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The Driving Factors of Italy's CO_2 Emissions Based on the STIRPAT Model: ARDL, FMOLS, DOLS, and CCR Approaches

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Abstract: As the sustainability of the environment is a very much concerning issue for developed countries, the drive of the paper is to reveal the effects of nuclear, environment-friendly, and non-friendly energy, population, and GDP on CO_2 emission for Italy, a developed country. Using the extended Stochastic Regression on Population, Affluence, and Technology (STIRPAT) framework, the yearly data from 1972 to 2021 are analyzed in this paper through an Autoregressive Distributed Lag (ARDL) framework. The reliability of the study is also examined by employing Fully Modified Ordinary Least Square (FMOLS), Dynamic Ordinary Least Square (DOLS), and Canonical Cointegration Regression (CCR) estimators and also the Granger causality method which is used to see the directional relationship among the indicators. The investigation confirms the findings of previous studies by showing that in the longer period, rising Italian GDP and non-green energy by 1% can lead to higher CO_2 emissions by 8.08% and 1.505%, respectively, while rising alternative and nuclear energy by 1% can lead to falling in CO_2 emission by 0.624%. Although population and green energy adversely influence the upsurge of CO_2, they seem insignificant. Robustness tests confirm these longer-period impacts. This analysis may be helpful in planning and developing strategies for future financial funding in the energy sector in Italy, which is essential if the country is to achieve its goals of sustainable development.

Keywords: ARDL; CO_2 emission; renewable energy; fossil fuels; STIRPAT model; Italy

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1. Introduction

Efforts to transition energy networks away from environmentally hazardous fossil fuels and toward cleaner, more sustainable forms of power have led to a greater emphasis on shifting the energy balance in nature [1]. Most of the climate-altering and planet-warming chemicals we release into the atmosphere are carbon dioxide (CO_2).

Environmental issues on a global scale, such as warming temperatures are becoming worse. The rise in carbon dioxide emissions (CO_2) is one of the most critical environmental problems confronting the world today. To boost industrial production also causes less eco-friendly technology to use more fossil fuels and CO_2 [2–6]. Dynamic development of individual countries and increasing production will increase Co2 emissions, and no one will stop it anytime soon. Unfortunately, situations where the politics and interests of ruling parties have a negative impact on the development of energy policy are increasingly noticed [7–9], unless the government introduces tax incentives which have positive and considerable outcomes on CO_2 [10]. Yuelan et al., in the Chinese case, and Halkos and Paizanos, in the case of the United States, both study fiscal instruments and obtain results, which stress that economic policies have significant effects on CO_2 and environmental degradation [11,12].

The energy transition to a system completely free from carbon sources is considered a necessary objective to respect the limits in the growth of global temperatures established in international agreements and treaties. This is now the most important problem facing the whole world. However, there are studies that show a positive relationship between the increase in the share of renewable energy and the growth of gross domestic product. Bogdanov et al. [13] analyzes the positive relationship between the production of renewable energy and the reduction of CO_2 emissions in South America over the period 1980–2010. A. Hdom [14] verifies the presence of a positive relationship between renewable energy production, CO_2 reduction, and gross domestic product growth in a panel of 84 countries between 1991 and 2012. Another research considers the positive effects that the political economic incentive for renewable energy installations has had on households in Germany and other countries [15–17].

Another study analyzes the positive impact of renewable energy in terms of economic growth in 38 countries during the period between 1990 and 2018 [18]. The results show the presence of a positive relationship between renewable energy production and economic growth.

However, it should be taken into account that the transition towards renewable energy is associated with an initial increase in energy prices, which should be associated with appropriate government support for households. If the government also points out that such changes will have a positive impact on the environment and the health of citizens, the direction of changes should be one of support, regardless of the economy, economic development, and costs.

Italy's CO_2 output in 2021 was 311.2 million metric tons. In spite of significant fluctuations in recent decades, Italy's carbon footprints have generally been decreasing since 1972, and are projected to reach 311.2 million tons in 2021 [19,20]. Disentangling the most crucial triggers of CO_2 releases is pertinent for responding rapidly to the climate crisis and reducing emissions.

Energy is a key economic input often overlooked in environmental discussions [21]. Energy remains crucial to a thriving economy, but it also challenges in reaching environmental sustainability objectives and cutting carbon emissions. The Arctic set a record-breaking high temperature of 38 degrees Celsius on 14 December 2021, according to the World Meteorological Organization, which should serve as a wake-up call for people everywhere to reduce their carbon footprints and embrace greener ways of living so that we can help Mother Nature heal and regenerate her natural wealth in a sustainable way for the benefit of generations to come [22]. Extreme weather occurrences are becoming more of a problem for people and ecosystems as a consequence of global warming. A rising human population and improved infrastructure both contribute to an increase in the frequency with which catastrophic events cause annual financial losses. Recent progress in reducing carbon pollution can be attributed to technological breakthroughs, patenting, and renewable energy [23].

This research will use this context as a jumping-off point to look into the primary factors that led to variations in CO_2 emissions in Italy between 1972 and 2021. Since Italy is an upper-earning nation divided into North and South zones, a phenomenon not frequently observed among European Union (EU) member states, it makes for an intriguing case study [24]. The investigation enlarges the existing empirical works by expanding the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model to include not just one but three different pathways of atmospheric carbon release: the economic channel's path, the population channel, and the technological infrastructure pathway [25].

In 2019, renewable energy sources (RES) comprised 18% of Italy's total energy production. By 2030, the government aims to have the nation rely 30% on renewable energy, primarily wind and solar. While incentives are primarily geared toward businesses and households, the construction building stock and transportation sectors are major focal points of energy-saving initiatives [26]. One practical strategy for cutting emissions, says Dogan and Seker [27,28], involves boosting the proportion of renewables in the energy balance. By 2030, the Italian government will project 4 million electric vehicles and 2 million hybrids on Italian roads. The innovative biofuels, mainly biomethane, will help Italy reach its goal of a 22% renewable energy proportion in transportation by 2030. By the year 2030, Italy anticipates that its electricity production from wind and solar power will have risen by respective factors of three and two. Italy's energy policy seems to be an example for many countries. The basic document presenting the assumptions of Italy's energy policy is the National Integrated Plan for Energy and Climate (PNEIC) adopted in January 2020. PNEIC assumes that in 2030, 55% of national electricity production is to come from renewable sources. For this purpose, the following assumptions have been made:

- The promotion of electromobility is to be a means to reduce carbon dioxide emissions.
- Increase the infrastructure created to use alternative energy sources.

Italy also makes very good use of its geographical conditions. In steeply sloping areas such as the Alps and mountains in general, hydropower plays a major role and has been one of the most widespread alternatives to fossil fuels since the beginning of the last century. Where the sun is stronger, as in the south of the country, there is room for photovoltaic technology, which in recent years, thanks to various government incentives, has become increasingly popular in private homes and businesses. On large islands such as Sicily and Sardinia, there are also many wind turbines that can convert wind energy into electricity distributed throughout the territory. In addition, those who do not want to go for the most advanced energy production systems are increasingly choosing to use energy sources located in their garden, installing heat pumps that can extract energy from the air or groundwater and using it for heating or cooling rooms in their apartments. It seems, therefore, that the actions presented in Italy's energy strategy have so far been a model to be followed by other countries.

