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Asymmetric Nexus between Green Technology Innovations, Economic Policy Uncertainty, and Environmental Sustainability: Evidence from Italy

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Abstract: Over the last few decades, climate change and global warming have intensified a serious threat that may deteriorate global sustainable development. The factors significantly contributing to global warming are greenhouse gases, mainly carbon dioxide emissions. Therefore, it is crucial to consider the variables affecting carbon emissions considerably. This study examines symmetric (linear) and asymmetric (non-linear) effects of green technology innovation (GTI), economic policy uncertainty (EPU) along with foreign direct investment (FDI), and economic development (GDP) on carbon emissions (CO_2) by utilizing yearly time series data between 1970–2018 in Italy. We employed linear and non-linear autoregressive distributed lag (ARDL) approaches to examine short- and long-run estimates. The symmetric results show that GTI and EPU mitigate environmental degradation in the long run and intensify in the short run, whereas FDI increases environmental issues over the long and short run. Nevertheless, the asymmetric outcomes demonstrate that positive shocks in GTI lessen CO_2 emissions, whereas negative shocks in GTI significantly escalate CO_2 emissions. Furthermore, EPU and FDI positive and negative shocks significantly enhance environmental degradation. Based on these findings, important policy implications for policymakers to make strong policies to achieve carbon neutrality targets and achieve sustainable economic growth are proposed. Finally, because positive and negative changes in GTI, EPU, and FDI have different consequences on CO_2 emissions, policymakers should consider asymmetry across these variables when assessing their impact.

Keywords: CO_2 emissions; green technology innovation; economic policy uncertainty; foreign direct investment; GDP

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1. Introduction

Climate change has recently gained prominence on a global scale as a major threat to achieving sustainable development. Rapid economic development in some nations has necessitated the use of a lot of resources, which has caused substantial environmental harm, such as high pollution and overuse of resources [1]. It is commonly accepted that the world will experience major environmental disasters if appropriate climate initiatives are not implemented to stop global warming [2]. In order to limit the extent of damage from global warming, scholars believe that maintaining the increase in global temperature below 1.5 °C and lowering CO_2 emissions to net zero is essential [3,4]. The greenhouse gases that are the main contributors to climate change are mainly caused by human activities geared toward economic growth that results in the emission of CO_2, and these emanations are brought on by the usage of conventional energy (fossil fuels). As a result, fossil fuel consumption exacerbates environmental issues. The future of a nation can be jeopardized by dependence on fossil fuels and being a major contributor to global climate change. For instance, more than 40% of the European Union's (EU) natural gas supplies originate from Russia, and as a result, strongly reliant European nations such as Italy may be particularly severely struck by the consequences of the Ukraine crisis. Italy was the second-highest CO_2 emitter in the EU in 2018, after Germany (see Figure 1).

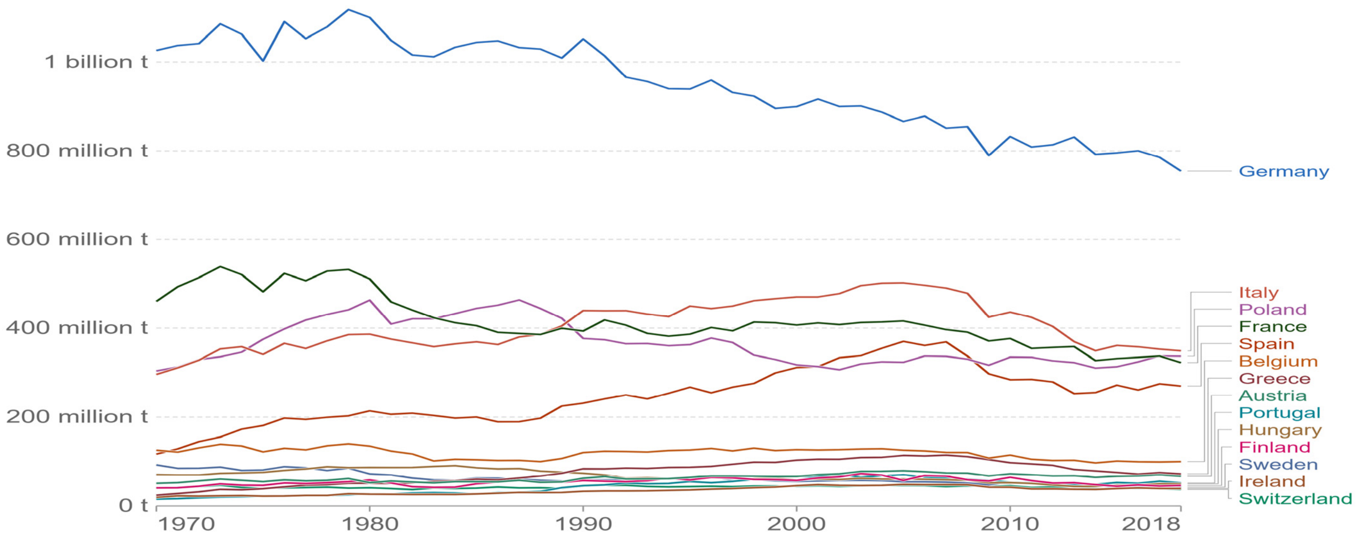

Figure 1. Annual growth of CO_2 emissions in EU countries (source: Our World Data).

