RESEARCH ARTICLE

Exploring the role of renewable energy and foreign and non-foreign patents on mitigating emissions: evidence for Tunisian economy

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Abstract

This study investigates the relationships among renewable energies (RE), carbon dioxide (CO_2) emissions, foreign direct investment (FDI), foreign and non-foreign patents (FP, NFP), and trade (TR) for the case of Tunisia using time series data spanning the period 1980–2017. The autoregressive distributed lags (ARDL) model approach of Pesaran et al. (J Appl Econ 16:289–326, 2001) and the causality of Granger are employed to explore the dynamic association between the underlined variables. The results from the long-run elasticities show that FDI and TR have negative and statistically significant impacts on RE, while NFP has a positive and statistically significant effect on the consumption of RE. Both FP and CO_2 emission variables are insignificant in the long run. In the short run, there are no Granger causal links between RE and patents (FP and NFP), but we have one-way causality running from CO_2 emissions to patents (FP and NFP). In the long run, there are bidirectional causalities between RE, NFP, and TR. The Tunisian authorities must impose more stringent environmental standards to attract foreign investments that are more respectful of the environment, and import and export cleaner. It is also necessary to encourage R&D and innovation which appear to be beneficial for the environment.

Keywords Carbon dioxide emissions · Renewable energy · Foreign patents · Non-foreign patents · Foreign direct investment · Tunisia

JEL classification F21 · O32 · O55 · Q42 · Q54

Introduction

Tunisia's development program is based on ensuring environmental sustainability and stable growth. In COP21 (21st yearly session of the Conference of the Parties held in Paris,

France, 30 November–12 December 2015), the government suggested minimizing greenhouse gas (GHG) emissions in all sectors to reduce the country's carbon intensity by 41% in 2030, relative to the 2010 baseline year. The energy sector intending to decrease its carbon impact by 46% by 2030, in comparison to 2010, will require a particular focus on mitigation efforts. The sustained energy transition under the project will significantly enhance the achievement of this aim. It will also blaze a trail for further decarburization in the long term, to continue with the electrification of many energy uses, as well as a sustained transition from fossil fuels to renewable sources of electricity generation. The energy sector policies in Tunisia contain significant end-use effectiveness actions to control demand growth (World Bank 2019).

In 2001, Tunisia's status changed from an energy-exporting country to that of an importer. It made the right decision to develop numerous programs for the production of renewable energy and energy efficiency. Its goal is to become less dependent on energy imports and the volatility of oil and gas prices. For more than 20 years, Tunisia has

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developed a policy of energy conservation and promotion of renewable energies with a specific energy regulation framework. On January 22, 2003, it ratified the Kyoto Protocol even though, as a developing country, it is not bound by any reduction in GHG emissions under this protocol. The expansion of renewable energies is essential to meet the challenges and signals the dynamics of the electricity sector in Tunisia, especially towards significant private involvement. The integration of more profitable renewable energy sources will decrease the sensitivity of the Tunisian electricity and gas company (STEG) to international oil prices, thus helping to improve the financial performance of the electricity sector in general and to reduce the pressure on public finances. Electricity prices will remain stable over time and reduce the demands for rate increases that will influence consumers. Tunisia's renewable energy program marks Tunisia's evolution towards a broader electricity market, with the private sector gaining a significant share of the production sector (World Bank 2019).

According to the report of the UNESCO Institute for Statistics (2016), global spending on research and development (R&D) reached a record of 1000.7 billion US$ and indicates that only a very little number of countries concentrate 80% of these expenses. South Korea devotes 4.3% of its gross domestic product (GDP) to R&D, followed by Japan (3.6%). Tunisia spends about 0.6% of its GDP and has 1803 researchers per million inhabitants. In Tunisia, R&D investments are split between the government (50%), companies (19%), and universities (31%). Like several studies (Katila 2000; Wurlod and Noailly 2018; Ben Youssef 2020), as a proxy for R&D efforts, we use patent applications. This enables us to measure innovation externalities. We will distinguish between foreign patents that are filed by foreigners and non-foreign patents that are filled by residents. The former, i.e., foreign patents, can be considered as a good proxy for R&D externalities.

To the extent of our knowledge, no study on Tunisia has been notified investigating the relationships between patents (either foreign or non-foreign) and renewable energy consumption. This paper studies the relationships between carbon dioxide (CO_2) emissions, renewable energy (RE) consumption, foreign direct investments (FDI), foreign patents (FP), non-foreign patents (NFP), and trade (TR) in Tunisia by considering data ranging from 1980 to 2017. The autoregressive distributed lags (ARDL) approach and the causality of Granger are employed to explore the dynamic association between the underlined variables.

This paper is organized as follows. "Literature review" presents an overview of the literature review. Data will be discussed in "Data and descriptive statistics." "Methodology and results" is concerned with empirical findings. "Conclusion" summarizes the paper and presents some recommendations.

