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Research Article

Sustainable Intentions, Unsustainable Outcomes: Green Technologies, Environmental Taxes, and the Carbon Cost of Economic Growth

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ABSTRACT

Environmental degradation has become a global issue. CO_2 emissions lie at the heart of this issue. Therefore, the determinants of CO_2 emissions are becoming important. This study focuses on the relationship between CO_2 emissions and environmental technological innovation, environmental taxes and income for the Turkish economy. Traditional unit root tests and Fourier ADF unit root tests were used in the light of data for the period 1994-2022. Augmented ARDL method was used to determine the long-term relationship. FMOLS, DOLS and CCR were used as long-term estimators. Empirical findings revealed that environmental technical innovations, environmental taxes and increases in income increased CO_2 emissions. These results showed that technological innovations and environmental measures were not successful in reducing CO_2 emissions. The findings provide important insights into environmental and technology policy implementations for Türkiye, which is among the developing countries.

Keywords: Environmental technological innovations, environmental taxes, economic growth, jevons paradox, augmented ARDL.

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1. INTRODUCTION

Sustainability is one of the most debated topics in academic literature. The environmental dimension of sustainability is among the most important subcomponents. In this context, chemical compounds released into the atmosphere play a major role. Among these compounds, greenhouse gases such as carbon dioxide (CO_2), sulfur dioxide (SO_2), nitrogen oxides (NO_x), and methane (CH_4) stand out. These gases cause effects both through the activities of individuals and within the framework of natural processes. Greenhouse gases such as CO_2, SO_2, NO_x, CH_4 are among the important chemical threats in terms of environmental sustainability.[1] These threats can occur through different reactions. For example, acidic compounds are formed when sulfur and nitrogen oxides react with atmospheric water vapor. These compounds can cause acid rain, which leads to environmental degradation. The most common sources of these compounds are agricultural activities, fossil fuel use and industrialization processes. Undoubtedly, the most important chemical component of environmental threats from a global perspective is CO_2. The chemical reaction that occurs when fuels containing carbon react (burn) is formed as $C + O_2$. As a result of this burning, CO_2 emissions in the atmosphere increase. This increase is the main reason for the greenhouse effect.[2]

Carbon emissions from the burning of fossil fuels are primarily responsible for global warming, ocean and marine pollution and extreme weather events. Today, human-caused carbon emissions in 200 years are equal to the carbon emissions accumulated over millions of

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years in the past. By the end of this century, annual carbon emissions are expected to reach 75 billion tons.[3] Economic activities have increased CO_2 in the atmosphere by 50% since 1750.[4] Therefore, reducing carbon emissions is important for the environment. Transportation, electricity, production, industry and land use are among the main causes of CO_2 emissions. Increasing energy efficiency, decreasing energy consumption, switching to clean energy sources and utilizing carbon capture technologies can be effective tools in reducing carbon emissions.[68] Technological advances can reduce CO_2 emissions to the environment by enabling the transformation of energy systems and making production more environmentally friendly.[69] For these reasons, this study focuses on the impacts of technology on CO_2.

The machines, techniques and systems used to solve the problems faced by humanity in the development process are defined as technology. [5] Technological advances can have positive or negative impacts on life worldwide. Technology is a rapidly changing, developing and advancing process. Technology progress is frequently unavoidable and inescapable. As technology develops, it becomes more complex and its effects become more difficult to measure and control.[59]

Technology is a multidimensional process with different impacts in different fields such as social, economic and political. Technological innovations, which form the basis of technological advances, have endogenous and exogenous effects. While improvements that lead to productivity increases are internal effects, employment growth, economic development and life extension are external effects.[60]

The most obvious effects of technology are on the economy. The structuralist approach, based on neo-classical economics, argues that economic growth is driven by technological progress, not by capital accumulation and per capita income growth.[61]

The path to social development passes through technological progress. The social and cultural development of a society is measured by its technological progress. Technological progress increases the growth rate at the macro scale and the financial performance of firms at the micro scale. Thanks to technological advances, more output can be obtained with the same amount of input.[62] Hence, technological progress can increase economic growth by raising productivity.[63]

Today, more than one third of economic growth is based on technological developments. Technological advances contribute to sustainable economic growth.[64]
Technology is the key to sustainability, decoupling economic growth from environmental degradation.[65] Technological innovations, as a driver of technological advances, can contribute to environmental protection by enabling the development of environmental file technologies, reducing natural resource consumption and supporting eco-innovation activities.[66] Technology, when used correctly, can support UN sustainability goals. Technological advances can contribute to environmental protection by enabling the conversion to clean energy. Artificial intelligence can be used to design climate-friendly business models. Machine learning methods can increase efficiency in energy use. Morevoer, technological innovations can improve resource consumption, save water and reduce waste through smart agricultural practices. Technological advances therefore have significant potential to reduce environmental pressures.[67]

