage in the industrial sector on carbon dioxide (CO_2) emissions of Tunisia. The research mainly employs the Vector Autoregressive Model (VAR) to examine the factors driving the evolution of CO_2 emissions through the industrial sector from 2000 to 2018. The findings assess that natural gas as an energy source and efficiency are crucial for reducing CO_2 emissions. The study has shown the existence of the Environmental Kuznets Curve (EKC), which demonstrates that economic development in Tunisia has an inverted U-shape connection with CO_2 emissions. The results indicate that energy consumption and GDP significantly affect CO_2 emissions due to large-scale population movements and industrial structure transformation. In contrast, energy efficiency plays a dominant role in decreasing CO_2 emissions. The article will assist economic decision-makers and related authorities in formulating an appropriate energy policy for the industrial sector based on the study's outcomes to protect environmental degradation in the long run by reducing carbon emissions.

Keywords: Industrial sector, Carbon dioxide emissions, Vector autoregressive model, Tunisia.

1. Introduction

Oil is the World's most abundant energy source, accounting for roughly 33% of worldwide energy use (Rapier, 2020). According to International Energy Agency, the industrial sector is the most energy-intensive, participating in 54% of global energy consumption. Since 2010, energy consumption in the industry has upsurge by an average rate of 0.9% per year, dominantly a substantial rise of 1.6% in 2017 (IEA, 2020). In Tunisia, the industry is the second most energy-intensive sector, sharing more than a third of overall energy consumption (Jain, 2018). The industrial sector is incredibly reliant on fossil fuels, including natural gas, petroleum, and liquefied petroleum gas, contributing to greenhouse gas emissions. Although industrial CO_2 emissions in

Tunisia have been steadily increasing since 1990, the World's overall industry accounts for roughly 21% of all emissions (Pachauri & Meyer, 2014). The country has lowered its energy usage due to initiatives in energy efficiency to reducing greenhouse gas emissions. The utilization of mixed power and heat plants has been streamlined putting into action by the Tunisian central monitory system (IRENA et al., 2018). The country's representatives have advanced the expertise of industrial energy towards sustainable and efficient usage; still, this sector emitted around 32.1 million tonnes of CO2 in 2019 (CAIT, 2020).

Historically, carbon emissions from manufacturing industries have fluctuated significantly in recent years, with a prominent upward trend from 1995 to 2014, reaching 21.3% in 2014 (KNOEMA, 2016). It prompts various researchers to focus on the driven roots behind the emitting CO2 emissions in the sector. In the context of literature, different methodologies have been undertaken to determine the driving elements of CO_2 emissions of the industrial sector. For example, to study CO_2 emissions in heavy industry, Xu & Lin (2020) utilized a quantile regression model and exposed that economic expansion at the provincial level significantly impacts CO_2 emissions from heavy industry in the 25th to 50th quantile. On the other hand, urbanization has a more negligible impact on carbon emissions in the 10th to 25th lower quantile provinces than the other quantile provinces. Song et al. (2018) investigated the CO_2 emissions from China's steel industry by employing the index decomposition approach. As per the findings, economic development boosted demand for these industrial products, resulting in increased carbon emissions from steel manufacturers. They further stated that maximizing energy intensity reduction and upgrading manufacturing technologies that optimize the energy structure have aided in limiting CO_2 emissions rise (Adebayo et. al., 2021).

Moreover, Du & Lin (2018) employed the log-mean Divisia index approach to investigate CO_2 emissions in China's metallurgical industry. The findings uncovered that energy intensity and labor productivity have an adverse effect on carbon emissions, but industrial size positively impacts CO_2. Wen et al. (2019) investigated the linkages between the Chinese steel industry and carbon emissions, recommending that renewable energy and carbon recycling techniques are the most effective way to reduce CO_2 emissions in the long run in China. The study also quantified that regulating excessive expansion in the industrial sector is a key aspect in efficiently reducing carbon emissions. Tan et al. (2019) found similar results and suggested that curbing unauthorized industrial growth would be a substantial source to mitigate carbon emission. Another critical

research examined the impact of carbon emissions from China's power business and discovered the intensive use of coal in the power industry contributes to carbon emissions (Meng et al., 2017). The study also tells that coal usage improves power generation efficiency in the long run. However, Chebbi (2010) used ARDL and ECM methods and reports the interaction between energy consumption, economic growth, and environmental degradation varies by industry with no uniform connectedness across several sectors in Tunisia.

In the same way, Farhani et al. (2014) discovered a long-term and solid causal association between carbon emissions, economic growth, and trade through the ARDL approach. Engo (2021) recently examined that economic growth and energy consumption played a crucial role in decoupling sectoral carbon emissions in Tunisia and Morocco. Some scholars also used the VAR model to measure the dynamic connectivity of carbon emission with energy consumption and economic growth. For instance, Xu & Lin (2016) employed the VAR approach to estimate emissions from China's steel industry and found the natural gas usage is crucial to minimize carbon emissions. Dong et al. (2018) arrived at the same conclusion and validated the existence of EKC in the relationship between economic growth and carbon emissions.