Literature review

Our work is related to the literature dealing with environmental R&D and innovation (Scott 2005; Poyago-Theotoky 2007; Ben Youssef 2011; Yamazaki et al. 2012; Giuliani et al. 2016; Jeong et al. 2017; Costa-Campi et al. 2017). Ang (2009) defines the determinants of CO_2 emissions in China over the period 1953–2006. Empirical findings show a negative link between CO_2 emissions and technology transfer. Besides, CO_2 emissions can increase by higher trade openness, elevated income, and expanded energy use. Rahmouni et al. (2011) investigate the link between the attitude of exportation and the innovation tendency in Tunisian companies. Empirical results show that companies that manage nationally and internationally innovate better and use foreign sources of knowledge. Also, they find that internal efforts of R&D and cooperative agreements are necessary for innovation. Moreover, external knowledge sources have a fundamental role because companies can profit from them to achieve an important innovation proclivity. By using Japanese data, Inoue et al. (2013) investigate the determinants that promote environmental technological innovation, by concentrating on ISO 14001. These authors examine how the expertise level of ISO 14001 influences environmental R&D costs that upgrade environmental technological innovation. The results show that the maturity level of ISO 14001 is a significant element inducing the investment in environmental R&D. Ghisetti and Pontoni (2015) study the determinants of environmental innovation. To this end, they evaluate empirically the efficiency of two factors: R&D and policy. The results indicate that only some categories of policy can influence environmental innovation, especially rigor regulation. Ben Youssef and Zaccour (2014) highlight that a higher per-unit subsidy is given to inventive research when the free R&D spillover is sufficiently high. Nevertheless, absorptive research is encouraged to strengthen R&D externalities, when the free R&D spillover is low enough and the marginal damage cost of pollution is sufficiently high. Bretschger et al. (2017) discussed the consequences of knowledge dissemination on economic growth and the costs of environmental policy. Knowledge dissemination relies on availability and absorption capacity. The dissemination of knowledge contributes to the greening of economies, by stimulating the efficiency of clean, carbon-intensive activities. Knowledge dissemination reduces expenditures on climate policy. Dissemination of knowledge reduces global climate policy expenditures in emerging countries (China) by about 90% and in developed ones (Europe and the USA) by 20%, based on the interchangeability of different forms of knowledge. Ben Youssef (2020) uses annual data about the USA during the period 1980–2016. Long-run ARDL elasticities show that NFP increases carbon emissions, but FP reduces it. Both NFP and FP have a positive impact on RE and GDP.

Also, this research is concerned with the literature on renewable energy and pollution. In general, previous empirical analyses highlighted renewable energy's role in mitigating pollution levels and enhancing economic expansion. For this reason, this topic has attracted several academic researchers. Apergis et al. (2010) study the connection between economic growth, CO_2 emissions, renewable energy consumption, and nuclear energy consumption in 19 developed and developing countries by using annual data ranging from 1984 to 2007. Long-run estimates revealed a negative and statistically significant impact of nuclear energy use on CO_2 emissions and a positive and statistically significant effect of renewable energy use on emissions. Besides, Fatima et al. (2020) assess the implications of renewable energy and rising incomes on the quality of the environment. Empirical results indicate that a rise in income moderates the ratio between renewable energy use and CO_2 emissions. Higher-income increases the share of non-renewable energy in the total energy mix, which causes environmental damage. Also, Doğan et al. (2020) examine the impact of renewable energy consumption, economic progress, population growth, and economic complexity on CO_2 emissions, in 28 OECD countries during the period 1990–2014. Results show that renewable energy and economic complexity contribute to the reduction of CO_2 emissions.

Besides, energy (renewable and non-renewable) use and international trade have attracted several researchers. Various studies revealed that international trade is an important topic that could have a critical influence on the environmental situation and in the use of energy. Grossman and Krueger (1991) and Copeland and Taylor (2004) highlighted three environmental effects that could result from trade liberalization: the scale effect, the structural effect, and the technical effect. Kukla-Gryz (2009) examines how international exchange and economic expansion influence the level of air pollution. The findings indicate that in the developing economies, world trade and revenue per capita imply changes in the pattern of economic activity and thus higher levels of air pollution. Ben Jebli and Ben Youssef (2015) study the interaction between per capita CO_2 emissions, GDP, consumption of renewable and non-renewable energy, and international trade (exports or imports) in Tunisia by considering data ranging from 1980 to 2009. Long-run estimates indicate that there is a positive effect of trade and non-renewable energy on CO_2 emissions, while renewable energy has a small and negative effect on CO_2 emissions for the model with exports. Dogan and Deger (2016) investigate the relationships between economic growth, overall energy use, and globalization in BRIC (Brazil, Russia, India, China) countries. They find a unidirectional causality running from globalization and overall energy use to economic growth. However, there is no causality between globalization and energy consumption. Bashir et al. (2020) use a sample of 29 OECD economies during the period

1990–2015. They investigate the impact of three export diversification measures (intensive margin, extensive margin, and export product diversification) on carbon and energy intensity. Results show that the three export diversification indicators contribute to decreasing energy intensity and could be applied as a policy instrument to ameliorate energy efficiency and environmental sustainability. Also, Shahzad et al. (2021a) examine the effect of extensive margin, intensive margin, and export product diversification on the demand for energy in emerging countries using a sample of 10 newly industries countries and annual panel data ranging from 1971 to 2014. Findings indicate that these three indicators contribute to decreasing total energy demand. Also, urbanization, economic growth, and natural resources raise energy consumption. Shahzad et al. (2021b) study the impacts of extensive margin, intensive margins, and export diversification on the use of renewable energy in G-7 and E-7 countries. The outcomes indicate that, in both advanced and emerging countries, product diversification strategies act positively on the demand for renewable energy.