However, not all technologies positively affect the environment.[5] Technological advances may lead to a surge in energy consumption and hence emissions due to increased demand as increases in energy efficiency reduce energy prices. In the literature, this is coined as Jevons Paradox.[6] The green paradox can take three different forms: weak, strong and extreme. Accordingly, a weak paradox is when policies to protect the environment unintentionally worsen environmental quality in the short run. Strong green paradox is when policies lead to environmental degradation higher than the rate of welfare growth. If environmental degradation increases in addition to the decline in welfare due to poorly implemented policies, we can talk about the effects of the extreme green paradox.[7] The green paradox has subsequently been referred to in the literature as the energy rebound effect. Accordingly, as technology reduces energy efficiency and thus unit energy prices, energy becomes available at a much lower cost, which leads producers and consumers to consume more energy and increases carbon emissions.[8] Therefore, technological advances may not be a sufficient solution for environmental protection.[9] It is essential to conduct more research on the environmental impacts of green technologies and to explore the interaction in economies with different dynamics. In addition, technology policies need to be supported by other policies.

Policies on environmental taxes are likely to be considered together with technology policies. An increase in environmental taxes can be an effective tool to reduce energy consumption.[10] Moreover, environmental taxes can enhance environmental protection by encouraging businesses to invest in clean energy and individuals to consume renewable energy.[11] Therefore, strict legal regulations and high environmental taxes can reduce energy consumption. However, a surge in economic growth can trigger energy consumption.[12]

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Mardani et al.[13] elucidated the linkage between CO_2 and economic growth by summarizing 175 articles in the period 1995-2017. The authors emphasize that past research has generally agreed that limiting economic growth is necessary to protect the environment. However, there are also studies showing that increases in economic growth are not effective on CO_2 emissions.[14] Therefore, the role of economic growth on green technology-environmental degradation nexus should not be overlooked. Due to the deterrent consequences of environmental taxes on energy consumption, it is included in the research model.

When the literature on the subject was examined, the first group of studies examining the effects of green technologies on the environment found that environmental health could be improved thanks to technological developments. The first group of studies examining the consequences of green technologies on the environment found that environmental health can be improved through technological advances. Accordingly, Bilal et al.[15] stated that technological innovations reduce CO_2 emissions in One Belt One Road countries, thus technological advances can contribute to the protection of environmental health. Oğul[16] obtained a similar result using environmental innovation and ecological footprint variables. Kirikkaleli and Ali[17] found that environmental technologies reduce production-based CO_2 emissions in Iceland. Shan et al.[18] found that green technologies and the use of renewable energy reduce carbon emissions in Türkiye, thus contributing to carbon neutrality targets. Ahmad et al.[19] reported that technological advances contribute to a sustainable economic growth and environmental sustainability in China. Khan et al.[20] highlighted that technological innovations reduce CO_2 emissions in CEMAC countries. The findings showed that a 1% increase in technological innovation mitigates CO_2 emissions by 0.184%.

On the other hand, there are also studies emphasizing Jevons paradox in the literature. Kirikkaleli and Adebayo[21] showed that technological innovations increase CO_2 on a global scale using FMOLS, DOLS, and CCR analyses. Polimeni and Polimeni[9] found evidence supporting Jevons' paradox in 154 countries. Adebayo and Kirikkaleli[22] stated that green technologies increase CO_2 emissions in Japan using wavelet analyses. Khan et al.[23] stated that while technological innovations reduce CO_2 in belt and road initiative countries, patent applications of nonresidants increase environmental degradation. The authors found that a 1% surge in nonresidants' patent applications boosts CO_2 emissions by 2.9%. The authors attributed this result to the insufficiency of innovations to increase energy efficiency. This finding showed that technological innovations cannot always positively affect environmental health. Wang et al.[6] argued that technological advances in China lower energy prices and increase demand and thus CO_2 emissions, and that Jevons' paradox is valid. Gunderson and Yun[24] argued that Korea's green growth policies are highly uncertain and that measures to protect the environment may increase environmental degradation by boosting energy consumption in Korea. Li et al.[25] focused on the environmental impacts of technological innovations of Chinese enterprises. The researchers found that there is an inverted U-shaped linkage between technological innovation and environmental degradation.