Many environmental problems, such as soil, water, and air pollution, climate change, loss of biodiversity, and overexploitation of natural resources, have been getting worse with the development of technology [5]. Since the term "sustainable development" was coined, many market players, including institutional and private investors, have expressed a desire to consider environmental sustainability when making investment decisions. However, attaining sustainable development was difficult before the rise of environmental, social, and governance (ESG) investing, which is directly linked to sustainability and carbon neutrality targets [6]. It has led to the widespread adoption of green technology innovation, clean energy, and the circular economy concept as effective methods of environmental management to achieve carbon neutrality targets.

Despite the recent decline in the global CO_2 emissions level, the World Energy Outlook 2017 anticipated that, under the new policies scenario, global CO_2 emissions will increase gradually until 2040. However, this result is insufficient to stop the worst effects of climate change. Because of this, human activity is to blame for global warming. Therefore, humans must take immediate action to save the planet from disastrous climate change. Experts believe that the only way to enhance the quality of the environment without compromising the level of economic growth is the adoption of green innovation (clean energy and energy efficiency), and these environmentally friendly technologies substantially influence the reduction of environmental degradation. In recent years, clean energy sources have become a substitute for traditional ones. These clean energy sources not only improve the environment but also have several other favorable economic benefits [7,8]. Thus, to fight against climate change and global warming, the world should reduce its dependence on fossil fuels. However, the spread of green technology innovation often does not progress simultaneously in different countries or locations. As a result, certain social and economic factors may influence the real impact of green technology developments [9]. Therefore, understanding the intricate connection between technological developments, EPU, and CO_2 emissions may help protect the environment we rely on.

Recent advancements in green technology innovation have greatly reduced environmental degradation globally [10,11]. Even though it is theoretically assumed that prospects of addressing environmental challenges increase with the number of environment-related technology, there is little empirical evidence to support this argument [12]. According to the existing literature, the impact of breakthroughs in eco-innovation on the environment might vary depending on the situation and might also be affected by factors such as income and time [13,14]. Furthermore, [15] stated that even though eco-innovations are usually seen as crucial elements of a green growth approach, the influence of environmentally friendly technologies on the environment has long been a subject of discussion because of the presence of the rebound effect. According to [10], green technologies boost environmental productivity in Italy but have minimal impact on lowering CO_2 emissions.

Economic policy uncertainty (EPU) may have environmental and economic consequences. For instance, EPU might push firms to degrade the environment by promoting conventional and environmentally harmful manufacturing techniques. On the other hand, EPU could also influence spending and consumption patterns, which would reduce CO_2 emissions. Additionally, because of the high EPU, a decline in R&D, innovations, and usage of clean energy sources can lead to a rise in environmental deterioration. Therefore, it is essential to study the connection between EPU and CO_2 emissions to suggest strategies for addressing environmental deterioration.

Furthermore, the inflow of foreign investment is frequently seen as one of the essential instruments for the economic prosperity of nations, as well as a channel for the transmission of breakthrough technologies in host nations [16]. The potential for negative environmental effects has been one of the most crucial and widely discussed aspects of inward foreign direct investment [17]. Because FDI may occur concurrently with large environmental discharges, the development associated with an increase in inward FDI will likely be wiped out by potential environmental costs [18].

Based on the discussion above, it is crucial to research the dynamic connections among GTI, EPU, FDI, GDP, and CO_2 emissions to help policymakers provide a more precise and accurate picture of environmental quality strategies. In the given context, the present study adds to the current literature in various ways. First, to our best understanding, no empirical study has yet explored the consequences of GTI, EPU, and FDI on CO_2 emission in symmetric and asymmetric frameworks, particularly in Italy. The current study fulfills this gap by analyzing the symmetric and asymmetric effects of GTI, EPU, and FDI on CO_2 emissions for Italy over the period 1970–2018. Earlier literature only examined the symmetric impacts of GTI, EPU, and FDI on the environment. However, the asymmetric impact of GTI, EPU, and FDI on CO_2 emissions has not yet been studied in the literature. The most unique and comprehensive contribution of the current study is that it analyzes the linear and non-linear effects of GTI, EPU, and FDI on CO_2 emissions in a single study by employing the symmetric and asymmetric ARDL approaches advanced by [19,20]. The non-linear autoregressive distributed lag (NARDL) approach enables us to analyze the positive and negative effects of GTI, EPU, and FDI on environmental degradation.

Second, the economic policy uncertainty (EPU) index created by [21] is generally utilized by various researchers in the literature as a measure of policy uncertainty (see, e.g., [22–24]. However, the EPU index has several drawbacks and is criticized by scholars for its incomplete nature. For instance, the EPU index only accounts for monetary, trade, and fiscal policy uncertainty; it does not account for political events [25]. Furthermore, there are problems with accuracy, dependability, and ideological bias because the index of EPU for various nations is not computed from a single base. In order to overcome these drawbacks, [26] developed a new index world uncertainty index (WUI) for 143 nations. This index is computed using country reports from the EIU (economist intelligence unit). Moreover, WUI is preferable to EPU since it considers political and economic changes (events) in a nation and is derived from a single foundation (i.e., EIU reports). Therefore, the current study uses the WUI as a stand-in for the EPU. It also investigates how the WUI affects the quality of the environment.