Recently, Italy has adopted a new policy regarding fossil fuels, and this fresh legislation will enable SACE (Servizi Assicurativi del Commercio Estero, an export authority of Italy) to assist with a variety of fossil fuel initiatives, such as exploration, production, storage, and distribution. The decision has encountered harsh denigration from climate experts. The experts contend that it would violate commitments globally and impede the transition to a green economy that the country is undergoing [29]. Air pollution caused by burning fossil fuels and driving automobiles, as asserted by Dogan and Aslan [30], is a major contributor to the buildup of global warming gases in countries. When it comes to fossil fuels, Italy is a net consumer. This means Italy must rely on foreign suppliers for its natural gas needs. After Germany and the United Kingdom (UK), Italy was Europe's third-largest gas importer and user in 2017. Over 90% of Italy's gas supply comes from abroad, mainly as fossil fuel imports [31]. In 2020, nearly 80% of Italy's aggregate power generation originated from fossil fuels. In 2020, nearly 80% of Italy's gross electricity production was generated from non-green energy, including non-clean fuel accounting for the vast majority of this figure. Thermal power plants generate most of Italy's new electricity capacity [32]. If Ember is correct, Italy will generate more significant amounts of electricity from fossil gas than any other European Union (EU) country by 2030 [33].

Nuclear energy plays a crucial role as an alternative to green power in the meantime when the expense of the power is high, but supply is inadequate, and demand is massive and when it is an urgent need to alleviate pollution because CO_2 is strongly correlated with economic activities and development [34]. Even though there was a 2011 referendum in which 94% of Italians voted against bringing back nuclear power, a new referendum has been proposed in Italy to encourage different nuclear power plants, which would be the country's first since the closure of nuclear power plants in 1990. Even as the European

Commission mulls over whether or not to officially recognize nuclear energy and gas from the ground as green sources of generated energy, the notion that moving back to nuclear power could help Italy lower its energy costs is currently being supported there [35]. A boost in nuclear-powered electricity production may help mitigate the impact of global warming [36–38]. As oil costs rise, nuclear power is touted as a way to reduce reliance on foreign countries to meet domestic energy needs while also lowering environmental impact.

Therefore, the core theme of the research is to investigate the influence of energies like alternative and nuclear, transparent and non-clear, population, and gross domestic product (GDP) on CO_2 upsurges in Italy. This is also the research question regarding whether these variables influence CO_2 emanation in Italy. Moreover, the research hypothesis (alternative hypothesis) is that nuclear, transparent and non-clear energy, population, and GDP have an impact on CO_2 emission. More precisely, GDP, population, and non-clear energy have a positive influence on CO_2 and clean and nuclear energy have a negative influence on CO_2. As these variables are ignored altogether in the previous literature, this research contributes a new aspect regarding sustainable environment in Italy which is very much concerning. This paper also contributes to filling the study gap on the importance of nuclear, renewable, and alternative energies in production without carbon emission in Italy. Also, this paper is unique in terms of using Autoregressive Distributed Lag (ARDL) as well as Dynamic Ordinary Least Square (DOLS), Fully Modified Ordinary Least Square (FMOLS), and Canonical Cointegration Regression (CCR) methods which have not yet been employed in this type of research. Citizens, academic researchers, economists, and politicians will benefit from a deeper comprehension of the issue and the crucial data and evidence provided by this study's findings. The conclusions of this research have significant policy and regulatory ramifications for environmental safeguarding authorities.

This research is divided into the following sections: a description of previous works, methods used, results found, and an ending note.

2. Literature Review

The stimulus of gross domestic product, green energy, and technical progress in Group of Seven (G7) countries' efforts toward lowering CO_2 emissions from 1990 to 2020 was analyzed by Mehmood et al. [39]. CO_2 emissions negatively correlate with GDP and renewable energy usage in this CS-ARDL (Cross-Sectional Autoregressive Distributed Lag Model) analysis. Rising GDP and cleaner power sources have helped lower emissions. In ten African nations from 1997 to 2021, Voumik et al. [40] employed the Augmented Mean Group (AMG) and Mean Group (MG) procedure to look into the implications of GDP, renewable energy, and fossil fuels on ecological quality. Findings showed that decreasing ecological harm was achieved through greater utilization of green power and increasing efficiency, whereas the utilization of non-green power elevated atmospheric carbon dioxide emissions. Utilizing the ARDL approach, Bento and Moutinho [41] looked at data for Italy between 1960 and 2011 to see how GDP and green energy affected CO_2 emissions. Growth in GDP was found to reduce pollution levels in the predicted model. Renewable energy generation lowered the ecological damage level. Ali et al. [42] examined how GDP and population changed CO_2 emissions in Malaysia between 1970 and 2014. A larger population and higher GDP were found to be significant factors in higher levels of ecological damage in Malaysia.

Another study used the AMG method to examine the implications of various energy sources, including renewables, fossil fuels, and nuclear power, on CO_2 emissions in SAARC (South Asian Association for Regional Cooperation) nations from 1982 to 2021 [43]. The findings revealed that fossil fuels boosted the ecological deterioration level, in contrast to green energy and nuclear energy, which were found to reduce pollution levels. Omri and Saadaoui [1] analyzed how nuclear power, fossil fuels, and income influenced CO_2 emissions in France from 1980 to 2020. The concluding result of the Nonlinear ARDL (NARDL) demonstrated that nuclear power supported lowering France's ecological footprint. However, these emissions were exacerbated by the utilization of green power. Using data from the world's top ten nuclear-generating nations, Zhang et al. [44] compared the effects of nuclear and renewable power on CO_2 emissions. The findings implied that population, GDP, and nuclear or renewable power all contributed to ecological damage and pointed to the need for measures to reduce the population's size and improve its quality, as well as the implementation of a sustainable economy and the improvement of nuclear and green energy that is secure.

Jahangir et al. [45] and Sadiq et al. [46] demonstrated that nuclear power boosted the ecological compatibility level in top nuclear power usage countries. Another study researched by Kartel et al. [47] looked into the implications of nuclear power, GDP, and renewable power on ecological compatibility levels in the United States between 1965 (1st quarter) and 2018 (4th quarter). According to the findings, nuclear energy, green energy, and financial advancement all slow the progression of environmental deterioration in the middle and higher tails of the distribution. In contrast, improving the economy negatively impacts environmental compatibility in the upper quarters. Majumder et al. [48] looked into the impression of various kinds of electricity production upon the number of CO_2 emanations produced in South Asian nations from 1972 to 2015. As per the outcomes of the Quantile Regression (QR) analysis, all of the different types of power generation and the variables that are connected to them receive beneficial encouragement on CO_2 emanations. The environmental quality is adversely squeezed by power stations that burn coal as fuel. On the contrary, sustainable energy sources have the least detrimental effect on the deterioration of the environment.

Another study on the G7 nation's ARDL method revealed that sustainable power, urbanization, and nuclear power alleviated the ecological impairment from 1979 to 2019 [49]. After reviewing the relevant literature, this research concludes that rising population, GDP, and energy usage contribute to environmental deterioration and rising CO_2 emissions [50–60]. The proof presented here considers these factors a major contributor to climate deterioration that boosts emissions.