Ghazouani et al.[26] found that carbon tax is successful to reduce CO_2 emissions in European countries. Omodero et al.[27] showed that the type of environmental taxes has a different effect on CO_2 emissions. They found that the petroleum profit tax increases the control over CO_2, while the gas tax has a negative impact on policies to reduce CO_2. Similarly, Al Shammre et al.[28] reported that the environmental impacts of resource utilization, pollution and energy taxes differ in OECD countries. Accordingly, the effect of resource utilization tax on the environmental quality is quite limited. The authors found that environmental taxes are more effective when they reach high levels. Iyke-Ofoedu et al.[29] showed that environmental taxes in South Africa reduce CO_2 emissions by increasing businesses' investments in carbon capture. Accordingly, environmental taxes can be a long-run policy instrument for improving environmental quality. Scrimgeour et al.[30] found that in New Zealand, carbon taxes were the most effective instrument for reducing environmental degradation, but the petroleum tax was less effective and the energy tax was only moderately effective. On the contrary, Loganathan et al.[31] argued that carbon taxes failed to reduce CO_2 emissions in Malaysia.

There are many studies examining the economic growth-CO_2 emission relationship. Onofrei et al.[32] found that economic growth increases CO_2 in EU countries. Lee and Brahmasrene[33] found that economic growth triggers CO_2 in ASEAN countries. Wang et al.[34] demonstrated that economic growth is a major source of environmental degradation in China. Kizilkaya[35] reached aligned outcomes for Türkiye. Cowan et al.[36] identified that the economic growth-environmental degradation nexus differs across countries and that economic growth is not responsible of CO_2 in India and China. Bengochea-Morancho et al.[37] showed that the economic growth-environmental degradation interaction differs among industrialized economies. Accordingly, in the EU, economic growth subject to certain conditions and specific industrial structure can only improve environmental quality. Ritchie[38] reported that some of the developed countries have been able to achieve economic growth without causing environmental degradation.

In general, the findings show that green technologies can improve environmental health as well as worsen environmental quality in the context of Jevons' paradox. In addition, previous studies have reached different

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results on the consequences of environmental taxes on environmental health and the effects of economic growth have been found to vary across countries.

The contributions of this study can be presented under different headings. (i) First, this research draws attention to the Jevons paradox in achieving environmental sustainability by focusing on the impacts of green technologies on the environment. (ii) Second, this study addresses the implications for Türkiye, which is often overlooked in the literature. According to IEA[39] data, Türkiye is the second country in the region that consumes the most fossil fuels. Therefore, Türkiye is included in the analysis. The second section of the article explains the data and methodology. The third section presents the findings, and the fourth section discusses the results and concludes the article.

2.DATA, MODEL CONSTRUCTION and METHODOLOGY

In this section, environmental variables and economic growth variables are used for the factors determining CO_2 emissions. Economic development is among the most important goals for the Turkish economy.[40,41] In this context, CO_2 emissions, environmental technological innovation, environmental taxes and income variables belonging to the Turkish economy are used. The relationships of the variables in question are revealed with empirical methods having various power characteristics. First, information about the variables is given. Then, the model is established. Finally, the methodology is introduced.

2.1. Data and Model

This section includes information on the variables and data sources used in the study. The information in question is given in Table 1.

Table 1. Data descriptions.

Symbol	Variables	Description and Measurement	Source
CO2	CO_2 emissions	Per capita (tons)	EDGAR[42]
ETI	Environmental Technological Innovations	Climate change mitigation technologies related to energy generation, transmission or distribution	OECD[43]
ET	Environmental Tax	Environmental tax as a percentage of GDP	OECD[43]
GDP	Income	GDP per capita (constant 2015 USD)	World Bank[44]

Table 1 provides information on the data for the 1994-2022 sample period of the Turkish economy. The variables specified in Table 1 will be established and the relationship between the CO2 variable and ETI, RT and GDP will be investigated. The study focuses on the relationship between CO2 and environmental variables. GDP was included in the model based on the theoretical relationship between the national income per capita and the environmental variable, which was included in the model as an income variable. On the other hand, in the empirical methods used in the study, the natural logarithm of all variables was taken to eliminate problems related to the dynamic properties of the data. It is suggested that the models will produce more consistent and robust results through these transformations.[45,46] The empirical model used in the study is specified in (1).

$$lnCO_{2_t} = \beta_0 + \beta_1 lnETI_t + \beta_2 lnET_t + \beta_3 GDP_t + \varepsilon_t \#(1)$$

In model (1), the dependent variable is CO2, while the explanatory variables are ETI, ET and GDP. In (1), t is the sample period (1994-2022), $\boldsymbol{\beta_0}$ is the constant term, $\boldsymbol{\beta_1}$ is the parameter of the ETI variable, $\boldsymbol{\beta_2}$ is the parameter of ET and $\boldsymbol{\beta_3}$ is the parameter of GDP. Since the natural logarithm of all variables is taken, each parameter can be interpreted as an elasticity coefficient. The error term is indicated by $\boldsymbol{\varepsilon_t}$.