The rest of the research is arranged as follows. The appropriate literature on factors that affect CO_2 emissions is evaluated in Section 2. Section 3 covers the data and methodology that we utilized in this study. The outcomes and their discussions are explained in the Section 4. The final section concludes the investigation, which also offers policy suggestions.

2. Literature Review

During the last few decades, the relationship between CO_2 emissions and its determining factors has drawn the attention of both academics and policymakers. As a result, several studies have investigated the association among CO_2 emissions, GTI, EPU, FDI, and GDP. However, the results of these studies are contradictory and ambiguous. In this study, we classified the literature into four categories. The first phase of the literature shows how developments in green technology and the environment are related. The second phase explains the nexus between EPU and CO_2 emissions.

Furthermore, the third phase of the literature explains how FDI and CO_2 emissions are related. Moreover, the final part of the literature investigates the association between GDP and CO_2 emissions. Table 1 provides an overview of the prevailing literature.

Table 1. Literature summary.

Authors	Country	Period	Estimation Technique	Findings
Part 1: GTI and CO_2 emissions				
[27]	Singapore	1990–2018	Bootstrap ARDL	↓
[28]	OECD	1990–2014	GMM	↓
[29]	27 developed economies	1997–2009	REM	↑
[30]	BRICS nations	1990–2017	Quantile-on-Quantile regression	↓
[31]	27 countries of European Union	1992–2014	GMM	↓
[32]	OECD	1990–2015	ARDL, Granger causality test	↓
[33]	N-11 countries	1980–2018	CS-ARDL	↓
[5]	Italy	1994–2018	Dynamic ARDL	↓
Part 2: EPU and CO_2 emissions				
[25]	10 most CO_2 emitters economies	1990–2015	PMG-ARDL	↑
[34]	USA	1985–2017	Causality in quantiles	↑
[35]	China	2008–2011	STIRPAT	↑
[23]	UK	1985–2017	ARDL	↑
[36]	USA	1960–2016	ARDL	↑
[37]	BRICS	2000–2019	FMOLS, DOLS	↑
Part 3: FDI and CO_2 emissions				
[38]	France	1995–2016	Bootstrap ARDL	↑
[39]	Pakistan	1980–2014	3SLS	↑
[40]	Turkey	1974–2013	DOLS, Hacker and Hatemi-J causality method	↑
[41]	Top five carbon emitters of countries	1982–2016	Panel quantile regression	↑
[42]	Bangladesh	1972–2016	Dynamic simulated ARDL	↓
[43]	Latin America	1970–2019	Spatial Models	↑
[44]	BRICS	2000–2018	Panel ARDL	↑
Part 4: GDP and CO_2 emissions				
[45]	Mexico	1990–2018	ARDL	↑
[46]	BRICS	1992–2016	PMG and GMM	↑
[47]	Azerbaijan	1992–2013	Johansen, ARDLBT, DOLS, FMOLS, and CCR	↑
[48]	Pakistan	1971–2014	ARDL-NARDL	↑
[49]	Pakistan	1965–2015	ARDL	↑
[50]	Greece	1970–2014	ARDL	↑
[51]	OECD	1991–2012	PMG test	↑
[52]	Bangladesh	1972Q1–2020Q4	ARDL	↑

Note: ↑, ↓, denote positive, negative, and no effect of GTI, FDI, and GDP carbon emissions.

3. Methodology and Data

This study aims to analyze linear and non-linear effects of GTI, EPU, FDI, and GDP carbon emissions by employing the yearly time series data from 1970–2018 for Italy. Carbon dioxide emission (CO_2) measured in (metric tons per capita) is explained variable. In contrast, the explanatory variables are green technological innovations (GTI) is based on the (related environmental technologies as % total technologies), and EPU is used as a proxy of the world uncertainty index (WUI). WUI is accessible quarterly. Using the average of the previous four quarters, we transformed the data into an annual frequency [25]. By counting the number of times, the word "uncertainty" (or its synonyms) in reports from EIU (economic intelligence unit), [26] computed the world uncertainty index. In addition, a high value of WDI denotes a high degree of EPU.

Furthermore, the inflow of foreign direct investment (FDI) is defined as the net inflow of FDI% of GDP, and per capita, gross domestic product (GDP) is defined in constant 2010 USD as a proxy of economic growth. The FDI, GDP, and CO_2 emissions data are collected from the World Bank. The green technological innovation data are gathered from the OECD database, while data on EPU is gathered from the World Uncertainty Index. Furthermore, to eradicate the problem of heteroscedasticity, we transformed the data series into a logarithmic form. Table 2 briefly depicts the study variables, unit of measurement, and sources.

Table 2. Variable's description and data sources.

Variables	Symbol	Measurement	Sources
Carbon dioxide emissions	CO_2	Metric tons per capita	WDI
Green technology innovation	GTI	Patents related to the environment as (% total patents)	OECD Statistics
Economic policy uncertainty	EPU	World uncertainty index	WUI
Foreign direct investment	FDI	Net inflows (% of GDP)	WDI
GDP per capita	GDP	Per capita (constant 2010 USD)	WDI

Furthermore, Figure 2 illustrates the flow chart of the methodology utilized. In the first step, we analyzed the stationarity properties of the underlying variables by employing three different stationarity tests. In the second step, we examined the long-term cointegration between the variables by applying linear and non-linear cointegration approaches. The long- and short-run relationship among the variables are investigated in the third step by using linear and non-linear ARDL approaches. Finally, we also performed some diagnostics tests to confirm the validity of our estimated models.