The industrial sector occupies the second place of energy consumption in Tunisia; it represents more than a third of the total energy consumption (Safdar, 2020). The consumption of natural gas increased between 2000 and 2012 (more than 6% per year) and remained stable until 2014. However, it increased by 3.4% per year compared to 2015 and stood at 65 bcm in 2018 (Abid, 2020). The primary gas market remained of electricity production 67% in 2018. In the same year, the total energy consumption of natural gas in the industrial sector was 907 ktoe (IAEA, 2018).

In 2014, the manufacturing industries' CO_2 emissions for Tunisia were around 21.3%. However, the country's CO_2 emissions have fluctuated considerably in recent years, and it tended to increase during the period 1995-2014, ending at 21.3% in 2014 (ANME, 2019). In 2019, the CO_2 emissions per capita for Tunisia were 2.72 tonnes of CO2 per capita. It grew with the rate of 0.84 tonnes of CO_2 per capita to 2.72 tonnes from 1970-2019, increasing at an average annual rate of 2.52% (World Bank, 2020).

Energy efficiency is a way to reduce energy consumption and help companies to reduce their production costs. The German experience shows that the reduction in energy consumption can be obtained through innovative solutions (cogeneration, audits, self-consumption, etc.), which can, thus, reduce greenhouse gas emissions (Czarnitzki et al., 2020). A project to reduce greenhouse

gas emissions from the Tunisian industry is carried out in partnership between GIZ and the National Agency for Energy Management (ANME, 2019). This project aims to promote new energy efficiency methods and technologies to carry out specific energy diagnostics within several industrial companies to select practical actions to generalize them. The use of this technology saves resources and reduces greenhouse gas emissions.

Throughout the debate, it becomes clear that there is a paucity of literature on detailed empirical findings of industrial sector carbon emissions and their potential sources, particularly in Tunisia. Therefore, we employ a robust multivariate time series VAR methodology to primarily investigate the dynamic connections of influencing drivers of carbon emission from Tunisia's industrial sectors throughout 2000-2018. To this end, our research is unique and contributes to the existing body of knowledge in the following ways. The undertaking econometric technique has the advantage of capturing parameter variation over time since it is assumed that every variable in the research is a linear function of it and other variables' past lag values. So, it helps to restore the study's dynamic system and provides reliable factual insights on the dynamic relationship between factors. In this context, Evangélique (2020) stated that the VAR model increases the credibility of economic policies that are primarily designed based on the findings of this methodology. The potential benefits of VAR modeling can be summarized as follows: (i) a priori restrictions (endogenous and exogenous variables are known automatically), (ii) arbitrary causal structure (direction of causality between variables not or poorly identified), and (iii) inadequate treatment of expectations. Hence note that, unlike the simultaneous equation system, which suffers from identification problems, autoregressive vector modeling removes the constraints associated with identifying structural equations, making it less restrictive than simultaneous equations.

To disregard the notion of simultaneity effects between variables and the shift of all endogenous variables to exogenous ensures that the VAR equations are correctly identified, adjusted, and adapts to changes in the socio-economic environment, such as shocks. Thereupon, our research will provide more robust and reliable insights to regulators, allowing them to form effective policies to limit the harmful effects of the different factors on industrial carbon emissions while promoting those initiatives that reduce CO_2 emissions.

The paper's remaining contents are laid out as follows: Section 2 discusses the econometric technique used in the study. The empirical findings and discussion are presented in Section 3. Lastly, the conclusion and policy recommendations are shown in the final section.

2. Econometric Methodology

2.1 VAR Model

Since we analyze the impact of the lag phase of a described variable on its own or explanatory variables, it is relatively hard to examine the dynamic relationship while using generic simultaneous equations model. As the variables must be specified as endogenous or exogenous variables in generic simultaneous equations, and every so often, they ignore certain critical lag variables. All variables are treated as endogenous in the VAR model, diminishing the incorrectness caused by subjective patterns in the model (Valipour et al., 2013). The Vector Autoregressive (VAR) model was introduced by Sims (1980) and is used in forecasting, structural inference, and policy analysis (Stock & Watson, 2001). A first plus of the VAR model makes it possible to apprehend the dynamic behavior of variables linearly dependent on the past. The VAR model makes it possible to explain and analyze the evolution of a series by considering the connections between many variables. The second advantage of VAR is that it avoids having to decide situations, which are the exogenous and endogenous variables of the model, as it only includes endogenous variables. The third benefit is that the VAR model is an empirical and form of linear dynamic model with having several equations. Each equation denotes a linear relationship where a variable is expressed as a combination of its own past values and the past values of other variables. All of these model variables are endogenous. Each equation is completed by an error term which is either endogenous or exogenous. Existing research has found a plethora of dynamic correlations amid CO_2 emissions and the mechanisms that drive them. Therefore, the VAR model is used to examine the dynamic impact of Tunisia's CO_2 emissions driving elements.

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

$$y_t = A_1 y_{t-1} \dots\dots\dots\dots + A_p y_{t-p} + B x_t + \varepsilon_t \qquad (1)$$

Where y_t is a k vector of endogenous variables, x_t is a d vector of exogenous variables, and $A_1 \dots\dots\dots\dots\dots A_p$ 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 uncorrelated with their own lagged values and uncorrelated with all right-hand-side variables.