2.2. Methodology

In this section, the methods to be used in explaining the relationships between the variables in the model used in the study will be introduced. The time series methodology is used in the study. In this context, firstly, the unit root process is determined for all variables. Then, the cointegration test methodology will be presented for the long-term relationship. Finally, information will be given about the methods for long-term coefficient estimates.

2.2.1. Unit Root Test

In determining the unit root process, the ADF unit root test proposed by Dickey and Fuller[47] and the PP unit root test proposed by Phillips and Perron[48] are first used. Then, the extended ADF unit root test is performed with Fourier functions that include soft breaks in the ADF unit root test. The Fourier ADF unit root test in question was developed by Enders and Lee[49]. When the graphs of the variables used in the study are examined, it is seen that the Fourier functions can strongly determine the time path of the series. The series and Fourier functions in question are shown in the figures below.

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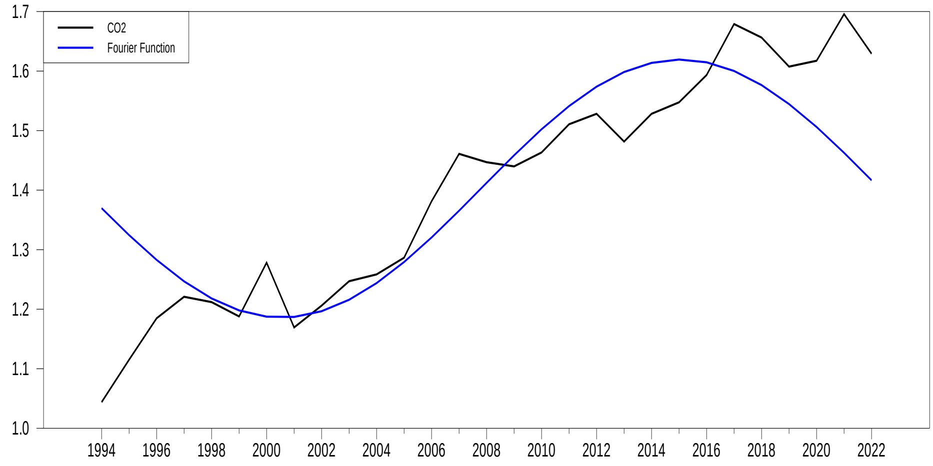

Figure 1. CO_2 and fourier function.

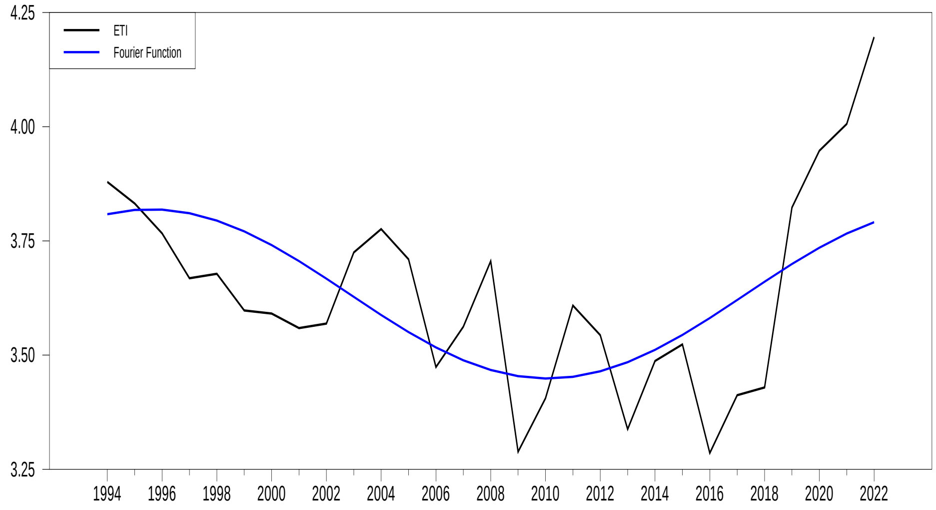

Figure 2. ETI and fourier function.