Furthermore, to explore the connection among research variables, the econometric model, which we developed by following the literature, is given below:

$$lnCO2_t = \beta_0 + \beta_1 lnGTI_t + \beta_2 lnEPU_t + \beta_3 lnFDI_t + \beta_4 lnGDP_t + \varepsilon_t \quad (1)$$

where $lnCO2_t$ denotes the logarithm of carbon dioxide emissions, $lnGTI_t$ signifies the logarithm of green technology innovations, $lnEPU_t$ symbolizes the logarithm of economic policy uncertainty, $lnFDI_t$ indicates logarithm of foreign investment, and $lnGDP_t$ indicates the logarithm GDP per capita. While β_0 is constant, β_1 to β_5 are the coefficients. ε_t denotes the error term, and t is the time.

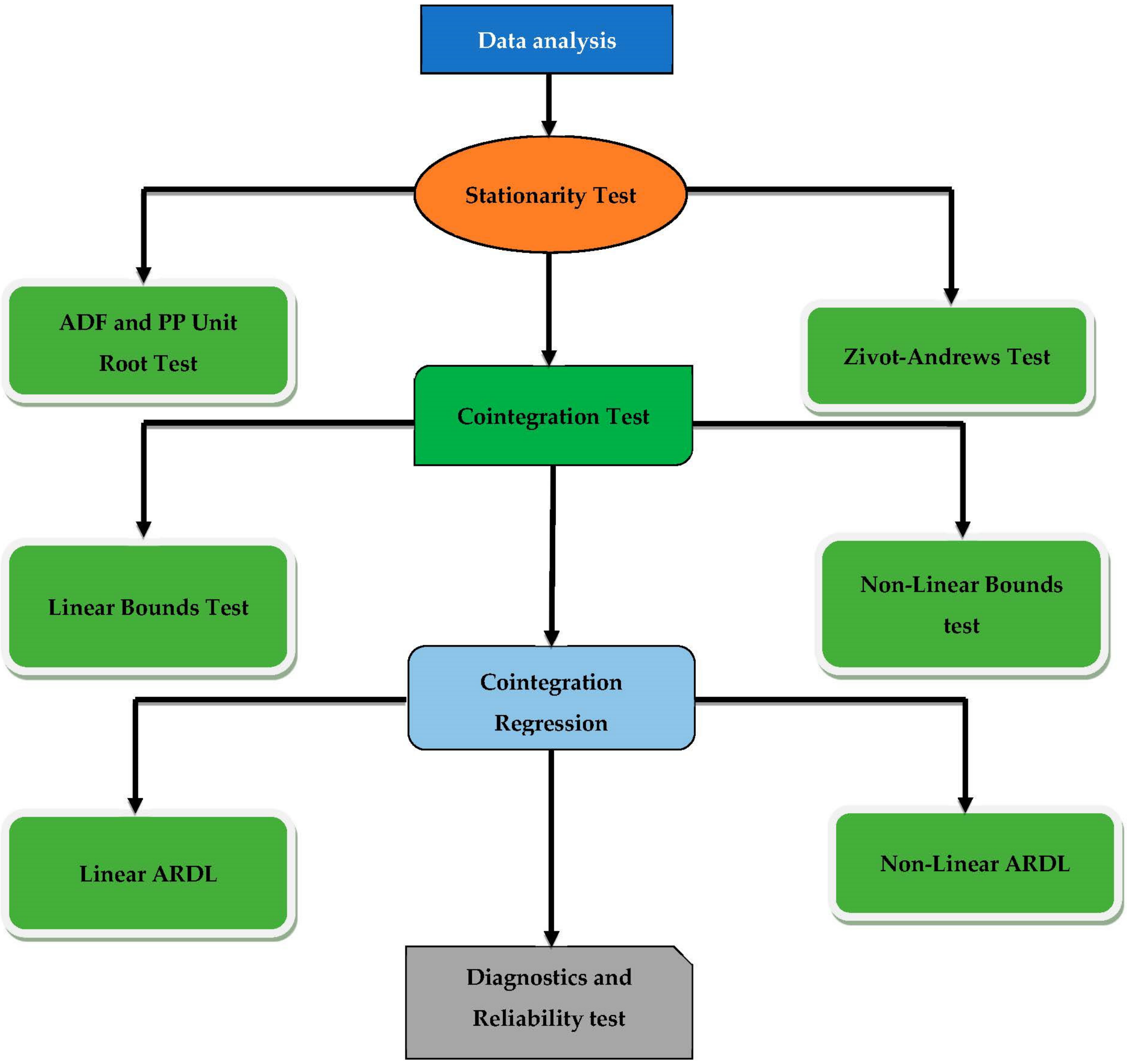

Figure 2. Methodological flow chart (source: authors' creation).