The present study tries to investigate the interactions that may exist between CO_2 emissions, renewable energy consumption, foreign direct investment, foreign and non-foreign patents, and international trade for the case of Tunisia using the ARDL bounds test to cointegration and Granger causality. We aim to evaluate particularly the role of patents (foreign and non-foreign) in the expansion of renewable energy and environmental quality when renewable energy is a dependent variable. Also, the short and long-run directions of causalities between variables are discussed.

Data and descriptive statistics

Tunisia's annual data for the period 1980–2017 are acquired from different databases. Used variables are CO_2 emissions measured in kilotons (kt); foreign and non-foreign patents are measured as the number of patents[1]; foreign direct investments are net inflows measured as a percentage (%) of GDP; trade of goods and services is measured as a % of GDP; renewable energy consumption is measured in quadrillion Btu then converted to Btu value. Data on CO_2 emissions are collected from World Data Atlas (2020); renewable energy consumption data are collected from the US Energy Information Administration (2020); and the rest of the variables are obtained from the World Bank (2020). Time series are limited to the year 2017 due to their availability. Eviews 10.0 software is used for all estimates.

The empirical analysis starts by studying some descriptive statistics before the log-transformation of variables. The

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[1] For the FP value of the year 1982, we take the mean of the 2 years 1981 and 1983.

descriptive statistics of the chosen time series are provided in Table 1. These statistics are computed to assess the tendency of the variables under consideration.

Figure 1 reports the graphical representations of CO_2 emissions, renewable energy consumption, foreign and non-foreign patents, foreign direct investment, and trade over the period 1980–2017 for the case of Tunisia. Table 1 reports some descriptive statistics of the analysis variables under investigation. According to these statistical data and plots, the tendency of CO_2 emissions is increasing continuously over the period. The number of foreign patents was unstable over time. Its evolution recorded some falls until 2002, and from 2003, it rises permanently until 2011, and then it decreases again. The maximum number of foreign patents was equal to 543 in 2011, while the minimum was equal to 58 in 2002. The non-foreign patents increased slowly across time and recorded some slights fluctuations. The highest number of patents was in 2016, while the lowest number was equal to 12 in 1984. The evolution of the FDI rate across time is characterized by important dynamic fluctuations. The biggest peak was in 2006 with a share of 9.42%. Renewable energy consumption was almost steady with nearly the same values from 1980 to 2004. However, from 2014 to 2017, its evolution showed a continuous rise. Trade was unsteady over the considered period with a rising trend. The minimum reached a share of 67.48% in 1986, and the maximum share was equal to 114.35% in 2008.

Methodology and results

The objective of this article consists of investigating the interaction among the consumption of renewable energy, FDI, CO_2 emissions, number of patents (foreign and non-foreign), and trade for the case of Tunisia and during the period 1980–2017. The empirical part employs the ARDL boundary method and the tests of Granger causality to check for the association that may occur between the analysis variables in the short and long run. The modeling of the analysis explains renewable energy consumption (dependent) in the function of the other factors taken as explanatory variables in our model.

The following model will be developed as follows:

$$RE = f(FDI, CO_2, FP, NFP, TR) \tag{1}$$

To explore the long-run relationships between the variables, the log-linear equation between variables can be expressed as follows:

$$re_t = \alpha_0 + \alpha_1 fdi_t + \alpha_2 co_{2t} + \alpha_3 fp_t + \alpha_4 nfp_t + \alpha_5 tr_t + \varepsilon_t \tag{2}$$

where t, α_0, and ε designate the time, the constant, and the white noise term, respectively; α_i, $i = 1, \ldots, 4$ designate the long-term elasticity of renewable energy variable with respect to each corresponding explanatory variable.

The empirical study requires the examination of long-run cointegration between the variables when renewable energy is dependent on the other variables. The ARDL bounds test to cointegration will be considered in this case. This approach is practically based on the bounds recommended by Pesaran et al. (2001). This test uses the joint significance of the Fisher statistic test (Wald test) to verify the long-term relationship among time series data. Several advantages are recorded from this technique of estimation against the other methods. First, time series could be either integrated of order zero (I(0)), of order one (I(1)), or fractionally (both of them). Secondly, the short- and long-run estimated coefficients can be

Table 1 Descriptive statistics of the variables

	RE	CO_2	FDI	FP	NFP	TR
Mean	3.34E+12	19410.30	2.472764	244.8158	63.86842	89.26600
Median	3.50E+12	19493.76	2.178409	198.5000	41.50000	88.98144
Maximum	6.00E+12	31840.00	9.424248	543.0000	235.0000	114.3548
Minimum	1.00E+12	9345.906	0.600417	58.00000	12.00000	67.48506
Std. dev.	1.28E+12	6366.371	1.658371	141.4036	54.45066	10.63994
Skewness	−0.113394	0.056640	2.080652	0.674733	1.443303	0.144576
Kurtosis	2.713434	1.933081	9.348047	2.025576	4.288847	2.759307
Jarque-Bera	0.211458	1.822652	91.22242	4.386722	15.82323	0.224109
Probability	0.899668	0.401991	0.000000	0.111541	0.000366	0.893996
Observations	38	38	38	38	38	38