Only a few studies exist regarding the Italian region, and no studies have occurred in recent years. Therefore, this paper will fill this gap by applying the theoretical STIRPAT model and the ARDL model. In addition, the heftiness of the ARDL, the DOLS, FMOLS, and CCR methods are also employed for inspection. Moreover, the Granger causality method has also been utilized to see the association between the regressand and regressors. In Italian regions, no studies applied this econometric application to observe the implication of GDP, population, green power, non-green power, and nuclear energy on CO_2. Therefore, this investigation perfectly matches this regard and will fill the literature gap.

3. The Methodology of the Research

3.1. Outline of the Theory

The aim of this paper can only be attained with the help of a model that considers the influence of fossil fuels, energy from nuclear plants, and green power usage on damage to the environment. STIRPAT is the most renowned theoretical framework to assess the consequences of CO_2 emissions in the modern period. The STIRPAT model analysis is the most common approach to predict future carbon pollution. Starting with the assumption that people, wealth, and technology are the primary drivers for ecological pressing pressure, followed by a population (P), affluence (A), and technology (T) impact (I) (IPAT) model [61] for which Dietz and Rosa [62] developed an enhanced version called STIRPAT.

The widely used STIRPAT structure was put to use in this investigation. A common approach among academics, the STIRPAT framework is a modification of the IPAT framework explicitly developed to address the challenge of alleviating ecological stress. Population (P), wealth (A), and technology (T) have an ongoing connection in terms of their effect on the ecosystem, and this relationship was first articulated by American environmentalists Ehrlich and Holdren [61] and Commoner et al. [63] in the form of the IPAT equation. Although the IPAT framework has randomness and can estimate each coefficient as a separate parameter, it is limited in its ability to account for the interplay of the people, economy, and technology. The extended version of the technique is suggested to address the shortcomings of the original STIRPAT framework and has found widespread application [64,65].

Without considering the influence of wealth, population growth, and technological advancement, the IPAT-identifying method is doomed to failure. This section explains the IPAT's Equation (1):

$$\text{I} = \text{PAT} \tag{1}$$

For each "I" in "Impact" and "P" in "Population", A describes the level of wealth experienced, such as GDP, and T describes energy efficiency innovations that benefit the environment. Due to its shortcomings, the IPAT paradigm will be replaced by STIRPAT. It performs better and takes up less time. The STIRPAT framework, stated as the resulting formula, offers a robust quantifiable structure to observe the impact of environmental variables. Equation (2) demonstrates the association between population, affluence, technology, and environment and describes how these variables impact the environment.

$$I = \beta P_t^{\alpha} \cdot A_t^{\gamma} \cdot T_t^{\varphi} \varepsilon_t \tag{2}$$

Given that the IPAT model precludes non-comparative changes in the robust mechanisms, its usefulness remains severely limited [66]. In contrast to the IPAT model, which includes all of the IPAT's drawbacks, the STIRPAT approach includes only the IPAT's pros. The STIRPAT model allows a precise calculation of all coefficients and factor separation. The STIRPAT paradigm also investigates the causes of shifts in the ecosystem and recognizes the critical reasons for policy interventions [67]. The STIRPAT paradigm produces more reliable results in nearly all types of data [68]. The STIRPAT paradigm is utilized current research investigations to see the factors that encourage CO_2 emanations [69,70].

The following framework in Equation (3) is proposed for studying the impressions of people, GDP, green power, nuclear energy, and fossil fuels on CO_2 emission:

$$\text{CO}_2 = \int (\text{GDP, Population, Technologies}) \tag{3}$$

All of these crucial metrics are incorporated into the augmented STIRPAT framework. This research employs GDP as a stand-in for affluence (A), following the technique of other researchers [67–70]. Recent research has integrated renewable and nuclear power to better reflect tech-how (T) into the STIRPAT framework [69,71,72]. Here, nuclear power, fossil fuels, and renewable energy are employed as technology. Furthermore, the population was adopted to examine the impact of the population on CO_2. There were three technological factors employed in the assessment.

Equation (2) can be rewritten as follows:

$$\text{CO}_2 = \int (\text{GDP, POP, REN, FOS, NUC}) \tag{4}$$

where GDP is for gross domestic product, POP is for population, REN is for renewable energy, FOS is for fossil fuels, and NUC is for nuclear energy.

The accompanying Equation (5) displays the adjusted version of (4):

$$CO2_t = \beta_0 + \beta_1 POP_t + \beta_2 GDP_t + \beta_3 REN_t + \beta_4 FOS_t + \beta_5 NUC_t + \varepsilon_t \tag{5}$$

The corresponding logarithmic expression is as follows:

$$LCO2_t = \beta_0 + \beta_1 LPOP_t + \beta_2 LGDP_t + \beta_3 LREN_t + \beta_4 LFOS_t + \beta_5 LNUC_t + \varepsilon_t \tag{6}$$

where LCO_2 represents CO_2 emanations at time t in logarithmic (log) notation, *LRENt* is the amount of green energy available at time t in log notation, *LNUCt* is the log of nuclear energy, and *LFOSt* is the amount of fossil fuel available at time t in log notation.

Several researchers today have utilized the STIRPAT framework to explain the environmental implications [73–79].

3.2. Data

Yearly numerical information for Italy from 1972 to 2021 is used in this study. The World Development Indicators database was primarily used to accumulate the data.

Table 1 demonstrates the features of the variables (symbol, source, and definition) chosen for the analysis. The variables of interest rate include CO_2 emission employed as an explained indicator, and the regressors are gross domestic product, population, and energy consumption (renewable, fossil fuels, and nuclear energy).

Table 1. Details of regressors and regressand.

Variable	Symbol	Definition	Source
CO_2 emissions	LCO_2	CO_2 emissions (kt)	World Bank Development Indicator
Gross domestic product per capita	LGDP	GDP per head (fixed 2015 USD)	
Population	LPOP	The aggregate number of people	
Renewable energy consumption	LREN	Green energy usage (% of aggregate ultimate energy usage)	
Fossil fuels	LFOS	Non-green energy usage (% of aggregate ultimate energy usage)	
Nuclear energy	LNUC	Substitute and nuclear power (% of aggregate ultimate energy usage)	

Table 2 shows a compilation of the variables' summary statistics. There are no surprising tendencies in the numerical information. The average information is trustworthy for all indicators. Some factors, including population and fossil fuel, are more prone to fluctuations than others, as illustrated by the standard deviation. The POP ranks highest, while alternative nuclear energy is towards the bottom.

Table 2. Summary of the data.

Variables	N	Mean	SD	Min	Max
T	50	1997	14.58	1972	2021
LCO_2	50	12.90	0.0942	12.67	13.07
LGDP	50	10.21	0.207	9.708	10.44
LPOP	50	17.87	0.0286	17.81	17.92
LREN	50	2.083	0.414	1.330	2.849
LFOS	44	4.505	0.0476	4.364	4.549
LNUC	44	1.356	0.385	0.789	1.955

3.3. Econometric Methodology

Through the help of the cutting-edge, dynamic ARDL simulations method, the expected shorter- and longer-period coefficients of the regressors in question have been identified [80,81]. This model can autonomously assess the shorter- and longer-period associations amidst indicators, as well as induce and visualize charts of (upward and downward) shifts in those indicators. This model can autonomously assess the shorter- and longer-period associations amidst indicators, as well as induce and visualize charts of (upward and downward) shifts in those indicators. Moreover, ARDL is appropriate for the mix of I(0) and I(1) data. According to Abumunshar et al. [82], to confirm the long-run estimation of ARDL methods, FMOLS, DOLS, and CCR has to be used which have been applied in this paper also. These chronological econometric procedures are also used by Olorogun [83] and Adebayo et al. [84]. Following Abumunshar et al. [82], this paper also utilized several model stability tests. Therefore, the steps of the econometric procedures of this paper are valid and justified.