The VAR model assumes that the dynamic effects are the same in the k regions and the interregional effects are absent. Indeed, there are two ways of including interregional effects. The first way is to introduce one or more variables called shifted variables into the model. The second

way is to specify a spatial process for the errors. For example, we can assume that errors follow an autoregressive process. However, in a VAR, there are no lagged variables. The error terms are uncorrelated white noise (in a forecasting model) or correlated shocks (in a structural model).

The VAR model has a basic flaw: the longer the lag period, the more parameters must be estimated, and the smaller the degrees of freedom (Michieka et al., 2013). A balance between the degree of freedom and the lag periods must be found. The basic rule is to choose lag periods when both the the Akaike Information Criterion (AIC) and Swartz Criteria (SC) statistical values are the lowest. The equations could be expressed as follows for both:

$$AIC = 2\mathrm{l}/\mathrm{n} + 2\mathrm{k}/\mathrm{n} \tag{2}$$

$$SC = 2\mathrm{l}/\mathrm{n} + \mathrm{k}\log \mathrm{n}/\mathrm{n} \tag{3}$$

The number of parameters to be estimated is given by k = m (qd + pm). The sample size is n, and calculated by using the formula below.

$$l = -\frac{\mathrm{nm}}{2}(1 + \log 2\pi) - \frac{\mathrm{n}}{2}\log\left[det\left(\sum_t \hat{\varepsilon}_t\, \hat{\varepsilon}'_t/n\right)\right] \tag{4}$$

When calculating quantitative parameters of the population by using sample statistics, the degree of freedom is freely changing variables or the number of independents in the sample (Hu et al., 2015). The evaluating equations have fewer degrees of freedom since the VAR model has more factors and greater lag periods. With constraints on panel data, we thoroughly examine the range of parameters and lag periods in this article to assure estimation robustness. We believe that the degree of freedom in VAR enables an accurate estimation to achieve the study's aims. This assumption is based on our hands-on experience synced with other researchers working on similar challenges.

2.2. Stationary Test

The sequences of the immense majority of variables of economics are not stable. So, the sample data must be stationary in general for an econometric model to work. As a result, the time series must be transformed to a stationary sequence before undertaking a simulation study. Otherwise, the projected parameters would be skewed, making it impossible to explain the actual model adequately. The unit root test is the most common way of ensuring that a sequence is data stationarity. The multiple widely utilized test technique checks data stationarity as we have taken the Augmented Dickey-Fuller (ADF) test in this study. The ADF test avoids the effects of higher-order Cointegration by including a lagged difference term for the dependent variable yt in

the equation. The ADF test is a parametric test based on the estimation of an autoregressive process. The general ADF model is written as follows:

$$\Delta \ln y_t = \alpha + \beta_t + \delta \ln y_{t-1} + \sum_{i=1}^{k} \beta_i \ln y_{t-i} + \varepsilon_t \qquad (5)$$

The following assumption then tested

$$H_0: \delta = 0, \;\; H_0: \delta < 0 \qquad (6)$$

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

Dickey and Fuller (1981) consider three basic models: model without constant nor deterministic tendency, the model with constant without deterministic tendency, and model with constant and deterministic tendency. From these equations, we test the null hypothesis of unit root against the alternative hypothesis of no unit root. The application of the ADF test requires the selection of the number p of delays.

2.3. Impulse response function

The lag structure of the VAR model always passes the interference influence towards other variables. Because interference terms are correlated for the same period, a single shock in the VAR model would influence multiple interference terms simultaneously. The model's standard analytical approach is the impulse response function, which may look at the impact of a shock on all endogenous determinants in the present and upcoming periods. As a result, the impulse response function has been applied as an essential investigation technique. The following is the econometric equation of impulse response function.

$$\begin{aligned} I(n/q, II_{t-1}) &= E(y_{t-n} \,|\, e_t = q, e_{t+1} = e_{t+2} = \ldots e_{t+n} \\ &= 0, II_{t-1}) - y_{t-n} \,|\, e_t = 0, e_{t+1} = e_{t+2} = \ldots\ldots\ldots e_{t+n} \\ &= 0, II_{t-1}) \quad n = 1, 2, 3 \ldots\ldots \qquad (7) \end{aligned}$$

As q is the shock vector, II_{t-1} is the time information set t. $I(njq, II_{t-1})$ is the difference in the functioning of two similar systems, which has clear economic implications. However, the states of the two systems are identical before time t. From t + n, the first system is subjected to shock with an influence strength of q. The reference system, which receives no shocks between t and $t +$

n times is the second system. The impulse response function in linear models takes the following form:

$$I(n/q, II_{t-1}) = E(y_{t-n}|e_t = q, II_{t-1}) - E(y_{t-n}|e_t = 0, II_{t-1}) \;\; n = 1, 2, 3, \dots\dots \quad (8)$$