3.1. Autoregressive Distributed Lag Model (ARDL)

We utilized the ARDL cointegration approach suggested by [19,53] to observe the long-run connection between GTI, EPU, FDI, GDP, and CO_2 emissions. Several researchers have extensively used the ARDL model to inspect long- and short-run correlations among variables. The ARDL model has several advantages in contrast to other approaches [54–56]. First, this methodology can be utilized when research factors are integrated into I(0) and I(1) or a combination of both. Second, this model estimates short- and long-run factors simultaneously. Third, this approach can be utilized even with a small sample size. Fourth, the ARDL model resolves endogeneity and serial correlation problem between the variables by selecting an appropriate lag length. So, due to the above-stated characteristics of the ARDL cointegration approach, we utilized the ARDL model to assess long-run relations among researched variables. The model we utilized for the evaluation of long-run relationships is given below:

$$\begin{aligned}\Delta lnCO2_t = \beta_0 + & \sum_{i=1}^{p} \beta_1 \Delta lnC02_{t-1} + \sum_{i=1}^{p} \beta_2 \Delta lnGTI_{t-1} + \sum_{i=1}^{p} \beta_3 \Delta lnEPU_{t-1} \\ & + \sum_{i=1}^{p} \beta_4 \Delta lnFDI_{t-1} + \sum_{i=1}^{p} \beta_5 \Delta lnGDP_{t-1} + \lambda_1 lnC02_{t-1} \\ & + \lambda_2 lnGTI_{t-1} + \lambda_3 lnEPU_{t-1} + \lambda_4 lnFDI_{t-1} + \lambda_5 lnGDP_{t-1} + \varepsilon_t\end{aligned} \quad (2)$$

In the equation above, Δ stands for the first difference and ε_t denotes the error term. While β_1 to β_5 and λ_1 to λ_5 illustrates short- and long-run coefficients, respectively. Additionally, $t-1$ indicates the best lag choices as defined by Akaike's information criteria (AIC). [53] recommended utilizing the F-Statistics joint significance test to examine long-run cointegration among studied variables. According to the F-Statistics joint significance test, the following are the null and alternate hypotheses: $H_o = \lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = 0$, and $H_1 = \lambda_1 \neq \lambda_2 \neq \lambda_3 \neq \lambda_4 \neq 0$.

The calculated value of F-statistics determines whether null and alternative hypotheses are accepted or rejected. A long-run relation exists among research variables if the computed value of F-statistics exceeds upper bound critical values. On the other hand, no long-run cointegration exists if the calculated value is below the lower critical boundary. However, judgment will be uncertain if the computed value falls between lower and upper critical boundaries. If a long-run relationship exists, we look at short-run association among the studied variables. The short-run ARDL model uses the following error correction model:

$$\begin{aligned}\Delta lnCO2_t = \beta_0 + & \sum_{i=1}^{p} \beta_1 \Delta lnC02_{t-1} + \sum_{i=1}^{p} \beta_2 \Delta lnGTI_{t-1} + \sum_{i=1}^{p} \beta_3 \Delta lnEPU_{t-1} \\ & + \sum_{i=1}^{p} \beta_4 \Delta lnFDI_{t-1} + \sum_{i=1}^{p} \beta_5 \Delta lnGDP_{t-1} + \lambda_1 lnC02_{t-1} + \lambda_2 lnGTI_{t-1} + \lambda_3 lnEPU_{t-1} \\ & + \lambda_4 lnFDI_{t-1} + \lambda_5 lnGDP_{t-1} + \theta ECT_{t-1} + \varepsilon_t\end{aligned} \quad (3)$$

where θ is the error correction term (ECT) coefficient and calculates the disequilibrium correction speed in response to any shock. ECT ranges from -1 to 0. Therefore, the coefficient value of ECT must be negative and significant, and it is recommended that each shock adjusts towards equilibrium in the following time.

3.2. Non-Linear Autoregressive Distributed Lag (NARDL) Model

The linear ARDL model only investigates the variables' short- and long-run cointegration. However, it does not depict the asymmetric effect of the studied variables. In order to capture the asymmetric effects of GTI, EPU, and FDI on CO_2 emissions, we employed the NARDL model recommended by [20]. We split GTI, EPU, and FDI into their negative and positive components using the partial sum method of [20] to examine the asymmetric influence of the underlying factors on CO_2 emissions. Moreover, the partial sum of GI, EPU, and FDI are as follows:

$$LnGTI_t^+ = \sum_{j=1}^{t} \Delta LnGTI_j^+ = \sum_{j=1}^{t} \max\left(\Delta GTI_j^+, 0\right) \quad (4)$$

$$LnGTI_t^- = \sum_{j=1}^{t} \Delta LnGTI_j^- = \sum_{j=1}^{t} \min\left(\Delta GTI_j^-, 0\right) \quad (5)$$

$$LnEPU_t^+ = \sum_{j=1}^{t} \Delta LnEPU_j^+ = \sum_{j=1}^{t} \max\left(\Delta EPU_j^+, 0\right) \quad (6)$$

$$LnEPU_t^- = \sum_{j=1}^{t} \Delta LnEPU_j^- = \sum_{j=1}^{t} \min\left(\Delta EPU_j^-, 0\right) \quad (7)$$

$$LnFDI_t^+ = \sum_{j=1}^{t} \Delta LnFDI_j^+ = \sum_{j=1}^{t} \max\left(\Delta FDI_j^+, 0\right) \tag{8}$$

$$LnFDI_t^- = \sum_{j=1}^{t} \Delta LnFDI_j^- = \sum_{j=1}^{t} \min\left(\Delta FDI_j^-, 0\right) \tag{9}$$