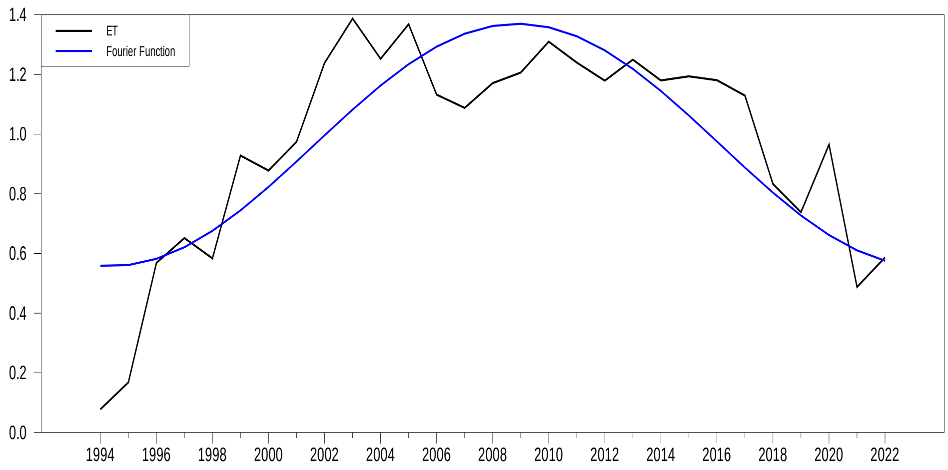

Figure 3. ET and fourier function.

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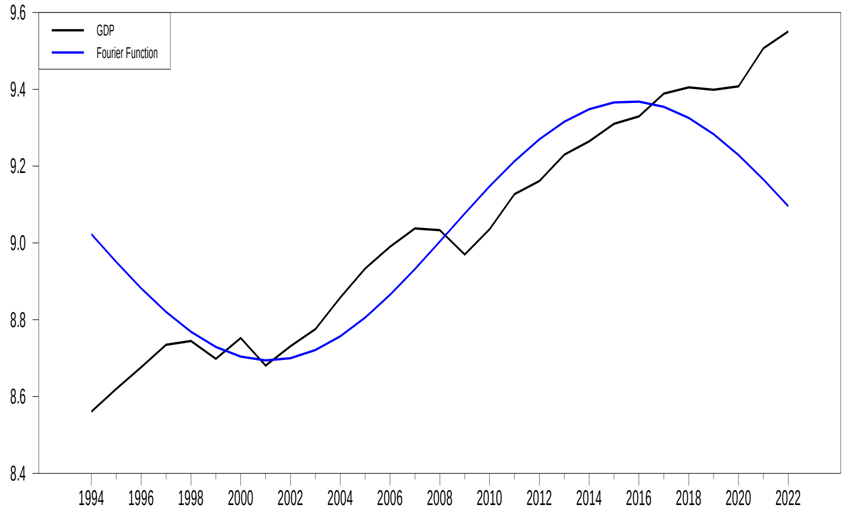

Figure 4. GDP and fourier function.

When the graphs are examined, it is seen that Fourier functions imitate the graphs of CO2, ETI, ET and GDP variables to a high degree. This situation shows that models extended with Fourier functions can produce stronger results in determining the unit root process. When the graphs are examined, the presence of a trend is detected in some variables, while a time course suitable for the constant model is seen in some variables. Although these findings create high expectations, they need to be tested. This situation is tried to be overcome by reporting both the constant and the constant & trend model in all empirical methods to be used throughout the study. The Fourier ADF unit root test used in the study investigates the unit root process by taking into account soft breaks.[50] The Fourier ADF unit root test used in the study investigates the unit root process by taking into account soft breaks. In the test in question, first, the test statistics are compared with the relevant critical values. In the Fourier ADF test, if the null hypothesis cannot be rejected, the presence of a unit root is understood. In the case of rejection of the null hypothesis, the presence of stationarity is understood. However, in order to decide on stationarity, the significance of the F test statistic should be checked. Becker et al.[51] is compared with the critical values calculated by the F test to decide the significance of the Fourier functions. In case of significance of the F test, the validity of the stationarity is decided according to the Fourier ADF test. However, if the F test is insignificant, the traditional ADF unit root test findings are taken into account.