Notes: CO_2 (carbon dioxide emissions, measured in kilo tons, kt); RE (renewable energy consumption, converted to Btu); FDI (foreign direct investment, net inflows, measured as a share of GDP); FP (foreign patent applications, measured as a number); NFP (non-foreign patent applications, measured as a number); TR: trade (measured as a share of GDP)
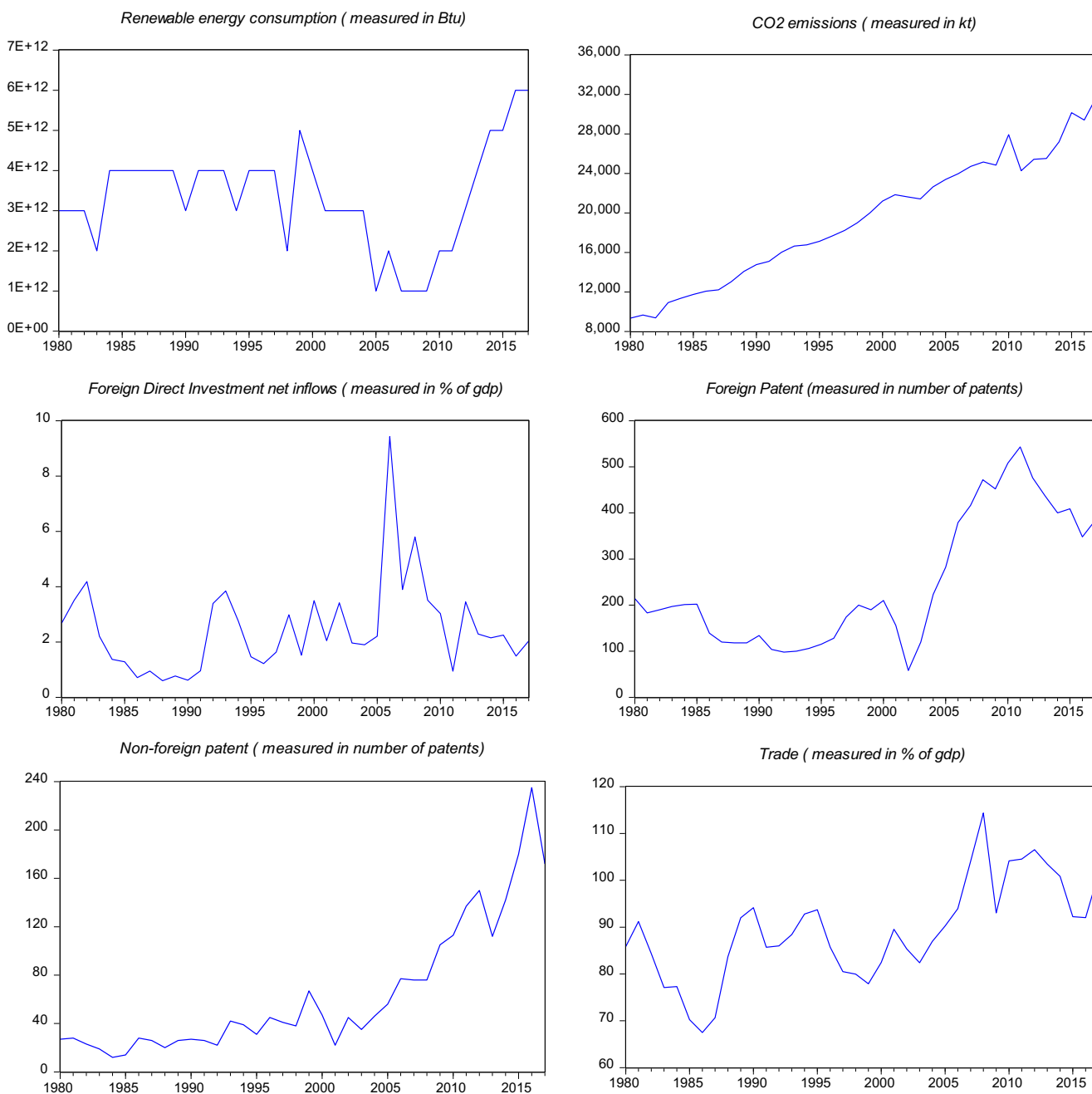
Fig. 1 Plots representation of the analysis variables

considered in the same model. Thirdly, with a small sample, the results are more efficient. For our case, the number of observations is equal to 38 which implies that our sample is small.

Before studying the cointegration, the integration order should be examined for each time series data. To do that, two-unit root tests are employed which are the augmented Dickey-Fuller (ADF, 1979) and Phillips and Perron (P-P, 1988). All these tests are estimated for three cases which are: (i) intercept; (ii) intercept and trend; (iii) no intercept

and trend. The findings from these statistics are reported in Table 2 and indicate that, for both tests, all our variables are stationary after the first's difference, meaning that they are integrated of order one, at the 1% significance level.