where $LnGI_t^+$, $LnGTI_t^-$, $LnEPU_t^+$, and $LnEPU_t^-$ explain positive and negative variations in green technology innovation and economic policy uncertainty. Similarly, $LnFDI_t^+$, $LnFDI_t^-$ represents positive and negative variations in foreign direct investment. Equations (4), (6) and (8) show the increase in GTI, EPU, and FDI, while Equations (5), (7) and (9) demonstrate the decrease in GTI, EPU, and FDI, respectively. We expand our basic model by first splitting the variables into their positive and negative components, then substituting these negative and positive parts into Equation (2) as follows:

$$\begin{aligned}\Delta lnCO2_t = \delta_0 + & \sum_{i=1}^{p} \delta_\mathrm{i} \Delta lnC02_{t-\mathrm{i}} + \sum_{i=1}^{p} \delta_\mathrm{i} \Delta lnGTI_{t-i}^+ \\ & + \sum_{i=1}^{p} \delta_\mathrm{i} \Delta lnGTI_{t-i}^- + \sum_{i=1}^{p} \delta_\mathrm{i} \Delta EPU_{t-i}^+ + \sum_{i=1}^{p} \delta_\mathrm{i} \Delta lnEPU_{t-i}^- + \sum_{i=1}^{p} \delta_\mathrm{i} \Delta lnFDI_{t-i}^+ + \sum_{i=1}^{p} \delta_\mathrm{i} \Delta lnFDI_{t-i}^- \\ & + \lambda_1 lnCO2_{t-1} + \lambda_2 lnGTI_{t-1}^+ + \lambda_3 lnGTI_{t-1}^- + \lambda_4 lnEPU_{t-1}^+ + \lambda_5 lnEPU_{t-1}^+ + \lambda_6 lnFDI_{t-1}^+ \\ & + \lambda_7 lnFDI_{t-1}^- + \varepsilon_t\end{aligned} \tag{10}$$

Equation (10) above describes the NARDL model of Shin et al. (2014) due to the partial sum of positive and negative changes in GTI, EPU, and FDI. However, the model revealed by Equation (2) is established as an asymmetric ARDL approach.

The NARDL model is the extended form of ARDL. It follows the same steps taken under the ARDL technique. Furthermore, we performed the bounds F-test recommended by [53] to validate long-run co-integration between variables. The null hypothesis of no correlation is tested against the alternative hypothesis. After establishing the long-run cointegration amongst the variables, we conduct additional tests to determine whether or not GTI, EPU, and FDI have asymmetric effects on CO_2 emissions. First, we confirm the existence of asymmetry if the number of lags connected to ($LnGTI_t^+$, $LnEPU_t^+$, and $LnFDI_t^+$) are different from the numbers of lags taken by ($LnGTI_t^-$, $LnEPU_t^-$, and $LnFDI_t^-$), we confirm the existence of dynamic asymmetry. Secondly, we confirm asymmetric consequences of GTI, EPU, and FDI on CO_2 emissions if estimates of $\left(LnGTI_t^+, LnEPU_t^+, \text{and } LnFDI_t^+\right)$ are significantly different from the estimates of ($LnGTI_t^-$, $LnEPU_t^-$, and $LnFDI_t^-$). Finally, a long-run Wald test is used to determine whether we can reject the hypothesis that $\frac{\lambda_2^+}{\lambda_1} = \frac{\lambda_3^-}{\lambda_1}$, $\frac{\lambda_4^+}{\lambda_1} = \frac{\lambda_5^-}{\lambda_1}$, $\frac{\lambda_6^+}{\lambda_1} = \frac{\lambda_7^-}{\lambda_1}$, and, therefore, validate the asymmetric impacts of GTI, EPU, and FDI. Furthermore, the asymmetric cumulative dynamic multiplier impact is evaluated, where the 1% change in $lnGTI_{t-1}^+$, $lnGTI_{t-1}^-$, $lnEPU_{t-1}^+$, $lnEPU_{t-1}^-$, $lnFDI_{t-1}^+$, and $lnFDI_{t-1}^-$ on $lnCO2_t$ can be obtained, respectively, as follows

$$\begin{gathered} m_h^+ = \textstyle\sum_{j=0}^{h} \frac{\phi lnCO2_{t+j}}{\phi lnGTI_t^+}, m_h^- = \textstyle\sum_{j=0}^{h} \frac{\phi lnCO2_{t+j}}{\phi lnGTI_t^-}, \\ h = 0,1,2,3,\ldots \text{Noting that h} \to \infty, m_h^+ \to \lambda_2^+, m_h^- \to \lambda_3^- \\ m_h^+ = \textstyle\sum_{j=0}^{h} \frac{\phi lnCO2_{t+j}}{\phi lnEPU_t^+}, m_h^- = \textstyle\sum_{j=0}^{h} \frac{\phi lnCO2_{t+j}}{\phi lnEPU_t^-}, b \\ = 0,1,2,3\ldots \text{Nothing that h} \to \infty, K_b^+ \to \lambda_4^+, K_b^- \to \lambda_5^- \\ m_h^+ = \textstyle\sum_{j=0}^{h} \frac{\phi lnCO2_{t+j}}{\phi lnFDI_t^+}, m_h^- = \textstyle\sum_{j=0}^{h} \frac{\phi lnCO2_{t+j}}{\phi lnFDI_t^-}, b \\ = 0,1,2,3,\ldots \text{noting that h} \to \infty, m_h^+ \to \lambda_6^+, m_h^- \to \lambda_7^- \end{gathered} \tag{11}$$

The equation above describes the asymmetric cumulative dynamic multiplier effects. In addition, it explains the asymmetric reaction of independent variables to their corresponding (positive and negative) shocks on the explained variable. We also performed several diagnostic tests to evaluate the goodness of ARDL and NARDL models, including the Jarque–Bera normality test. In addition, we used ARCH LM and Breusch–Pagan–Godfrey tests for heteroscedasticity issues and Breusch–Godfrey for the problem of serial correlation. Finally, we also use CUSUM and CUSUM-Sq stability tests to evaluate the dynamic stability of the models.