3.3.1. Unit Root Test

Before looking into potential relationships between the periods, it is perilous to determine if the data are stable. Before continuing, the paper performed a regression test to ensure that none of the variables had unit roots. This matters since factors with a unit root or non-stationary data need help clarifying a larger percentage of the outcomes or else, they might contribute to erroneous conclusions [85,86]. This paper employed the well-established Augmented Dickey–Fuller (ADF) test, Kapetanios and Shin unit root (KSUR) test, and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) standard unit root techniques to look for a unit root. The ADF test has gained widespread favor because of its capacity to regulate serial autocorrelation [87]. The ADF technique is extra robust and can be applied to more complex methods as opposed to the Dickey–Fuller (DF) procedure [88].

Due to its ability to model time series nonlinearity and asymmetry, the KSUR test procedure is used in this work. Nonlinearities caused by the recession's depth and duration, as Blanchard claimed [89], are linked to departures from the natural rate theory. If there are major discrepancies in the data, the KSUR method outperforms the linear stationarity model [90]. The KSUR test stands for an expansion on the original stationary procedure developed by Kapetanios et al. [91], and that is extra comprehensive than the original stationary procedure. The KSUR test is modified by Otero and Smith [92], who use Monte Carlo models and "response surface regressions" to improve the original method.

Researchers in [93] developed the first version of the KPSS test. In contrast to the ADF test, this stationarity test was initially conceived as an adjunct to the stationarity check. The technique proposes that the yearly data be disintegrated into a stationary error, an arbitrary component, and a deterministic pattern.

The following Equation (7) illustrates the outline of the standard ADF evaluation:

$$\Delta Y_t = \beta_0 + \beta_1 + \delta Y_{t-1} + \Delta Y_{t-i} + \mathrm{E_t} \tag{7}$$

where ΔY_t represents associated variable; β_0, β_1 represent model parameters; i represents lag order for the Dickey–Fuller enhancement; period pattern; $\mathrm{E_t}$ is zero-mean Gaussian white noise that may exhibit correlations over some time interval t.

For the KPSS test, the time sequence can be depicted as follows:

$$Y_t = \delta_t + r_t + e_t \tag{8}$$

where δ_t reflects a deterministic pattern, r_t shows a random component and e_t narrates the error term. An illustration of the random walk is given below:

$$r_t = r_{t-1} + v_t \tag{9}$$

The null hypothesis asserts that $\sigma_v^2 = 0$. If Y_t is stationary, the KPSS test is tested in $\mathrm{r_t}$ when δ is not zero.

The hypothesis for the KPSS procedure is illustrated below:

$\mathbf{H_0}$. *There is no discernible pattern in the data.*

$\mathbf{H_1}$. *Non-stationarity is present in the yearly data.*

The test measure, a one-sided Lagrange Multiplier, is deduced as follows:

$$LM = \frac{\sum_{t=1}^{t} S_T^2}{\hat{\sigma}_e^2} \tag{10}$$

where $\hat{\sigma}_e^2$ is the error variance and ${S_T}^2$ shows the sum of the error.

3.3.2. ARDL Cointegration Method

The following phase is established based on the fixed outcomes and integration levels. When examining indicators with I(0), I(1), or diverse orders of integration (but no I(2) or greater orders), the Autoregressive Distributive Lag (ARDL) Bounds method is applicable [93,94]. This overcomes the restrictions imposed by the cointegration stages [85,95], which require variables to be integrated in similar order. This paper considers the ARDL Bounds testing [95] method to evaluate the sturdiness of the cointegration test proposed by Bayer and Hanck [96]. Unlike conventional cointegration tests, the ARDL Bounds testing method can be utilized if the indicators are integrated at the I(0) or I(1) level. This method is helpful because it can yield reliable results even when working with a limited sample number. It is possible to gauge both shorter- and longer-period factors simultaneously. The Formula (8) demonstrates the longer-period association between CO_2, GDP, POP, REN, FOS, and NUC. This approach was developed to help establish ARDL Bounds:

$$\begin{gathered}\Delta(LCO2)_t = \theta_0 + \textstyle\sum_{i=1}^{t} \theta_1 \Delta LCO2_{t-i} + \sum_{i=1}^{t} \theta_2 \Delta LGDP_{t-i} + \sum_{i=1}^{t} \theta_3 \Delta LPOP_{t-i} + \sum_{i=1}^{t} \theta_4 \Delta LREN_{t-i} + \\ \textstyle\sum_{i=1}^{t} \theta_5 \Delta LFOS_{t-i} + \sum_{i=1}^{t} \theta_6 \Delta LALNUC_{t-i} + \lambda_1\ LCO2_{t-1} + \lambda_2\ LGDP_{t-1} + \lambda_3\ LPOP_{t-1} + \lambda_4\ LREN_{t-1} + \\ \lambda_5\ LFOS_{t-1} + \lambda_6\ LNUC_{t-1} + \varepsilon_t\end{gathered} \quad (11)$$

Here t represents the time, $t - i$ represents the previous time, and the Akaike information criterion (AIC) determines the optimum lag. Moreover, ε_t is the error notation, Δ represents the first difference operator, and λ analyzes the longer-period correlation. The bound approach necessitates a hypothesis assessment with the intent to figure out a sustained relationship between the analyzed variables. With no cointegration and proof of cointegrations, both the null and alternate hypothesis is derived below:

$$\begin{gathered}H_0: \text{ lag coefficient 1} = \text{lag coefficient 2} = \text{ lag coefficient 3} = \text{lag coefficient 4} = \text{lag coefficient 5} \\ = \text{ lag coefficient 6} = 0\end{gathered}$$

$$\begin{gathered}H_1: \text{ lag coefficient 1} \neq \text{lag coefficient 2 } \neq \text{ lag coefficient 3} \neq \text{lag coefficient 4 } \neq \text{lag coefficient 5} \\ \neq \text{ lag coefficient 6} \neq 0\end{gathered}$$

This method checks the calculated F values against the tabulated numbers established by the low and high limits. Estimated F statistics that fall short of the upper bound number do not disprove the null hypothesis. If the estimated F value is larger than the tabulated value, then the alternative hypothesis is accepted, and the variables are likely to be related over the long run [97–100].

3.3.3. ARDL Long-Run Estimation

In this study, the longer- and shorter-period factors were projected utilizing the dynamic ARDL replications method generated by Jordan and Philips [97,98]. To better understand the longer- as well as shorter-period connections amidst the factors of interest, this model was developed to address the shortcomings of the canonical ARDL structure. Further, the dynamic replicated ARDL method can evaluate, model, and produce charts to foretell the impact of hypothetical changes to a single predictor variable on the explained indicator, with the rest of the explanatory indicators held unchanged [97,98,100]. To implement the dynamic ARDL modeling method, the included data must be integrated at I(1), and the series should be cointegrated [97,98]. In addition, this technique produces both longer- and shorter-period coefficients, which can be used to draw practical policy conclusions. Similarly, the ARDL approach includes a word for error correction that explains how near-term actions can eventually lead to far-reaching outcomes [101].