Our study follows the same empirical procedure considered by Ben Jebli and Ben Youssef (2015) for the case of Tunisia. As we have mentioned before, we will use the ARDL technique previously recommended by Pesaran and Pesaran (1997), Pesaran and Smith (1998), Pesaran and Shin (1999),

Table 2 Unit root test results

	Variables	ADF test				P-P test			
		Level	k	1st difference	k	Level	k	1st difference	k
Intercept	co_2	−1.617237	1	−8.547592***	0	−1.939032	9	−8.690305***	3
	fdi	−2.129151	0	−8.393434***	0	−2.005271	3	−9.322809***	7
	fp	−1.196617	0	−5.151552***	0	−1.196617	0	−5.106690***	3
	nfp	0.394366	2	−6.790885***	1	−0.641221	1	−8.249387***	4
	tr	−0.404815	0	−6.019221***	0	−0.364923	3	−6.019183***	2
	re	−2.860900*	4	−9.187937***	0	−2.352089	3	−8.981000***	3
Intercept and trend	co_2	−2.485898	0	−8.712956***	0	−2.485898	0	−11.39999***	9
	fdi	−3.285228	0	−8.272515***	0	−3.241292*	3	−9.166313***	7
	fp	−2.247794	0	−5.108402***	0	−2.355739	1	−5.055548***	3
	nfp	−3.910529**	0	−6.979817***	1	−3.874598**	1	−9.302539***	6
	tr	−2.579292	0	−5.923849***	0	−2.579292	0	−5.924468***	2
	re	−2.950319	4	−9.171825***	0	−2.254583	3	−9.006633***	3
None	co_2	4.840327	1	−2.413754**	1	6.066515	4	−5.708042***	4
	fdi	0.227186	1	−8.500766***	0	0.958969	36	−9.343032***	7
	fp	0.222311	0	−5.199761***	0	0.209442	2	−5.160139***	3
	nfp	1.917258	2	−6.293822***	1	1.437515	4	−7.301785***	0
	tr	3.103750	0	−4.983915***	0	3.381757	3	−5.084753***	3
	re	0.436876	1	−9.282163***	0	0.381882	3	−9.052875***	3

Notes: "***," "**," and "*" indicate statistical significance at the 1%, 5%, and 10% levels, respectively. ADF and P-P denote augmented Dickey-Fuller and Phillips-Perron tests, respectively. For the ADF test, k is the optimal lag length based on the Schwarz information criterion (SIC). For the P-P test, k is the Newey-West Bandwidth using Bartlett Kernel

and finally developed by Pesaran et al. (2001). The representation of our ARDL model is given by the following equation:

$$\Delta re_t = \alpha + \sum_{i=1}^{q} \alpha_{1i}\Delta re_{t-i} + \sum_{i=0}^{q} \alpha_{2i}\Delta co_{2,t-i} + \sum_{i=0}^{q} \alpha_{3i}\Delta fdi_{t-i}$$
$$+ \sum_{i=0}^{q} \alpha_{4i}\Delta fp_{t-i} + \sum_{i=0}^{q} \alpha_{5i}\Delta nfp_{t-i} + \sum_{i=0}^{q} \alpha_{6i}\Delta tr_{t-i} \quad (3)$$
$$+ \alpha_7 re_{t-1} + \alpha_8 co_{2,t-1} + \alpha_9 fdi_{t-1} + \alpha_{10} fp_{t-1}$$
$$+ \alpha_{11} nfp_{t-1} + \alpha_{12} tr_{t-1} + \varepsilon_t$$

where Δ, ε, and q indicate the first difference, the error term, and the number of lags selected, respectively. To proceed with the modeling of the ARDL technique for cointegration developed by Pesaran et al. (2001), it is necessary to think about estimating the optimal number of lags. The corresponding number of lags will be properly estimated based on the selection criteria which is mainly the Akaike Information Criterion (AIC). The detection of a long-run association using the ARDL method consists of testing the joint significance of the long-run coefficients. This test is inspired by the Wald test which is based on the Fisher statistic. The null hypothesis of this test suggests that all coefficients are jointly null $(\alpha_7 = \alpha_8 = \alpha_9 = \alpha_{10} = \alpha_{11} = \alpha_{12} = 0)$, meaning that there is no long-run interaction among the variables. The alternative

hypothesis assumes that there is a long-run relationship between the variables $(\alpha_7 \neq \alpha_8 \neq \alpha_9 \neq \alpha_{10} \neq \alpha_{11} \neq \alpha_{12} \neq 0)$. There are two bounds critical values that Pesaran et al. (2001) proposed to check for cointegration. The first bounds is a lower critical value denoted by C(0) and the second bounds is an upper critical value denoted by C(1). The estimated value of the Fisher statistic will then be compared to the two limits critical values. Thus, there are three cases to discuss: (i) if the estimated Fisher statistic value is higher than the upper critical value, then there is a cointegration; (ii) if the estimated Fisher statistic value is less than the lower critical value, so there is no cointegration; and (iii) if the calculated value of the Fisher statistic is between the two critical bounds values, then we cannot conclude and the significance of the error correction term (ECT) is required to check for a long-run relationship between the variables. The validity of the estimated results will be verified using diagnostic tests (normality, residual heteroskedasticity, and serial correlation tests).