Such as, future interference has no bearing on the impulse response function of linear models. In case the VAR model is stationary in equation 11, the following equations hold as:

$$y_t = v + A_1 y_{t-1} \dots\dots + A_p y_{t-p} + \mu_t, \qquad t = 0, \pm 1, \pm 2 \dots\dots \quad (9)$$

$$\left(l_M - A_1 L - A_2 L^2 - \cdots A_p L^p\right)^{-1} = l_M + F_1 L - F_2 L^2 \dots\dots\dots \quad (10)$$

L stands for the lag operator. Matrix $F_{n(M\times M)}$ has the following general formula:

$$F_n = \sum_{l-1}^{p} A_1 F_{n-1} \quad n = 1, 2, 3, \dots\dots \quad (11)$$

The primary value is

$$F_0 = l_M, F_{-1} = F_{-2} = \cdots = F_{-p+1} = 0 \quad (12)$$

Consequently, the VAR model can be stated as follows:

$$y_t = \mu_t + e_t + F_1 e_{t-1} + F_2 e_{t-2} + \cdots \quad (13)$$

Where $\mu_t = Qx_t + F_1 Qx_{t-1} + F_2 Qx_{t-2} + \cdots$. If $q = i_i$ is the unit response function, equation 9 can be modified as:

$$I(n/i_i, II_{t-1}) = F_n i_i = \frac{dy_{t+n}}{de_{ti}} \quad n = 1, 2, 3, \dots\dots \quad (14)$$

For instance, if the strength of impact is equal to the standard deviation, which is $q = s_i i_i$. In that scenario, equation 7 again could be altered as follow:

$$I(n/s_i i_i, II_{t-1}) = s_i F_n i_i = s_i \frac{dy_{t+n}}{de_{ti}} \quad n = 1, 2, 3, \dots\dots \quad (15)$$

It can be observed the positive impact strength of impulse response.

2.4. Model Specification and Description of Data

Before the regression analysis, this study first describes the trend in the level of urbanization, GDP per capita, energy efficiency, the energy consumption of natural gas, and CO_2 emissions in the Tunisian industrial sector. Based on the analysis of the various determining factors of CO_2 emissions in the industrial sector, the econometric model is established as follows:

$$CO_{2t} = f(GDP_t, URB_t, EC_t, EE_t) \quad (16)$$

$$LNCO_{2t} = \beta_0 + \beta_1 LNGDP + \beta_3 LNURB_t + \beta_4 LNEC_t + \beta_5 LNEE_t + \varepsilon_t \quad (17)$$

Where CO_2 is the total CO_2 emission in the industrial sector, GDP denotes economic development level measured in real per capita GDP, URB means urbanization, EC signifies energy consumption of natural gas of the industrial sector and EE represents energy efficiency. CO_2 is expressed in metric tons, GDP is measured at constant 2010 US$, URB expressed as a percentage of urban population from the total population, EC is defined in terms of (ktoe), and EE is calculated as GDP divided by total energy consumption that measured at the constant 2010US$ per 1000toe.

Real GDP is obtained from the World Bank (2020). The raw energy consumption of natural gas in the industrial sector and CO_2 emission were obtained from GIZ (2019) and National Agency for Energy Conservation (2018). The raw data of urbanization was from the National Institute of Statistics (NIC, 2019). All data is converted to natural logarithms. Figure 1 shows the evolution of the five variables over the period studied. Descriptive statistics for the five series are given in Table 1.

Table 1. Descriptive statistics.

	LCO_2	LEC	LEE	LGDP	LURB
Mean	7.494567	7.063834	3.686338	8.245977	4.581796
Median	7.493874	7.154144	3.688879	8.299593	4.574711
Maximum	7.644441	7.467537	4.941642	8.391259	6.228511
Minimum	7.401842	6.541510	2.302585	8.006960	3.135494
Std. Dev.	0.070703	0.334692	1.122359	0.131066	1.141361
Skewness	0.718736	-0.422397	-0.174456	-0.638364	0.291660
Kurtosis	2.887512	1.688099	1.331937	1.914975	1.543617