The error correction term is very important to prove cointegration in the present setting [102,103]. Sample numbers between 30 and 80 can be split into two groups with different critical values [104]. This research uses a large data set (51 observations) to estimate error-correcting models for short-run relationships, yielding proper critical values. To further investigate the link amidst CO_2 release and the analyzed regressors, both in the shorter as well as the longer period, the current study used the ARDL testing methodology, as shown in Equation (9), which provides a representation of the ARDL testing model.

Also, Equation (2) provides a visual representation of the error correction of the estimated model (ECT_{t-1}):

$$\Delta(LCO2)_t = \theta_0 + \sum_{i=1}^{t} \theta_1 \Delta LCO2_{t-1} + \sum_{i=1}^{t} \theta_2 \Delta LGDP_{t-1} + \sum_{i=1}^{t} \theta_3 \Delta LPOP_{t-1} + \sum_{i=1}^{t} \theta_4 \Delta LREN_{t-1} + \sum_{i=1}^{t} \theta_5 \Delta LFOS_{t-1} + \sum_{i=1}^{t} \theta_6 \Delta LNUC_{t-1} + \theta_7\, ECT_{t-1} + \varepsilon_t \quad (12)$$

Adjustment pace is represented by the θ_7 coefficient, the initials ECT indicate "error correction term", t symbolizes "time", and ε_t is an error symbol. A negative and statistically significant ECT value is required. After that, we run stability and diagnostic tests to ensure our model meets everything. Diagnostic tests look into problems like heteroscedastic nature, autocorrelation, and functional arrangement. The cumulative sum of squares (CUSUMSQ) procedure and cumulative sum (CUSUM) techniques are utilized to examine the consistency of shorter- and longer-period coefficients, correspondingly [105,106]. If the suggested model's coefficients are reliable and the plots of the CUSUM and CUSUMSQ graphs fall within the critical limits of a 5% significance value, then the null hypothesis could be rejected. The stability of the outcomes under scrutiny is confirmed via Lagrange Multiplier (LM), Breusch–Pagan–Godfrey and Ramsey's RESET tests. The heteroscedasticity was evaluated with the Breusch–Pagan–Godfrey and Autoregressive Conditional Heteroscedasticity (ARCH) tests, and the serial correlation was identified with the Breusch–Godfrey Lagrange Multiplier (LM) test. Finally, the Ramsey RESET test is used to verify the accuracy of the model's expression. These tests are followed by Abumunshar et al. [82].

3.3.4. FMOLS, DOLS, CCR

In the current research, yearly numerical information was analyzed utilizing Dynamic Ordinary Least Square (DOLS), an expanded formula of Ordinary Least Square (OLS). The DOLS procedure includes independent indicators along with leads and lags of their early difference expressions to control endogeneity and compute standard errors utilizing a covariance graph of errors tolerant to autocorrelation. The DOLS estimators provide a trustworthy measure of statistical significance. Assessing the endogenous indicator on exogenous indicators in levels, leads, and lags is an efficient method for dealing with varied orders of integration, as it permits the incorporation of distinct factors in the cointegrated framework [28]. On the other hand, the main advantage of the DOLS prediction is that it allows varied order integration of distinct factors within the cointegrated framework [106–108]. This approximation eradicates difficulties of shorter sample bias, endogeneity, and autocorrelation by combining information about when each explanatory variable was measured [109]. The DOLS estimation results will be found using Equation (13). Equation (13) estimates the long-run coefficient values in Indonesia from 1972 to 2021:

$$\Delta(LCO2)_t = \theta_0 + \sum_{i=1}^{t} \theta_1 \Delta LCO2_{t-i} + \sum_{i=1}^{t} \theta_2 \Delta LGDP_{t-i} + \sum_{i=1}^{t} \theta_3 \Delta LPOP_{t-i} + \sum_{i=1}^{t} \theta_4 \Delta LREN_{t-i} + \sum_{i=1}^{t} \theta_5 \Delta LFOS_{t-i} + \sum_{i=1}^{t} \theta_6 \Delta LNUC_{t-i} + \lambda_1\, LCO2_{t-1} + \lambda_2\, LGDP_{t-1} + \lambda_3\, LPOP_{t-1} + \lambda_4\, LREN_{t-1} + \lambda_5\, LFOS_{t-1} + \lambda_6\, LNUC_{t-1} + \varepsilon_t \quad (13)$$

This study used two additional methods, Fully Modified OLS (FMOLS) and Canonical Cointegrating Regression (CCR), to confirm the legitimacy of the DOLS results. Hansen and Phillips [110] created the FMOLS analysis. The FMOLS technique amends the least squares method when dealing with cointegration and its impacts on autocorrelation and endogeneity in the explanatory factors. The difficulties associated with high power regression of determined factors, unit root problems, and integrated procedures have been reduced.

Park [94] also invented the CCR method, which transforms numeric info using just the stationary part of an interconnected system. When data are transformed in this way, the cointegrating connection generated by the cointegration model remains unchanged. Error terms in cointegrating models are decoupled from zero-regularity explanatory variables using the CCR modification. This leads to a roughly effective estimation and simultaneously chi-square tests. FMOLS and CCR approaches achieve asymptotic cohesion by investigating the impact of correlation. As shown in Equation (13), the FMOLS and CCR coefficients are used to evaluate longer-period flexibility.

3.3.5. Granger Cause of Pairwise Variables

This paper aims to identify the factors that cause the detected correlations. Consequently, to find out the causal relationship amidst the indicators, the pairwise linear causality test suggested by Granger [111,112] was applied in the research. This research uses the "statistical concept of causality based on prediction". Granger causality is a prediction-based statistical notion that has numerous benefits over other methods of studying time series [113]. This test's primary benefit is that it can look at many lags simultaneously while discounting the significance of higher-order lags. Yearly Y is said to "Granger-cause" yearly *X* if it can be used to forecast X in the future. The yearly data for these two indicators consist of *T*, where X_t and Y_t (t = 1,2, . . ., T) are the numbers for the variables at time t, correspondingly. The following Equations (14) and (15) can be used to apply a bivariate autoregressive framework to models X_t and Y_t:

$$X_t = \sum_{t=1}^{\rho}(b_{11,1}\ X_{t-1} + b_{12,1}\ Y_{t-1}) + \varepsilon_t \tag{14}$$

$$Y_t = \sum_{t=1}^{\rho}(b_{21,1}\ X_{t-1} + b_{22,1}\ Y_{t-1}) + \xi_t \tag{15}$$

Here, ρ is the serial of the model, $b_{ij\prime 1}$ (i,j = 1, 2) represents the coefficients, and ε_t and ξ_t are the stochastic error. The coefficients can be calculated utilizing the OLS method, and Granger causation amidst *X* and *Y* are measured utilizing the F procedure.