The results of the ARDL bounds for cointegration are presented in Table 3 and show that the computed Fisher statistic is above the upper critical value signifying the presence of a long-run cointegration among the variables when renewable energy is endogenous. Also, the diagnostic tests are verified and revealed that our computed results are validated. Thus,

Table 3 ARDL bounds test to cointegration results

Estimated model	Bounds testing to cointegration	F statistics	Conclusion
F_{re} (re/ co$_2$, fdi, fp, nfp, tr)	Optimal lag length (1, 0, 1, 2, 2, 0)	4.081133**	Cointegration
Critical values	Lower bounds C(0)	Upper bounds C(1)	
1%	3.9	5.419	
5%	2.804	4.013	
10%	2.331	3.417	
Diagnostic tests			
F_{re} (re/ co$_2$, fdi, fp, nfp, tr)	LM test	Breusch-Pagan Godfrey test	Normality test
	0.1910	0.2461	0.420000

Notes: "**" indicates statistical significance at the 5% level. Critical values are obtained from Pesaran et al. (2001). F(.) statistics are estimated for the case of restricted constant. Diagnostic tests cover serial correlation (Breusch-Godfrey serial correlation LM test), heteroscedasticity Breusch-Pagan Godfrey, and normality (Jarque-Bera test): the given values correspond to the probabilities of rejecting the null hypothesis. The maximum number of lags selected is 2. The LM test is conducted with lags 2

there is no problem of serial correlation or residual heteroscedasticity, and the normality of residuals is proved.

The estimated coefficients of the long-run elasticities are reported in Table 4. If renewable energy is dependent, all explanatory variables are statistically significant except for CO$_2$ emissions and foreign patents. A 1% increase in foreign direct investment will reduce renewable energy consumption by 0.30% at the 5% significance level, and a 1% increase in trade leads to a decrease in renewable energy consumption by 2.17% with a significance level of 1%. These results can be explained by the pollution haven hypothesis: developed nations manufacture low-polluting products in their countries and transfer their polluting factories to developing areas where environmental regulations are low. Our first result is not consistent with that of Fan and Hao (2020) who show that foreign direct investment positively affects renewable energy consumption in China. However, our second result is following that of Mohamed et al. (2019) showing that trade openness reduces renewable energy consumption in France.

A 1% increase in non-foreign patents will raise renewable energy consumption by approximately 1.28% for a significance level of 1%. Thus, innovation and R&D help to use renewable energy production processes in Tunisia. This constitutes an interesting result as no previous study has evaluated the long-run impact of innovation or R&D on renewable energy consumption in Tunisia. This finding is similar to that of Ben Youssef (2020) who shows that resident patents result in higher consumption of renewable energy in the USA. The long-run impact of foreign patents on renewable energy consumption is not statistically significant, which is in contradiction with the work of Ben Youssef (2020) on the USA.

The long-term steadiness parameters have been verified using some efficient and powerful techniques such as the cumulative sum (CUSUM) and the cumulative sum of squares (CUSUM of squares) statistics established by Brown et al. (1975). The results from these statistical tests are presented in Fig. 2 indicating that the estimated coefficients are stable given that the graphical illustrations fall within the critical bounds at the 5% significance level.

Determining the optimal lag number is necessary before studying Granger causality. This step consists of estimating a suitable number of lags to launch the vector autoregressive (VAR) model. The determination of the optimal lag is based on various selection criteria: the Akaike information criteria (AIC), the Schwarz information criteria (SIC), Hannan-Quinn (HQ), Log-likelihood (LogL), Log-likelihood ratio (LR), final prediction error (FPE). The results from Table 5 indicate that all criteria choose an optimal lag equal to 1 except the Log-likelihood criterium. Thus, we consider a model VAR (1), and the discussion of the Granger causality approach can be treated.

The causality between the analysis variables can be investigated using Engle and Granger (1987) approach. This technique can be executed in two steps. The first one consists of
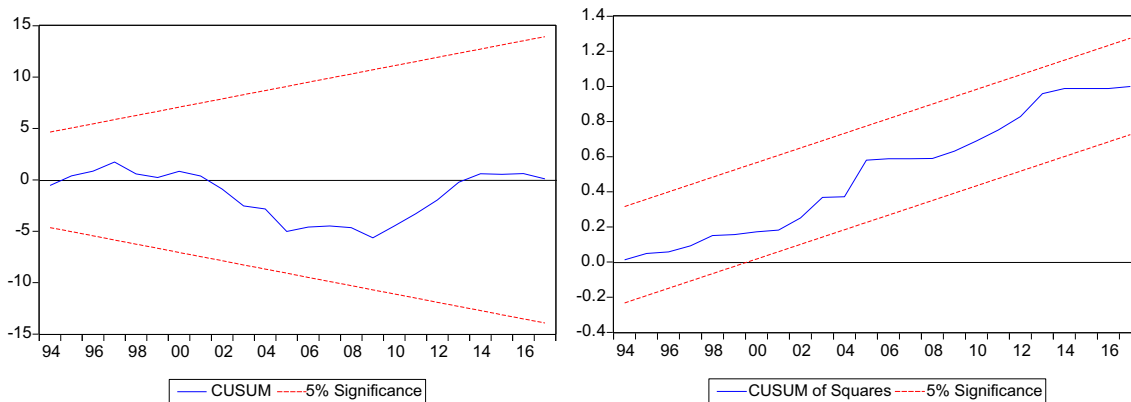
Table 4 Long-run elasticities