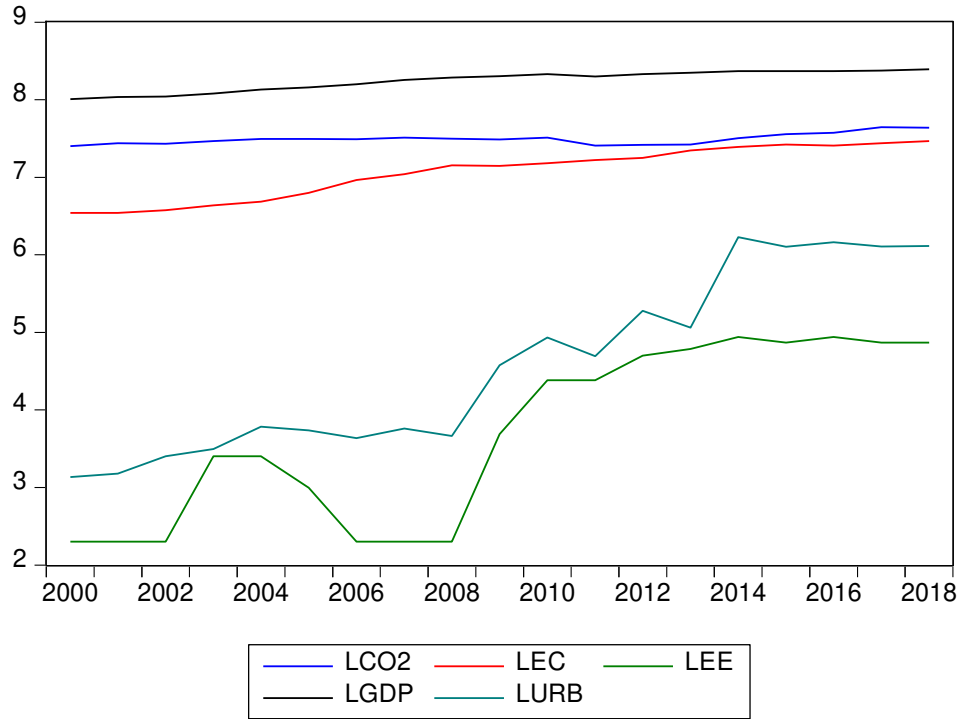

Fig.1. the evolution of the five series expressed in natural logarithms.

3. Empirical Results and Discussion

We test for the existence of unit roots of the five variables. Table 2 shows the results of the ADF tests. The results show that the series is not stationary in level but stationary in the first difference. Thus, all the studied variables are integrated of order one (I (1)) and can proceed to a cointegration test.

Table 2. Results of the stationary test using the ADF test.

Variables	Level	First difference	Verdict
LCO_2	-0.673359	-3.898204	I(1)
LEC	-1.231805	-2.866368	I(1)
LURB	-0.618106	-5.993987	I(1)
LGDP	-2.328766	-3.047814	I(1)
LEE	-1.023273	-3.104839	I(1)

3.2 Johansen Cointegration tests

The Cointegration test allows specifying long-term stable relationships between variables. In the literature, various approaches are used to determine the number of Cointegration relationships, including the Engle-Granger (1987) and Johansen (1991) approach. The first one is based on the

Dickey-Fuller unit root tests, and the second is based on two statistics: the trace test and the eigenvalue test. The Engle-Granger approach makes it possible to obtain only one Cointegration relation, while Johansen allows distinguishing several Cointegration vectors. In this work, we adopted the Johansen approach. The Johansen Cointegration rank test results for LCO_2, LEC, LEE, LGDP, and LURB are given in Table 3. Both of the two tests have rejected the null hypothesis at the 5% significance level and confirmed Cointegration between these economic variables.

Table 3.Unrestricted Cointegration Rank Test (Trace)

* denotes rejection of the hypothesis at the 0.05 level

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.996703	151.4075	69.81889	0.0000
At most 1 *	0.813309	54.25557	47.85613	0.0111
At most 2	0.571450	25.72442	29.79707	0.1372
At most 3	0.449819	11.31949	15.49471	0.1926
At most 4	0.066061	1.161857	3.841466	0.2811

**MacKinnon-Haug-Michelis (1999) p-values

Table 4. Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.996703	97.15190	33.87687	0.0000
At most 1 *	0.813309	28.53114	27.58434	0.0377
At most 2	0.571450	14.40493	21.13162	0.3327
At most 3	0.449819	10.15764	14.26460	0.2018
At most 4	0.066061	1.161857	3.841466	0.2811

* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

3.3 VAR model

This section uses the VAR model to study the impacts of different variables on the dependent variable in the industrial sector due to the varied lag period. In other words, the duration of the lag period (p) can be chosen, depending on the real correlations between variables.

3.3.1 The optimal lag order analysis

The appropriate selection of the delay period for the VAR model is essential because long delay structures can reduce the error term's autocorrelation and lead to an inefficient model. In this study, we choose a shift of 2 as dictated by the log-likelihood ratio (LogL), AIC, SC, the sequential modified LR test statistic (LR), FPE (final prediction error), and HQ information criterion (Hannan-Quinn) (Table 5).

Table 5. Lag selection criteria

Lag	Log L	LR	FPE	AIC	SC	HQ
0	51.86978	NA	2.77e-09	-5.514091	-5.269029	-5.489732
1	139.7718	113.7555	1.99e-12	-12.91432	-11.44395	-12.76817
2	196.5120	40.05195*	1.39e-13*	-16.6484*	-13.9527*	-16.3805*

Note: * indicates lag order selected by the criterion.

3.3.2 VAR specifications and estimates

Table 6. Vector autoregressive estimates.