4. Results and Discussion

4.1. Summary Statistics and Correlation

Table 3 displays the descriptive statistics of all variables. The statistics reveal that GDP has the highest mean value (10.1759), followed by GTI (5.4260), whereas the standard deviation illustrates that FDI shows higher volatility than variations in EPU and GTI. Figure 3 visualizes the trend of all the variables. The correlation between carbon emissions and all regressors is presented in Table 4. The findings illustrate that most variables positively correlate with carbon emissions, but EPU negatively impacts CO_2 emissions. GDP and GTI have a positive association. Additionally, a moderate positive association is also found between EPU and FDI.

Table 3. Descriptive statistics.

Statistics	LNCO2	LNGTI	LNEPU	LNFDI	LNGDP
Mean	1.9088	5.4260	−3.2852	−0.8276	10.1759
Median	1.9137	5.2891	−3.0997	−0.7691	10.2553
Maximum	2.1028	6.8727	1.0936	1.0936	10.4361
Minimum	1.6820	3.2189	−6.3936	−6.3936	9.6633
Std. deviation	0.1157	0.9798	1.0755	1.2063	0.2311
Obs	49	49	49	49	49

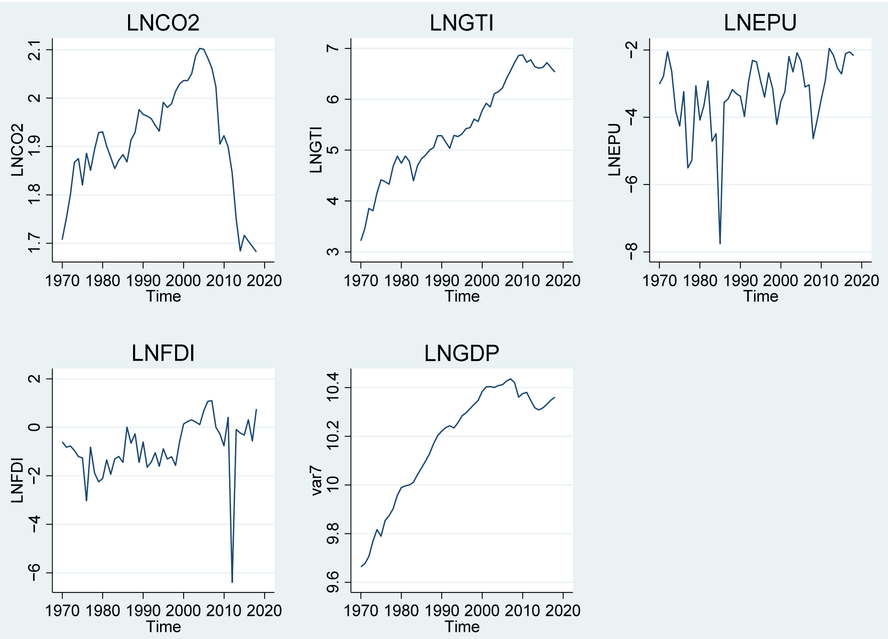

Figure 3. Annual time series trend plots.

Table 4. Correlation matrix.

Variables	LNCO2	LNGTI	LNEPU	LNFDI	LNGDP
LNCO2	1.0000				
LNGTI	0.1518	1.0000			
LNEPU	−0.0894	0.3038	1.0000		
LNFDI	0.1468	0.3001	0.1180	1.0000	
LNGDP	0.4300	0.9064	0.2774	0.3491	1.0000

4.2. Unit Root Results

The stationarity properties of GTI, EPU, FDI, GDP, and CO_2 emissions were evaluated after describing descriptive statistics and the correlation between the variables. Before modeling the time series data, it is critical to check the integration order because an inappropriate one produces unreliable results. Furthermore, the ARDL model necessitates the research variables to be integrated at I(0) and I(1) or a combination of both. For this reason, we employed ADF and PP unit root tests. The statistics are displayed in Table 5 and reveal mixed order of integration. According to the findings, EPU and FDI are stationary at levels, whereas GTI, GDP, and CO_2 emissions are non-stationary.

Table 5. Unit root tests.

	ADF		PP			
Variables	**Level**	**Δ**	**Level**		**Δ**	
	t-Stat.	**t-Stat.**	**t-Stat.**	***p*-Values**	**t-Stat.**	***p*-Values**
LNCO2	−0.6726	−6.1963 ***	−0.7870	0.9597	−6.1963 ***	0.0000
LNNGTI	−2.7550	−7.1456 ***	−2.8827	0.1770	−7.1617 ***	0.0000
LNEPU	−4.6264	−9.5954 ***	−4.6089	0.1254	−14.6208 ***	0.0000
LNFDI	−5.8317	−5.1664 ***	−5.9285	0.2389	−37.5067 ***	0.0000
LNGDP	−1.0182	−5.3671 ***	−0.6523	0.9709	−6.1557 ***	0.0000

Note: *** shows significance at the 1% level. Δ denotes the first difference.