In addition, the causative collaboration among LCO_2, LGDP, LPOP, LREN, LFOS, and LNUC is looked into using the Granger causality test in the present research and is narrated in Equations (16)–(21). Short-term variations in the series under scrutiny are identified using ECT for the causation test. As shown in the following equations, the EC-Model Equations (16)–(21) look like this:

$$\begin{aligned}\Delta(LCO2)_t = \theta_0 + \textstyle\sum_{i=1}^{t}\theta_1\Delta LCO2_{t-1} + \sum_{i=1}^{t}\theta_2\Delta LGDP_{t-1} + \sum_{i=1}^{t}\theta_3\Delta LPOP_{t-1} + \sum_{i=1}^{t}\theta_4\Delta LREN_{t-1} + \\ \textstyle\sum_{i=1}^{t}\theta_5\Delta LFOS_{t-1} + \sum_{i=1}^{t}\theta_6\Delta LNUC_{t-1} + \theta_7\ \mathrm{ECT}_{t-1} + \varepsilon_{1t}\end{aligned} \tag{16}$$

$$\begin{aligned}\Delta LGDP_t = \theta_0 + \textstyle\sum_{i=1}^{t}\theta_1\Delta LGDP_{t-1} + \sum_{i=1}^{t}\theta_2\Delta LCO2_{t-1} + \sum_{i=1}^{t}\theta_3\Delta LPOP_{t-1} + \sum_{i=1}^{t}\theta_4\Delta LREN_{t-1} + \\ \textstyle\sum_{i=1}^{t}\theta_5\Delta LFOS_{t-1} + \sum_{i=1}^{t}\theta_6\Delta LNUC_{t-1} + \theta_7\ \mathrm{ECT}_{t-1} + \varepsilon_{1t}\end{aligned} \tag{17}$$

$$\begin{aligned}\Delta LPOP_t = \theta_0 + \textstyle\sum_{i=1}^{t}\theta_1\Delta LPOP_{t-1} + \sum_{i=1}^{t}\theta_2\Delta LCO2_{t-1} + \sum_{i=1}^{t}\theta_3\Delta LGDP_{t-1} + \sum_{i=1}^{t}\theta_4\Delta LREN_{t-1} + \\ \textstyle\sum_{i=1}^{t}\theta_5\Delta LFOS_{t-1} + \sum_{i=1}^{t}\theta_6\Delta LNUC_{t-1} + \theta_7\ \mathrm{ECT}_{t-1} + \varepsilon_{1t}\end{aligned} \tag{18}$$

$$\begin{aligned}\Delta LREN_t = \theta_0 + \textstyle\sum_{i=1}^{t}\theta_1\Delta LREN_{t-1} + \sum_{i=1}^{t}\theta_2\Delta LCO2_{t-1} + \sum_{i=1}^{t}\theta_3\Delta LGDP_{t-1} + \sum_{i=1}^{t}\theta_4\Delta LPOP_{t-1} + \\ \textstyle\sum_{i=1}^{t}\theta_5\Delta LFOS_{t-1} + \sum_{i=1}^{t}\theta_6\Delta LNUC_{t-1} + \theta_7\ \mathrm{ECT}_{t-1} + \varepsilon_{1t}\end{aligned} \tag{19}$$

$$\begin{aligned}\Delta LFOS_t = \theta_0 + \textstyle\sum_{i=1}^{t}\theta_1\Delta LFOS_{t-1} + \sum_{i=1}^{t}\theta_2\Delta LCO2_{t-1} + \sum_{i=1}^{t}\theta_3\Delta LGDP_{t-1} + \sum_{i=1}^{t}\theta_4\Delta LPOP_{t-1} + \\ \textstyle\sum_{i=1}^{t}\theta_5\Delta LREN_{t-1} + \sum_{i=1}^{t}\theta_6\Delta LNUC_{t-1} + \theta_7\ \mathrm{ECT}_{t-1} + \varepsilon_{1t}\end{aligned} \tag{20}$$

$$\begin{aligned}\Delta LNUC_t = \theta_0 + \textstyle\sum_{i=1}^{t}\theta_1\Delta LNUC_{t-1} + \sum_{i=1}^{t}\theta_2\Delta LCO2_{t-1} + \sum_{i=1}^{t}\theta_3\Delta LGDP_{t-1} + \sum_{i=1}^{t}\theta_4\Delta LPOP_{t-1} + \\ \textstyle\sum_{i=1}^{t}\theta_5\Delta LREN_{t-1} + \sum_{i=1}^{t}\theta_6\Delta LFOS_{t-1} + \theta_7\ \mathrm{ECT}_{t-1} + \varepsilon_{1t}\end{aligned} \tag{21}$$

The research employs the pairwise Granger causality testing approach to figure out short-term causal associations among the factors to explore the potential for causation.

4. Results

4.1. Unit Root Test

Table 3 shows the stationarity outcomes of the KSUR [93], ADF [87], and KPSS [90] tests. KSUR shows that LCO_2, LGDP, LPOP, and LFOS are integrated at level one, as the test statistics of the respective variables are not significant at the base form when significant at level two at a 1% level of significance. On the other hand, LREN and LNUC are integrated at a level as the test statistics are significant at that level. ADF and KPSS tests of stationarity show similar results also. Here, the significance of statistics means not accepting the null hypothesis of not stationarity. Consequently, the results explain that LCO_2, LGDP, LPOP, and LFOS are I(1) while LREN and LNUC are I(0). As there is no I(2) or higher-level integrated found, ARDL tests can be applied.

Table 3. Stationarity tests.

Indicators	KSUR		ADF		KPSS		Comment
	Base Form	**1st Difference**	**Base Form**	**1st Difference**	**Base Form**	**1st Difference**	**I(1)**
LCO_2	−0.478	−4.387 ***	−0.350	−5.522 ***	−1.431	−6.993 ***	I(1)
LGDP	1.905	−3.380 ***	2.452	−3.531 ***	0.939	−7.733 ***	I(1)
LPOP	2.684	−3.531 ***	2.195	−3.380 ***	1.811	−7.319 ***	I(1)
LREN	−5.518 ***		−5.518 ***		−4.491 **		I(0)
LFOS	−0.124	−6.051 ***	−0.052	−6.512 ***	−0.7121	−6.921 ***	I(1)
LNUC	−4.142 **		−4.056 ***		−4.584 **		I(0)

(a) AIC and SIC chose the lag length. (b) Intercept and trend are assumed in the stationarity test. (c) More stars mean significant at less significant level (*** = less than 1% and ** = less than 5%).

4.2. ARDL Bounds Cointegration Test

Table 4 shows the Bounds Cointegration Test [113] to find the existence of a longer-period association amidst the explained variable and explanatory variables.

Table 4. Bounds Cointegration Test.

Test Statistic	Value	K
F-Statistic	3.077	5
	Critical Value Bounds	
Significance level	I(0)	I(1)
10%	2.26	3.35
5%	2.62	3.79
2.5%	2.96	4.18
1%	3.41	4.68

Table 4 shows that the alternative hypothesis of cointegration is established at the 2.5% level. Therefore, the longer-period association is confirmed in the model. Here, the longer-period imposing indicators are GDP, alternate and nuclear energy, renewable energy, fossil fuels, and population. The preceding conclusion has the consequence that variations in the mentioned variables are followed by variations in the release of CO_2.

4.3. ARDL Long- and Short-Run Results

As regressors and regressand are integrated at level or first difference, and there found longer-period cointegration, the ARDL test [80,81] is recruited to find the longer- and shorter-period value of coefficients. Table 5 represents all the results. In a shorter period, if GDP upsurges by 1%, then on average, CO_2 upsurges by 0.274%. Similarly, if LFOS upsurges by 1%, then CO_2 upsurges by 0.158% on average. Moreover, if LPOP, LREN, and LNUC upsurge by 1%, CO_2 declines by 1.663%, 0.0304%, and 0.0131%, respectively, on average. However, all these coefficients are insignificant as the p-value is greater than at least a statistically 10% significance.

Table 5. ARDL long-run and short-run outputs.