Dependent variable	re	
Regressors	Coefficient	t statistic
Long-run estimates		
co$_2$	1.582796	[1.701558]
fdi	−0.302921	[−2.301705]**
fp	−0.266730	[−1.122122]
nfp	1.278623	[4.055229]***
tr	−2.173189	[−2.965549]***
c	67.77517	[7.033040]***

Notes: "***," "**," and "*" indicate statistical significance at the 1%, 5%, and 10% levels, respectively. t statistics are presented in brackets

Fig. 2 CUSUM and CUSUM of squares plots

the estimation of the long-run equation (Eq. (2)) to recover the residuals. The second step involves the estimation of the short-run equilibrium. We use the pairwise Granger causality tests to check for the short-run causality between the variables based on the Fisher statistic. The long-run interaction between time series can be established using the meaning of the lagged error correction term (ECT_{t-1}). The representation of the vector error correction model (VECM) is given as follows:

$$\Delta re_t = \phi_1 + \sum_{i=1}^{p} \phi_{11i}\Delta re_{t-i} + \sum_{i=1}^{p} \phi_{12i}\Delta co_{2,t-i} + \sum_{i=1}^{p} \phi_{13i}\Delta fdi_{t-i}$$
$$+ \sum_{i=1}^{p} \phi_{14i}\Delta fp_{t-i} + \sum_{i=1}^{p} \phi_{15i}\Delta nfp_{t-i} + \sum_{i=1}^{p} \phi_{16i}\Delta tr_{t-i} \quad (4)$$
$$+ \tau_1 ECT_{t-1} + \zeta_{1t}$$

$$\Delta co_{2,t} = \phi_2 + \sum_{i=1}^{p} \phi_{21i}\Delta re_{t-i} + \sum_{i=1}^{p} \phi_{22i}\Delta co_{2,t-i} + \sum_{i=1}^{p} \phi_{23i}\Delta fdi_{t-i}$$
$$+ \sum_{i=1}^{p} \phi_{24i}\Delta fp_{t-i} + \sum_{i=1}^{p} \phi_{25i}\Delta nfp_{t-i} + \sum_{i=1}^{p} \phi_{26i}\Delta tr_{t-i} \quad (5)$$
$$+ \tau_2 ECT_{t-1} + \zeta_{2t}$$

$$\Delta fdi_t = \phi_3 + \sum_{i=1}^{p} \phi_{31i}\Delta re_{t-i} + \sum_{i=1}^{p} \phi_{32i}\Delta co_{2,t-i} + \sum_{i=1}^{p} \phi_{33i}\Delta fdi_{t-i}$$
$$+ \sum_{i=1}^{p} \phi_{34i}\Delta fp_{t-i} + \sum_{i=1}^{p} \phi_{35i}\Delta nfp_{t-i} + \sum_{i=1}^{p} \phi_{36i}\Delta tr_{t-i} \quad (6)$$
$$+ \tau_3 ECT_{t-1} + \zeta_{3t}$$

$$\Delta fp_t = \phi_4 + \sum_{i=1}^{p} \phi_{41i}\Delta re_{t-i} + \sum_{i=1}^{p} \phi_{42i}\Delta co_{2,t-i} + \sum_{i=1}^{p} \phi_{43i}\Delta fdi_{t-i}$$
$$+ \sum_{i=1}^{p} \phi_{44i}\Delta fp_{t-i} + \sum_{i=1}^{p} \phi_{45i}\Delta nfp_{t-i} + \sum_{i=1}^{p} \phi_{46i}\Delta tr_{t-i} \quad (7)$$
$$+ \tau_4 ECT_{t-1} + \zeta_{4t}$$

$$\Delta nfp_t = \phi_5 + \sum_{i=1}^{p} \phi_{51i}\Delta re_{t-i} + \sum_{i=1}^{p} \phi_{52i}\Delta co_{2,t-i} + \sum_{i=1}^{p} \phi_{53i}\Delta fdi_{t-i}$$
$$+ \sum_{i=1}^{p} \phi_{54i}\Delta fp_{t-i} + \sum_{i=1}^{p} \phi_{55i}\Delta nfp_{t-i} + \sum_{i=1}^{p} \phi_{56i}\Delta tr_{t-i} \quad (8)$$
$$+ \tau_5 ECT_{t-1} + \zeta_{5t}$$

$$\Delta tr_t = \phi_6 + \sum_{i=1}^{p} \phi_{61i}\Delta re_{t-i} + \sum_{i=1}^{p} \phi_{62i}\Delta co_{2,t-i} + \sum_{i=1}^{p} \phi_{63i}\Delta fdi_{t-i}$$
$$+ \sum_{i=1}^{p} \phi_{64i}\Delta fp_{t-i} + \sum_{i=1}^{p} \phi_{65i}\Delta nfp_{t-i} + \sum_{i=1}^{p} \phi_{66i}\Delta tr_{t-i} \quad (9)$$
$$+ \tau_6 ECT_{t-1} + \zeta_{6t}$$

where Δ represents the operator of the first difference; p is the VAR lag length; ECT_{t-1} denotes the lagged ECT associated with every equation; τ_j shows the velocity of adjustment from the short- to the long-run equilibrium; ζ_{jt} represents the residual term[2].