2.2.2. Cointegration Test

After determining the unit root process for the series used in the analysis, the long-term relationship is investigated. In this context, the Extended ARDL (AARDL) method proposed by Sam et al.[52] is used in the study. The AARDL method, which is obtained by expanding the traditional ARDL method frequently used in the empirical literature, has strong aspects with the flexibility it has brought recently. In the ARDL method developed by Pesaran et al.[53] (2001), there is a condition that the dependent variable must be stationary in the first difference. However, Sam et al.[52] relaxed this condition and suggested that the dependent variables, as in the explanatory variables, can be stationary at the level. The AARDL approach is modeled as (2);

$$\Delta CO_{2_t} = \beta_0 + \sum_{j=1}^{p-1} \beta_{1j}\,\Delta CO_{2_{t-j}} + \sum_{j=0}^{p-1} \beta_{2j}\,\Delta ETI_{t-j} + \sum_{j=0}^{p-1} \beta_{3j}\,\Delta ET_{t-j} + \sum_{j=0}^{p-1} \beta_{4j}\,\Delta GDP_{t-j} + + \beta_5 CO_{2_{t-1}} + \beta_6 ETI_{t-1} + \beta_7 ET_{t-1} + \beta_8 GDP_{t-1} + \varepsilon_t \quad (2)$$

There are three different test statistics in this model. The null and alternative hypotheses of the $F_{overall}$ test adapted to model (2) is given in (3).

$$H_0: \beta_5 = \beta_6 = \beta_7 = \beta_8 = 0, H_1: \beta_5 \neq \beta_6 \neq \beta_7 \neq \beta_8 \neq 0 \ \#(3)$$

The null and alternative hypotheses of the $t_{dependent}$ test adapted to the model (2) is given in (4).

$$H_0: \beta_5 = 0, H_1: \beta_5 \neq 0 \ \#(4)$$

The null and alternative hypotheses of the $F_{independent}$ test adapted to the model (2) is given in (5).

$$H_0: \beta_6 = \beta_7 = \beta_8 = 0, H_1: \beta_6 \neq \beta_7 \neq \beta_8 \neq 0 \ \#(5)$$

The three test statistics are arranged according to the variables used in the study. According to all test statistics, if the null hypothesis is rejected, the existence of a long-term relationship is reached according to the AARDL cointegration test. The critical values of the test statistics in question are presented by Narayan[54], Pesaran et al.[53] and Sam et al.[52], respectively.

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2.2.3. Cointegration Estimator Tests

In cases where long-term relationships are obtained, determining the elasticity coefficients in the model is considered important in terms of the degree of relationships. In this context, estimators with different power characteristics are used in the study. In this study, FMOLS estimators first proposed by Hansen and Phillips[55] (1990) and CCE estimators proposed by Park[56] (1992) are used. Then, DOLS estimator proposed by Stock and Watson[57] (1993) is used as a robustness test. If similar findings are detected by using these tests together, the reliability of the results increases.[58] The relevant estimators can produce reliable results in small samples. FMOLS is an estimator that is resistant to the endogeneity problem and problems arising from long-term correlations between cointegrated equations and stochastic processes. CCR estimator allows asymptotic chi-square test. DOLS is an estimator that is resistant to the feedback effect in the cointegration equation. In the

relevant test, an asymptotically efficient estimator is presented and lags are added in the coefficient estimation.

3. RESULTS and DISCUSSION

Table 2 includes descriptive statistics and correlation matrix for the variables used in the study.

Table 2. Descriptive statistics and correlation matrix**.**

Descriptive statistics	**CO2**	**ETI**	**ET**	**GDP**
Mean	1.402644	3.634030	0.963625	9.031404
Med.	1.446919	3.597826	1.129304	9.033144
Max.	1.695616	4.196274	1.387336	9.550741
Min.	1.043804	3.285567	0.077751	8.560599
Std. Dev.	0.191345	0.215977	0.348826	0.300352
Skew.	-0.128622	0.520721	-1.003071	0.132716
Kurt.	1.722796	3.077605	3.148938	1.689886
J-B (Prob.)	2.051056 (0.358607)	1.317839 (0.517410)	4.889869 (0.086732)	2.159114 (0.339746)
Sum.	40.67669	105.3869	27.94511	261.9107
Sum Sq. Dev.	1.025167	1.306084	3.407031	2.525915
Correlation Matrix	**CO2**	**ETI**	**ET**	**GDP**
CO2	1			
ET	0.2863919204340662	-0.5817817119797511	1	
GDP	0.876437658164575	0.01805176087467302	0.2095058713317454	1

Table 2 includes the descriptive statistics and correlation matrix information of the variables CO2, ETI, ET and GDP used in the analysis. The mean values of the variables in question are 1.40; 3.63; 0.96 and 9.03, respectively. The Jargue-Bera test statistics of the variables used in the study show that the null hypothesis indicating normal distribution cannot be rejected at the 5% significance level. This shows that all variables used in the analysis have a normal distribution. On the other hand, when the correlation matrix is examined, it is determined that there is no relationship at a height that could lead to a multicollinearity problem. Table 3 includes the ADF and PP unit root test findings.

Table 3. ADF and PP unit root test findings.