Variables	ADJ	LR	SR
D.LGDP			0.274 (0.240)
D.LPOP			−1.663 (2.565)
D.LFOS			0.158 (0.729)
D.LREN			−0.0304 (0.0388)
D.LNUC			−0.0131 (0.0320)
L.LGDP		8.08 *** (1.174)	
L.LPOP		−2.720(4.839)	
L.LFOS		1.505 *** (0.381)	
L.LREN		−7.717(0.44)	
L.LNUC		−0.624 *** (0.154)	
L.LCO_2	−0.172 (0.114)		
Constant			23.48 (18.78)
Observations	42	42	42
R−squared	0.653	0.653	0.653

Standard errors are given in the first bracket. More stars mean significant at less significant level (*** = less than 1%).

In the long run, if GDP upsurges by 1%, then on average, CO_2 upsurges by 8.08%. Kirikkaleli et al. [114] found similar results for Portugal using the NARDL model. Similarly, if LFOS upsurges by 1%, then CO_2 upsurges on average by 1.505%. A study on China using quantile ARDL (QARDL) found an adverse effect of fossil fuels on CO_2 emission [112–115]. Furthermore, if LPOP, LREN, and LNUC upsurge by 1%, CO_2 declines on average by 2.720%, 7.717%, and 0.624%, respectively. However, among these coefficients, LGDP, LFOS, and LNUC coefficients are significant as p-values of the respective coefficients are smaller than at least 1% statistical significance. Again, the coefficients of LPOP and LREN were found insignificant. Researchers [116] confirm the negative influence of nuclear power on CO_2 release. Again, Researchers [117] confirm that renewable power shows no long-run influence on CO_2 upsurges. Although Rehman et al. [118] challenge the not significant influence of population on CO_2 as they found a significant positive impact on CO_2 of population growth, they support the insignificant result of the impact of renewable energy on CO_2 upsurges. However, the system GMM technique of Jiang and Khan [119] found a negative but insignificant impact of population on CO_2 emission, which matches this research's findings. Therefore, a significant positive impact of LGDP and LFOS on CO_2 release and the negative impact of LNUC on CO_2 release has been established. Furthermore, the negative coefficient of the lag value of LCO_2 confirms the clarity of the results.

Finally, as for the discussion, an alternative hypothesis of the positive impact of GDP and non-clear energy on CO_2 is accepted as these long-run coefficients are positive and significant. However, an alternative hypothesis of the positive impact of population on CO_2 cannot be accepted as the coefficient of population was found insignificant. Moreover, another alternative hypothesis of the negative impact of clear and nuclear energy on CO_2 is accepted because of their negative sign and significant nature.

4.4. Robustness Check

The outputs of Table 5 found from the ARDL technique are assessed by using another solo formula estimator named DOLS (Dynamic Ordinary Least Square) method [107]. The main advantage of the DOLS technique is that it also considers the cointegrated method's mix order of integrating the relevant factors. Regressing each of the I(1) indicators with the other I(1) and I(0) indicators while taking the method's leads (p) and lags (−p) into account is how the DOLS is estimated. Thus, this estimate addresses the issues of probable endogenous variables and biases in tiny samples. Additionally, the cointegrating matrices produced by the DOLS estimates are asynchronously effective. FMOLS [110] and CCR [111] have also been applied (Table 6).

Table 6. Robust outputs.

	FMOLS	DOLS	CCR
LGDP	0.391 *** (0.141)	0.904 *** (0.137)	0.444 *** (0.158)
LPOP	−2.865(1.853)	−0.951(1.432)	−3.328 ** (1.853)
LREN	−0.235 (0.156)	0.143 (0.162)	−0.247 (0.159)
LFOS	1.452 ** (0.773)	4.238 *** (0.710)	1.500 ** (0.674)
LNUC	−0.136 *** (0.054)	−0.112 ** (0.069)	−0.126 *** (0.057)
C	53.266	1.079	50.740
R−squared	0.774	0.950	0.759

Standard errors are given in the first bracket. More stars mean significant at less significant level (*** = less than 1% and ** = less than 5%).

In the FMOLS model, a 1% increment in LGDP uplifts 0.391% of the CO_2 average, and a 1% increment in LFOS uplifts 1.452% of the CO_2 average. These values are significant and support the outputs regarding ARDL as shown in Table 5. On the contrary, a 1% increment of LPOP leads to a 2.865% decline in CO_2 average, a 1% increment of LREN leads to a 0.235% decline in CO_2 average, and a 1% increment of LNUC leads to a 0.136% decline in CO_2 average. Here, the coefficients of LPOP and LREN are insignificant, while the LNUC coefficient is significant, similar to the ARDL results.

In the DOLS model, a 1% increment in LGDP, LREN, and LFOS uplift an average of 0.904%, 0.143%, and 4.238% in CO_2 emission. These LGDP and LFOS values are significant, and the LREN value is insignificant, which supports the results of ARDL in Table 6 in terms of significance. On the contrary, a 1% increment of LPOP and LNUC leads to, on average, a 0.951% and 0.112% decline in CO_2, respectively. Here, the coefficient of LPOP is insignificant, while the coefficient of LNUC is significant, which is similar to the ARDL results.

CCR results also show a similar pattern except for the significant result in the case of LPOP. In the CCR model, a 1% increment in LGDP and LFOS uplift an average 0.444% and 1.500% of CO_2 emission. On the contrary, a 1% increment of LPOP, LREN, and LNUC lead to, on average, 3.328%, 0.247%, and 0.126% decline in CO_2, respectively.

4.5. Granger Causality

Table 7 represents the causal association between the explained and explanatory indicators. It is found that the alternative hypothesis of LGDP Granger causes LCO_2 cannot be accepted, as the *p*-value of F statistic is larger than 10% statistical significance. However, the alternative hypothesis of LCO_2 Granger causes LGDP is accepted at 5%. Therefore, there exists one-way causality from LCO_2 to LGDP. Similarly, there was found significant both-way causality amidst LPOP and LCO_2, significant one-way causality from LCO_2 to LREN, significant bidirectional causality amidst LFOS and LCO_2, and no significant causality between LNUC and LCO_2.

Table 7. Granger causality test results.

Alternate Hypothesis:	Obs	F-Value	Prob.
LGDP Granger causes LCO_2	48	1.20303	0.3102
LCO_2 Granger causes LGDP		4.65097 **	0.0148
LPOP Granger causes LCO_2	48	10.0298 ***	0.0003
LCO_2 Granger causes LPOP		4.67718 **	0.0145
LREN Granger causes LCO_2	48	2.3155	0.1109
LCO_2 Granger causes LREN		4.17895 **	0.022
LFOS Granger causes LCO_2	42	2.99743 *	0.054
LCO_2 Granger causes LFOS		3.46322 **	0.0418
LNUC Granger causes LCO_2	42	0.25927	0.773
LCO_2 Granger causes LNUC		0.8145	0.4506

(a) AIC and SIC chose the lag length. (b) More stars mean significant at less significant level (*** = less than 1%, ** = less than 5%, and * = less than 10%).

4.6. Diagnostic Check Outputs

For the validation of the model's coefficients, a few tests have been conducted related to the diagnostic check given in Table 8.

Table 8. Diagnostic check of the ARDL outputs.