LCO2(-1)	-0.119871	LGDP(-1)	-0.670769	LEE(-1)	0.024242
	(0.73680)		(1.33971)		(0.03909)
	[-0.16269]		[-0.50068]		[0.62021]
LCO2(-2)	1.167633	LGDP(-2)	2.344353	LEE(-2)	-0.023967
	(0.67199)		(1.31432)		(0.04862)
	[1.73757]		[-1.78369]		[-0.49296]
LEC(-1)	1.168651	LURB(-1)	0.095960	C	16.87692
	(0.47847)		(0.08496)		(5.23678)
	[2.44245]		[1.12950]		[3.22276]
LEC(-2)	0.136733	LURB(-2)	-0.028481	S.E. equation	0.037357
	(0.45625)		(0.06961)		
	[-0.29969]		[-0.40917]		
R-squared	0.891035	Log likelihood	40.61318	F-statistic	4.906353
Adj. R-squared	0.709427	Mean dependent	7.503361	Akaike AIC	-3.483904
Sum sq. resids	0.008373	S.D. dependent	0.069303	Schwarz SC	-2.944766

Note: standard errors in ( ) and t-statistics in [ ].

In order to check if the form of the model is correct or not, we perform a robustness test on the VAR model. As can be seen in Figure 2, all characteristic roots of the VAR model fall within the unit circle, indicating that the model estimation results are robust.

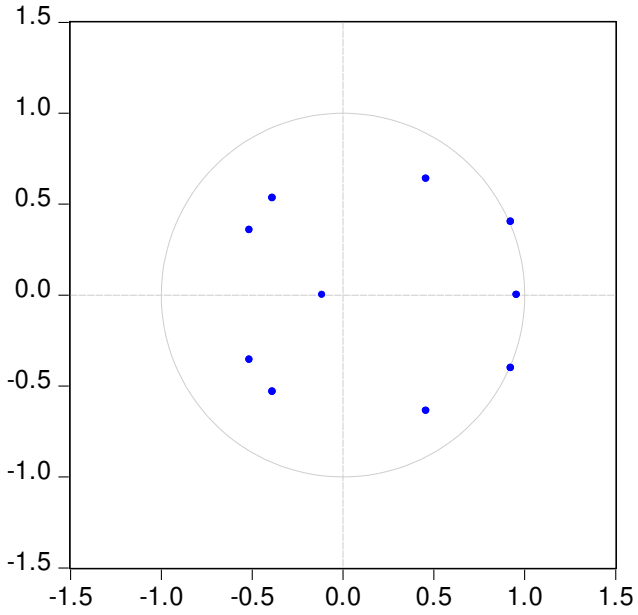

Fig. 2. VAR roots of characteristic polynomial.

3.3.3 Impulse response functions

In this section, the impulse response functions associated with the estimated VAR model are used to study the impacts of innovations in the explanatory variables. This methodology is very efficient and plays an imperative role in identifying shocks in model variables and measuring the impressions of such shocks. Figure 3 shows the responses of CO_2 emissions from the industrial sector to fluctuate in the short and long term.

CO_2 emissions in the industrial sector show a positive response to the energy consumption fluctuation in the short-term by reaching equilibrium, and then it displays a negative response (Figure 3). This indicates that energy consumption increases the CO_2 emissions from the industrial sector, while energy-saving technologies will remain fixed in the short term. Given the pressures of climate change, companies will increase R&D investments in energy-saving technologies such as hybrid, solar, and wind power plants. In the long term, energy consumption seems to drop down which helps to mitigate the CO_2 emissions level due to improved technologies.

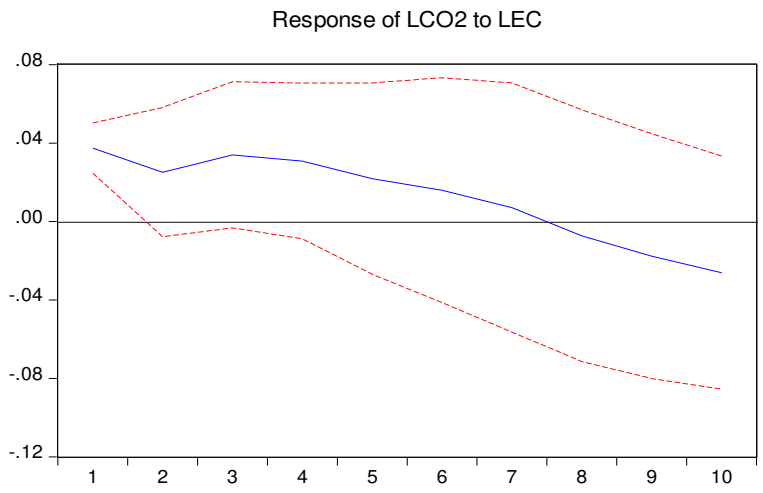

Fig.3 Response of CO_2 emission to energy consumption

Tunisia has a set of measures for the development of renewable energies. It is becoming an international pole of industrial production, as is the Tunisian solar plan (Ben Jebli & Ben Youssef, 2015). A planned installed renewable energy capacity of 3,815 MW is planned for 2030, aiming to help reduce its greenhouse gas (GHG) emissions by 41% in all sectors in order to decrease carbon intensity from levels 2010 (Mahlooji et al., 2020). Tunisia aims to achieve 30% renewable electricity production in its electricity mix by 2030, reducing the consumption of fossil fuels. A large part of the renewable energy installed comes from wind power and solar photovoltaic (PV) (UNDP, 2014). The country has also launched the BIOSOL project (Development and demonstration of a hybrid system for the gasification of biomass CSP (concentrated solar energy)) financed by the European program ERANETMED ("BIOSOL - Solar CSP hybrid gasification system of biomass boiler", 2018). It targets to integrate a prototype biomass gasification boiler in an existing CSP plant in Tunisia. Thus, the effect of the energy consumption of natural gas on CO_2 emissions changes from a negative impact to a positive. This means that optimizing the energy consumption structure and integrating renewable energies is essential to reduce CO_2 emissions in the industrial sector.