Variables	**ADF**	**PP**	**Variables**	**ADF**	**PP**
	t-Stat	**Adj. t-Stat**		**t-Stat**	**Adj. t-Stat**
CO2	-1.532865 (0.5026)	-1.598671^{***} (0.0047)	ΔCO2	-5.714200^{***} (0.0001)	-6.571311^{***} (0.0000)
ETI	-1.414016 (0.5631)	-1.468716 (0.5362)	ΔETI	-5.786547^{***} (0.0000)	-5.818748^{***} (0.0000)
ET	-2.622498 (0.1005)	-2.619285 (0.1011)	ΔET	-5.709261^{***} (0.0001)	-5.718237^{***} (0.0001)
GDP	-0.000527 (0.9508)	0.216010 (0.9688)	ΔGDP	4.768772^{***} (0.0007)	-4.768772^{***} (0.0007)

Note: Schwarz information criterion is used in ADF unit root test. Values in parentheses indicate probability values. Δ represents the difference operator. Values in parentheses indicate probability values. ***, ** and * indicate significance at the 10%, 5% and 1% levels, respectively.

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According to the findings of Table 3, it is seen that all variables have a unit root process in the level values in the ADF unit root test. According to the PP unit root results from the level analysis, it is determined that the dependent variable CO2 is stationary. The stationarity levels of the variables are important in determining the cointegration relationship. In the unit root research conducted by applying the difference operation to the variables in question, it is seen that all variables become stationary. According to this result, according to the ADF unit root test, all variables are I(1), and according to the PP unit root test, the dependent variable is I(0) and the other variables are I(1). These results will be strengthened with the Fourier ADF test. Table 4 includes the Fourier ADF unit root test findings.

Table 4. Fourier ADF unit root test results.

Variables	Frequency	FADF Test Statistics	F(k)	MinSSR	Crit. Val. (10%; 5%; 1%) FADF(k=1)	Crit. Val. (10%; 5%; 1%) F Test
CO2	1	-2.74627	25.71629***	0.34423	-3.52; -3.85; -4.43	4.133; 4.929; 6.730
ETI	1	-2.13314	7.99901***	0.80857		
ET	1	-3.46430	30.67532***	1.01411		
GDP	1	-1.31019	24.60632***	0.87317		

Note: FADF denotes the Fourier ADF test statistic. ***, ** and * indicate significance at the 10%, 5% and 1% levels, respectively.

It is seen that the FADF test statistics in Table 4 remain below the critical values determined according to k = 1. This situation indicates that all variables have a unit root process at the level. Fourier ADF soft breaks are taken into account. The breaks in question come to the median in deterministic terms. When the difference operation is used, the terms in question disappear. This situation can be seen by performing a graphical examination when the difference operation is applied to the series. Therefore, instead of performing the test by taking the difference operation, traditional unit root tests such as ADF and PP can be used directly in determining the degree of integration. Therefore, both the ADF and PP unit root test findings and the Fourier ADF unit root test results show that not all variables have an I(2) process. This result is of critical importance in determining the cointegration test to be used. As a result of the unit root tests, it was understood that the AARDL method, which was proposed by Sam et al.[52] and allows the dependent variable to be I(0) unlike the traditional model, can be used. The AARDL test findings are given in Table 5.

Table 5. AARDL cointegration test results.

Model	k	Test Statistics	I(1) Critical Values %1	I(1) Critical Values %5	I(1) Critical Values %10
AARDL (1, 1, 1,1)	3	$F_{overall}$ 4.18362*	7.063	5.018	4.150
		$t_{depentent}$ -4.28418**	-4.37	-3.78	-3.46
		$F_{independent}$ 4.32954*	7.72	5.14	4.11

Diagnostic Tests	Test Statistics	Probability Values
Breusch-Godfrey	1.997052	0.15760548
White	28.000009	0.41097306
Ramsey RESET	0.0015771	0.9683226
Jarque-Bera	0.883482	0.642916
CUSUM	Stable	
CUSUMQ	Stable	

Note: The relevant significance levels at critical values refer to the I(1) upper limit values. ***, ** and * indicate significance at the 10%, 5% and 1% levels, respectively.

Table 5 shows the results of 3 different test statistics in the AARDL method. The test statistics of Foverall, tdepentent and Findependent are compared with the critical values calculated by Narayan[54], Pesaran et al.[53] and Sam et al.[52], respectively. If there is a test statistic above the upper limit value of I(1), then the existence of a cointegration relationship is understood. According to the AARDL method, in order to have cointegration, it is necessary to reach the existence of cointegration according to the test statistic. According to the findings of Table 5, the existence of a long-term relationship is reached according to all three test statistics. In order to use these results, diagnostic tests need to be examined. According to these tests, there is no autocorrelation problem, constant variance is valid, there is no modeling error and the validity of the normal distribution is reached. According to the results of Table 5, the existence of a long-term relationship has been reached.