Name of the Test	Null Hypothesis	Statistic Value	*p*-Value
ARCH Heteroskedasticity test	H0: Homoskedasticity	0.348 (F-value)	0.558
Breusch–Godfrey autocorrelation LM test	H0: No autocorrelation up to 2 lags	1.916 (F-value)	0.170
Ramsey RESET test	H0: The functional form of the model is correct	3.192 (F-value)	0.086

Sources: The authors' estimates.

The diagnostic techniques include autocorrelation, heteroscedasticity, and specification of the regression. The outputs described in Table 8 specify that no misspecification, heteroskedasticity, or autocorrelation exists in the outputs. Moreover, the functional form used in the model is also correct, as the null hypothesis of the Ramsey RESET procedure is accepted. This makes it clear that the findings of this inquiry can be used to reliably draw conclusions.

For the stability test of the model, CUSUM and CUSUMQ tests have also been conducted (Figure 1). Both figures show that the blue curve remains in the middle of the boundary curves which confirms the constancy of the research.

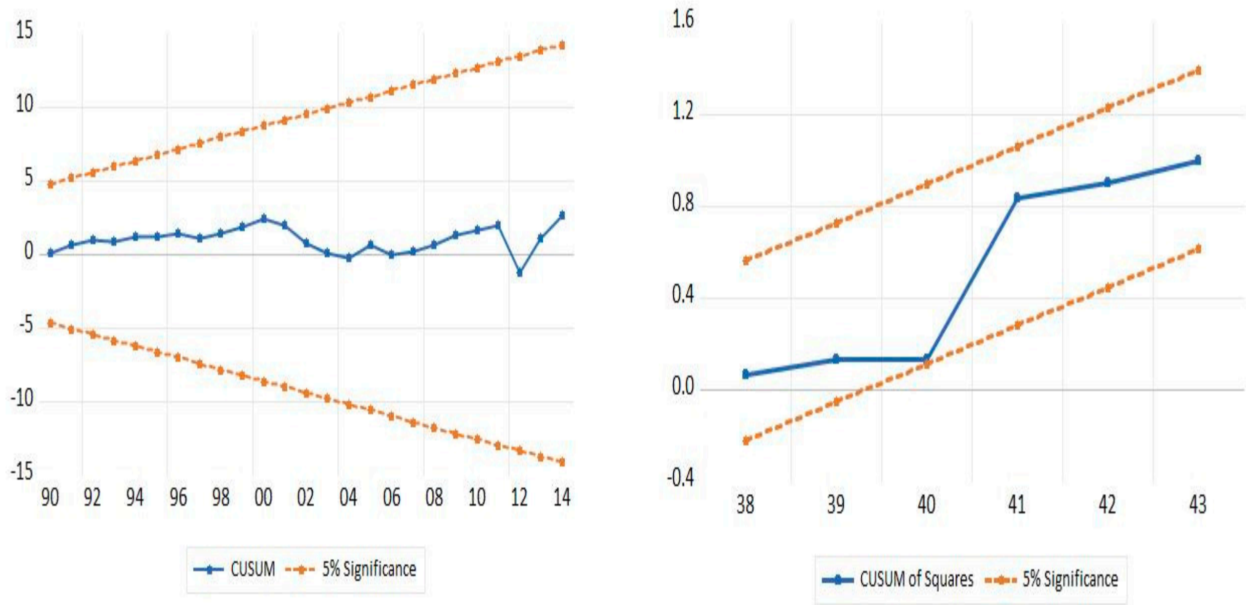

Figure 1. CUSUM and CUSUM square tests.

5. Conclusions

A sustainable environment is one of the critical challenges for developed countries in this century. This study tries to find a solution to reduce CO_2 emissions, which is a vital element of environmental degradation in Italy. Italy is an established developed country which makes good use of geographical and environmental conditions and systematically introduces renewable energy. Hence, this paper focuses on finding out the consequences of GDP, nuclear energy, green and non-green power, and population on CO_2 emissions in Italy. The data range used for this study is from 1972 to 2021. The ARDL model is used for analytical purposes, and FMOLS, DOLS, and CCR methods are applied for their confirmation. Moreover, the STIRPAT model gives the theoretical foundation of the research.

The STIRPAT model research shows that GDP and fossil fuel usage are the primary contributors to Italy's CO_2 emissions. This result received support from other researchers [114,115]. Although the data reveal that renewable energy has a role in lowering Italy's CO_2 emissions, increased utilization of renewable energy is correlated with decreased carbon emissions. A few other types of research [117,118] also found similar outcomes. However, nuclear energy appears to have a significant appreciable effect on Italy, lowering CO_2 emissions. Voumik et al. [116] confirm this relationship. The population is also found to reduce CO_2 emissions, which is found insignificant [119].

As a result, Italy's efforts to cut its carbon footprint should prioritize changing the nation's energy profile to be less reliant on carbon-based fuels and more toward renewable fuels.

5.1. Policy Recommendations

Italy can reduce the impression of GDP expansion on carbon release by adopting a number of policy measures. Firstly, lowering carbon emissions and stimulating economic growth can be accomplished by investments in sustainable infrastructure like renewable energy systems, sustainable transport systems, and green buildings. Secondly, firms' and industries' carbon footprints can be reduced while new economic opportunities are created by supporting innovation in sustainable technology and practices. Thirdly, sustainable finance laws, such as green bonds, can assist in channeling capital towards environmentally responsible endeavors and enterprises, boosting the economy and simultaneously lowering carbon emissions. Fourthly, firms and industries can benefit from increased growth and a smaller carbon footprint if they implement circular economy methods like decreasing waste and recycling resources. Promoting economic growth while lowering power usage and carbon release is possible by encouraging investments in energy-efficient technology and infrastructure. Incentivizing commercial and residential customers to make energy-efficient choices like appliance replacements and building redesigns would accomplish this goal. Solar and wind power, in particular, have enormous promise in Italy. Strategies that assure the usage of green power bases could lessen the consequences of GDP expansion on carbon release and cut down on our dependency on fossil fuels. Internalizing the cost of carbon emissions and incentivizing businesses and individuals to decrease their carbon footprint can be achieved through carbon-valuing appliances like carbon tax and cap-and-trade schemes. Carbon pricing could produce enough money to fund initiatives that advance sustainable energy and lifestyles. In Italy, a lot of the country's harmful gas releases originate in the transportation industry. Emissions can be reduced, and economic growth in the transportation sector can be boosted by encouraging the use of environmentally friendly modes of transportation, such as electric or hybrid vehicles, bicycling, and public transportation. All these solutions are slowly being introduced in Italy, which can be a model for other European countries.

5.2. Limitations and Future Research

The elements contributing to Italy's CO_2 emissions are clarified by examining the STIRPAT model. Nonetheless, it is important to keep in mind that this study has a number of important caveats. The assumption that the association between GDP, population, renewable energy, nuclear and fossil fuels and CO_2 release is linear is one of the model's limitations. Changes in land use, deforestation, and agricultural techniques are all outside this study's scope yet may affect Italy's CO_2 emissions.

The complexity of the associations amid CO_2 release and its key indicators may be better captured in future studies if additional variables are included in the analysis and more sophisticated statistical models are used. Carbon taxes, subsidies for renewable energy, and limitations on fossil fuel consumption are only a few examples of policy interventions that could be studied to understand better their impact on lowering Italy's carbon emissions. Last but not least, studies might investigate how carbon capture and storage and other promising new technologies could help reduce Italy's CO_2 output.

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