Figure 4 demonstrates the response of CO_2 emissions to urbanization. CO_2 emissions from the industrial sector show an adverse reaction to short-term urbanization, which will decrease over time. It indicates that in the long run, many residents have migrated to urban areas, leading to an increase in the urban population. Energy-intensive lifestyles due to high incomes lead to increased CO_2 emissions. However, with improvements in energy-saving technologies and long-term environmental awareness, the carbon intensity of urbanization would gradually decrease.

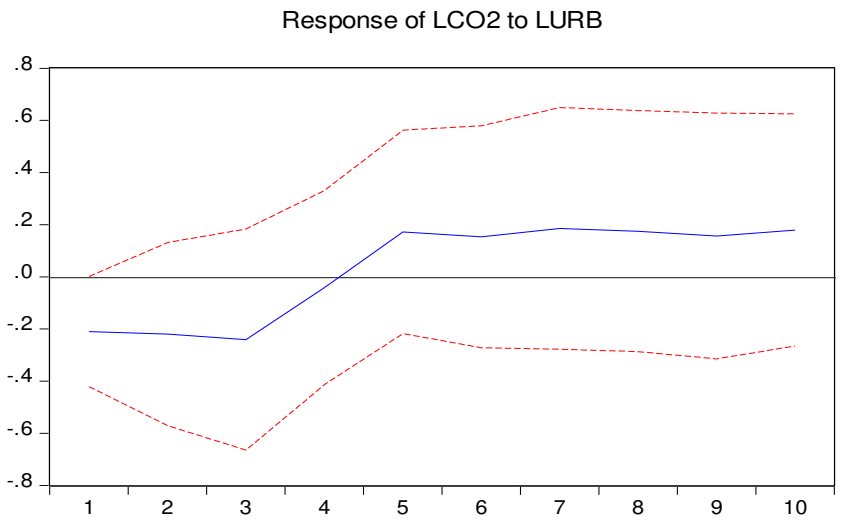

FIG.4. Response of CO_2 emission to urbanization

Fig. 5 expresses if there is a standard deviation shock on economic growth, the CO_2 emission has a positive response in the short run but a negative response in the long run. It confirms the EKC (Environmental Kuznets Curve) hypothesis, suggesting that economic development follows an inverted "U-shaped" pattern in relation to CO_2 emissions.

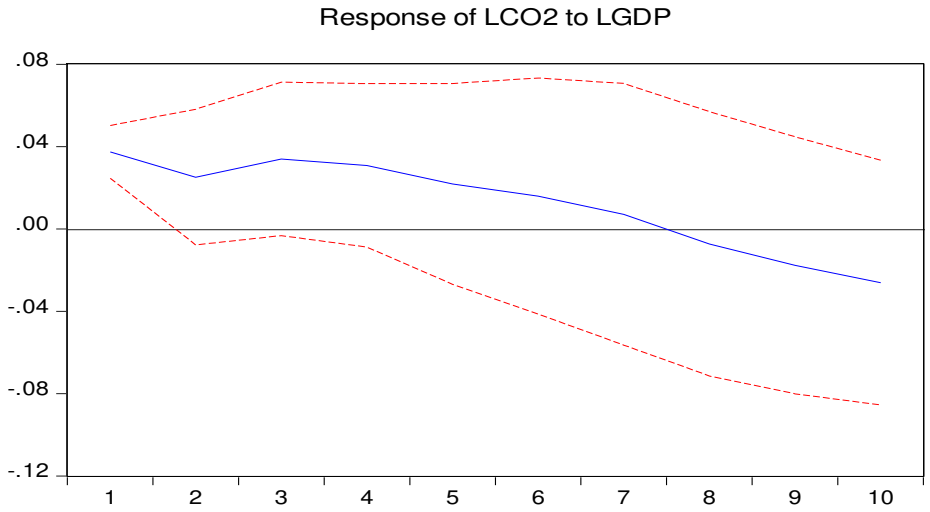

Fig.5. Response of emission CO_2 to GDP

CO_2 emission in the industrial sector displays a positive response to energy efficiency in the short term and a negative response in the long run (Figure 6), which means the energy efficiency plays a key role in sinking long-run CO_2 emissions. Tunisia has launched energy efficiency measures in the industrial sector and the creation of 3 taskforces:

Such as Working group to help large industrial energy users save energy; Task Force on natural gas to encourage the expansion of gas use in industry; Strength to work on cogeneration to achieve

cogeneration goals and to work with industrial companies to assist in the development and implementation of projects;

The energy efficiency industrial program contributed to energy savings amounting to 1,616 ktep, i.e., an annual average of 160 ktep per year, representing a 10% reduction in the annual consumption of the industrial companies concerned by the program (320 companies). Therefore, energy efficiency is vital in reducing CO_2 emissions.