This result allows the long-term coefficients to be obtained. Table 6 includes the FMOLS and CCR results.

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Table 6. FMOLS and CCR test results.

Variables	Coefficient	Standard Error	t-statistic	Probability values
FMOLS				
ETI	0.163697**	0.075518	2.167665	0.0403
ET	0.059843**	0.026497	2.258527	0.0333
GDP	0.677645***	0.043163	15.69976	0.0000
C	-5.362704	0.637579	-8.411045	0.0000
CCR				
Variables	**Coefficient**	**Standard Error**	**t-statistic**	**Probability values**
ETI	0.175879	0.103934	1.692211	0.1036
ET	0.062795**	0.024406	2.572975	0.0167
GDP	0.684365***	0.051101	13.39238	0.0000
C	-5.470679	0.808996	-6.762307	0.0000

Note: ***, ** and * indicate significance at the 10%, 5% and 1% levels, respectively.

According to the FMOLS results in Table 6, it is seen that all explanatory variables are statistically significant. According to the results, it is seen that 1% increases in ETI, ET and GDP cause an increase of 0.16%, 0.06% and 0.68% on CO2, respectively. According to the CCR results, it is determined that 1% increases in ETI, ET and GDP cause an increase of 0.17%, 0.06% and 0.68% on CO2, respectively. The fact that the FMOLS and CCR results are close to each other strengthens the findings. In the last stage, the DOLS estimator is used as a robustness test. Table 7 shows the DOLS results.

Table 7. DOLS robustness test.

Variables	Coefficient	Standard Error	t-statistic	Probability values
ETI	0.624400***	0.158918	3.929060	0.0017
ET	0.082964**	0.029444	2.817687	0.0145
GDP	0.875874***	0.081044	10.80739	0.0000
C	-8.844959	1.274107	-6.942084	0.0000

Note: ***, ** and * indicate significance at the 10%, 5% and 1% levels, respectively

The DOLS results in Table 7 show the statistical significance of all variables. According to the test findings, it is seen that 1% increases in ETI, ET and GDP cause an increase of 0.62%, 0.08% and 0.87% on CO2, respectively. Although the DOLS results show differences in coefficients compared to FMOLS and CCR, the main trend is strongly supported by the conclusion that ETI, ET and GDP increase CO2.

4.CONCLUSION

Environmental degradation is among the most important problems on a global scale. This issue is being studied by researchers in a multifaceted manner on a global scale. Multifaceted measures are being taken by many institutions and organizations in the international arena. These measures became concrete goals thanks to the sustainable development plans put forward by the United Nations. Although these plans have economic, social and environmental dimensions in the general framework, it can be said that the environmental dimension has a significant weight. In particular, sensitivity is emphasized on a global scale with the title of partnerships for the targets included in the 17 goals. This situation necessitates that the problem of environmental degradation be on the agenda of not only developed countries but also developing countries. In this context, a study was conducted on the Turkish economy, which is among the developing countries. In the study where environmental pollution is represented by CO2 emissions, the relationship between environmental technological innovations, environmental taxes and income was investigated. In the study where time series methods with various power characteristics were used in the 1994-2022 sample period, the results are quite interesting. The AARDL method results, which are among the current cointegration techniques, showed the existence of a long-term cointegration relationship between the relevant variables. Afterwards, the long-term coefficients were strengthened with robustness tests. According to the results, it was understood that the increases in environmental technological innovation increased CO2 emissions. This result is quite interesting. This result, which is not in line with general expectations, is based on various reasons. First of all, this situation can be explained by the rebond effect. Although this effect does not provide an increase in efficiency, it can lead to an increase in energy use. Considering the high rate of fossil fuel consumption in the Turkish economy, this result can be in line with expectations. As a solution proposal, environmental regulations can be made and the share of renewable energy in energy use can be increased. Another finding is that increases in environmental taxes increase CO2 emissions. This situation can increase costs and cause more polluting energy use. Optimization studies on tax rates can be effective for the solution. Finally, it has been concluded that increases in income, in other words, economic growth increase CO2 emissions. This result indicates an increase in environmental pollution during the economic growth process. This situation can be explained by the fact that the energy sources used in the production process are mostly obtained from fossil fuels. In the studies

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following this study, a similar study can be conducted for a developing country group similar to Türkiye. Thus, the findings of this study can be compared and policy measures can be discussed.

Conflict of Interest

There is no conflict of interest between the authors.

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