Granger causality findings are presented in Table 6 for the short- and long-run associations. The lagged ECT is statistically significant and negative for (4), (8), and (9) indicating that there is a long-run relationship between renewable energy consumption, non-foreign patents, and international trade. More precisely, there are long-run bidirectional causalities between RE, NFP, and trade. This result is different from that of Ben Jebli and Ben Youssef (2015) showing a long-run unidirectional causality running from exports to renewable energy consumption for the case of Tunisia. However, it is in line with the result of Sadorsky (2012) who found long-run bidirectional causality between trade (exports or imports) and energy consumption for the panel of 7 South American countries considered.

In the short run, we have one-way causality running from CO_2 emissions to foreign and non-foreign patents. This result is different from that of Ben Youssef (2020) who found no short-run interaction of carbon emissions with resident and non-resident patents in the case of the USA. Besides, we have a short-run causality running from non-foreign patents to foreign patents and foreign direct investments. This means that investments in R&D and innovation in Tunisia help domestic firms to benefit, even in the short-term, from foreign innovations while attracting foreign investments.

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[2] The robustness of the VECM model is checked using residuals Portmanteau tests for autocorrelations. The results from the test revealed no problem of autocorrelation. The result is available upon request.

Table 5 The optimal number of lag length selection criteria

Number of lags	LogL	LR	FPE	AIC	SIC	HQ
0	−55.75024	NA	1.24e-06	3.430569	3.694489	3.522684
1	84.48011	225.9267*	3.92e−09*	−2.360006*	−0.512568*	−1.715201*
2	119.5373	44.79533	4.92e−09	−2.307629	1.123328	−1.110133

Notes: "*" indicates the optimal number of lags selected for each criterion

Conclusion

The present paper tries to investigate the interdependence between renewable energy consumption, CO_2 emissions, foreign direct investments, foreign and non-foreign patents, and trade in Tunisia, using time series data during the period 1980–2017. The cointegration between the variables has been established by employing the ARDL bounds method for cointegration. The long-term coefficients have been estimated and the short and long-run interactions between the variables have been investigated using Granger causality tests. We find many interesting results.

Empirical findings mentioned that increasing the share of trade and foreign direct investments will decrease the consumption of renewable energy. Moreover, we have a one-way long-run causality running from FDI to RE consumption, and long-run bidirectional causality between renewable energy consumption and international trade. These results could be explained by environmental regulations, at the level of texts or the level of application, less strict compared to other countries such as the European Union, which attracts polluting foreign direct investments, production, consumption, import, and export of relatively polluting products.

In the long run, non-foreign patents have a positive impact on renewable energy consumption, which could be beneficial for the environment and combat climate change. Moreover, we have long-run bidirectional causality between renewable consumption and non-foreign patent use. This means that encouraging innovation and R&D can have good effects on the development of renewable energy projects ending in more renewable energy consumption and less environmental pollution.

Foreign patent use do not seem to have any long-run impact on renewable energy consumption in Tunisia, whereas a one-way long-run causality running from foreign patents to renewable energy consumption is detected. This may be because, at present, foreign patents are neutral concerning renewable energy consumption as they can be either more or less polluting. However, encouraging the use of cleaner foreign innovations may have a beneficial impact on renewable energy consumption in Tunisia.

Given our econometric results, we recommend that the Tunisian authorities should set up stronger environmental standards to attract foreign direct investments that are less polluting. This will incite foreign investors to use renewable energy, and even to invest in renewable energy projects to

Table 6 Granger causality test results

	Short run						Long run
Dependent variables	Δre	Δco$_2$	Δfdi	Δfp	Δnfp	Δtr	ECT
Δre	–	0.04633	1.79070	0.00257	0.08101	0.04294	−0.328873
		(0.8309)	(0.1897)	(0.9598)	(0.7777)	(0.8371)	[−2.09901]**
Δco$_2$	0.41140	–	0.24895	0.03179	0.69433	0.07310	−0.001018
	(0.5256)		(0.6210)	(0.8595)	(0.4105)	(0.7885)	[−0.02465]
Δfdi	1.23751	5.41957	–	1.21026	3.60414	7.07035	0.009581
	(0.2738)	(0.0260)**		(0.2790)	(0.0662)*	(0.0119)**	[0.26390]
Δfp	1.89478	2.89710	4.10741	–	7.32962	4.13430	−0.046782
	(0.1777)	(0.0979)*	(0.0506)*		(0.0105)**	(0.0499)**	[−0.78913]
Δnfp	1.01926	9.17095	0.97034	2.36588	–	15.3039	−0.859883
	(0.3198)	(0.0047)***	(0.3316)	(0.1333)		(0.0004)***	[−3.49985]***
Δtr	0.05481	5.26795	0.03500	0.20047	2.71177	–	−0.331812
	(0.8163)	(0.0280)**	(0.8527)	(0.6572)	(0.1088)		[−2.93501]***

Notes: "***," "**," and "*" indicate statistical significance at the 1%, 5%, and 10% levels, respectively; Probability values are reported in parenthesis and *t* statistics are between brackets. ECT denotes the error correction term corresponding to each equation

benefit from the renewable energy potential of Tunisia, in particular, that of solar energy. International trade will encourage the use of renewable energy as it becomes inciting to produce, consume, export, and import less polluting goods.

Declarations

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