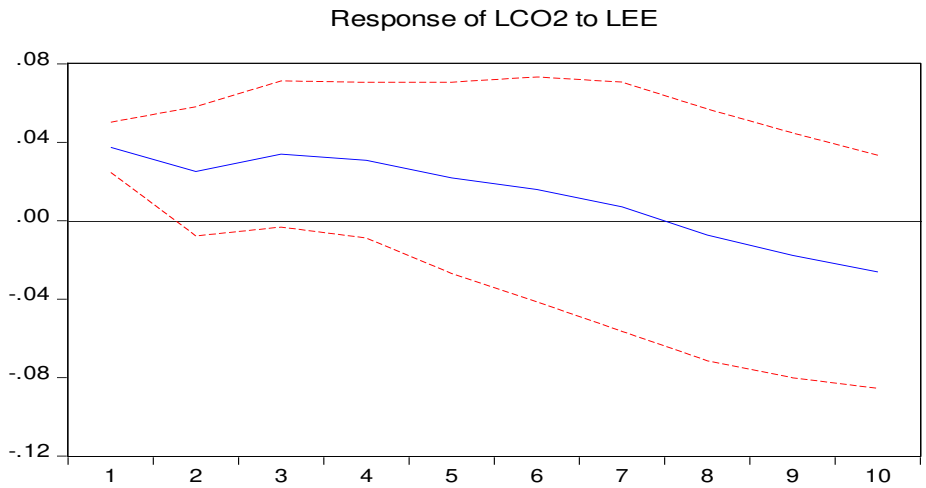

Fig.6. Response of CO_2 emission to energy efficiency

4. Conclusions and policy implications

Using time series data from 2000 to 2018, this paper explored the driving forces of reducing the potentials of CO_2 emissions in Tunisian's industrial sector by consideration of dynamic changes within the VAR model. The results indicate that energy efficiency plays a dominant role in decreasing CO_2 emissions. Energy consumption and GDP have a significant effect on CO_2 emissions due to large-scale population movements and industrial structure transformation. Urbanization was found to produce a negative impact in the short term and positively impact the long run. The findings are essential for Tunisian policymakers to pay close attention to since this study complements existing literature.

The first observation is that improving energy efficiency is the first contributor to the variation in CO_2 emissions. The government should put policy measures to reduce energy consumption and CO_2 emissions in the industrial sector. The officials must overcome the obstacles for investors to develop sustainable markets that encourage Tunisia's energy efficiency and savings. The government also needs to improve the competitiveness of industrialists by reducing production costs linked to high energy consumption. Energy efficiency measures have been identified in

particular: 1) Strengthening the energy audit programs related to the industrial sector of Tunisia by improving the quality of energy efficiency programs. 2) Strengthening the role of energy-providing companies by assisting them with new financing mechanisms. 3) Establish an information system on energy efficiency based on relevant indicators that allow continuous evaluation of energy efficiency policy in this sector.

The second observation is that urbanization has an effect on CO_2 emissions from the industrial sector. This is mainly because urbanization leads to an increase in the use of vehicles, which has favored the rapid development of industries related to automobile construction, thus increasing energy consumption and CO_2 emissions. In order to reduce CO_2 emissions, the government must develop a hybrid and electric public transport system and optimize the location of urban industrial zones linked to the intensive use of transport.

The third observation is that the energy consumption of natural gas has a positive effect in the short term and a negative effect in the long run. The government needs to quickly control natural gas consumption by developing and investing in new energy-saving technologies. The management of natural gas should discourage residents from consuming less and encourages them to shift to solar energy, biogas, and wind power. The government can also design a reasonable incentive and sanction mechanism to develop an appropriate system to guide the rational development and use of natural gas resources.

The fourth finding is that economic growth has a positive effect in the short run but a negative effect in the long run. Tunisia's economic growth depends on the industrial sector, especially energy-intensive heavy industries containing raw iron and steel machinery manufacturing, non-ferrous metals, and petrochemical industries. These industries consume a high amount of energy and emit high GHG gases; as a result, they polluted the environment, water, and haze. Therefore, the government must optimize the industrial structure by developing a modern manufacturing technique for industries to adopt; otherwise, impose heavy fines on those not being taking action according to the government's reforms.

Moreover, the vigorous development of new strategic industries is essential for improving new energy technologies and expanding the new energy industry. Hence, the government should optimize the investing environment to attract international high-tech manufacturing companies and develop technology-led strategic initiatives for industries.

Ethical Approval: This study follows all ethical practices during writing.
Consent to participate: Not Applicable
Consent to publish: Not Applicable

A**uthors Contribution:** Muhammad Ramzan- Introduction, methodology, Data Analysis interpretations, conclusion and policy implications. Hafiz Arslan Iqbal- Introduction and Editing. Besma - Main theme, Data Collection. Buhari-Supervision

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Transparency: The authors confirms that the manuscript is an honest, accurate, and transparent account of the study was reported; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained.

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