Additionally, we looked at the difference and discovered that variables turn stationary after taking the first differences. The results of ADF and PP demonstrate the mixed integration order I(0) and I(1), indicating that the ARDL models are appropriate for empirical research. Furthermore, due to wide criticism in the earlier studies regarding the inadequacies of traditional unit root tests to produce unreliable results in the presence of structural breakdowns. In this study, we also applied Zivot–Andrews [57] unit root test, which detects a structural break in the series. Table 6 results suggest that GTI, EPU, FDI, GDP, and CO_2 emissions are not stationary at their levels. However, turn stationary at first difference. These structural breaks lead us to use the NARDL approach since explanatory variables may affect the explained variable differently in case of non-linearity.

Table 6. ZA unit root test.

Variables	**Level**		**Δ**	
	t-Stat.	**Break-Year**	**t-Stat.**	**Break-Year**
LNCO2	−4.6392	2002	−7.1901 ***	2008
LNGTI	−4.3417	2006	−9.0863 ***	1983
LNEPU	−6.8478	1985	−10.6463 ***	1985
LNFDI	−8.6362	2011	−14.0022 ***	2014
LNGDP	−3.5662	1999	−7.0066 ***	2008

Note: *** shows significance at the 1% level. Δ denotes the first difference.

4.3. Autoregressive Distributed Lag (ARDL) Model

We utilized the ARDL approach to verify the long-run cointegration among research variables under examination. Table 7 displays bounds cointegration results. The results demonstrate that the computed F-statistics value (6.8264) surpasses the upper bounds critical value at a 1% significance level. These results provide evidence of long-run cointegration between GTI, EPU, FDI, GDP, and CO_2 emissions. After validation of cointegration existence, long- and short-run relationships amongst explained and explanatory variables are stated in Tables 8 and 9, respectively. We observed that GTI negatively and substantially influences CO_2 emissions under the symmetrical framework. This outcome suggests that a 1% surge in GTI corresponds to a 0.3037% drop in CO_2 emissions, while everything else is constant. This positive connection may be explained by the fact that GTI considerably lowers the cost of mitigating CO_2 emissions by advancing effective technologies and, as a result, lower contributions to GHG [58]. In addition, GTI contains capacity innovation such as energy-saving techniques, trash recycling, and pollution control measures, which lessen the adverse effects on the environment [59]. Contrarily, as demonstrated in Table 7, GTI holds a significant favorable association with emissions level in the short run. The results illustrate that a 1% intensification in GTI boosts CO_2 emissions by 0.0261. The findings are aligned with [49,60,61]. They stated that GTI enhanced emissions in many countries and promoted environmental degradation.

Table 7. ARDL bounds test.

F-Statistics		H_0: No Level of Relationship		
		Significance	**I(0)**	**I(1)**
F-statistics	6.8246 ***	10%	2.2	3.09
K	4	5%	2.56	3.49
		2.50%	2.88	3.87
		1%	3.29	4.37

Note: *** shows significance at a 2.5% level.

Table 8. ARDL long-run results.

Variables	Coeff.	Std. Err.	t-Stat.	*p*-Values
LNGTI	−0.3037 ***	0.0558	−5.4419	0.0000
LNEPU	−0.1015 ***	0.0274	−3.7031	0.0000
LNFDI	0.0632 **	0.0257	2.4647	0.0234
LNGDP	1.1650 ***	0.1530	7.6115	0.0000
Constant	−8.582 ***	1.3915	−6.168	0.0000

Note: ** and *** denote significance at 5% and 1%, respectively.

Table 9. ARDL short-run results.

Variables	Coeff.	Std. Err.	t-Stat.	*p*-Values
LNGTI	0.0261	0.0243	1.0764	0.2952
LNEPU	0.0206 ***	0.0061	3.3837	0.0031
LNFDI	0.0022	0.0030	0.7287	0.4751
LNGDP	0.7232 ***	0.1838	3.9343	0.0009
Coint. Eq(−1)	−0.2742 ***	0.0381	−7.1919	0.0000
		Diagnostic tests		
		χ^2	*p*-values	
Normality	0.0448		(0.9778)	
Serial-Corr.	0.1069		(0.8992)	
Hetero.	1.2125		(0.3394)	
ARCH	1.0816		(0.3057)	
CUSUM	Stability Confirmed			
CUSUM-Sq	Stability Confirmed			

Note: *** denotes significance at the 1% level.

Furthermore, findings reveal that EPU exerts a negative and significant effect on CO_2 emissions. The outcomes suggest a 1% surge in EPU lessens CO_2 emissions by 0.101% in the long run. A similar conclusion was also stated by [22]. The fact that can explain this positive relationship is that EPU may substantially influence the economy, which can affect overall business operations, lowering energy utilization and, as a result, lower emissions [34]. In contrast, results explain that EPU boosts CO_2 emissions over the short-run, indicating that a 1% rise in EPU contributes towards environmental deterioration by 0.0206%. There are two potential explanations for this discovery. First, EPU might hinder R&D expenditures, inventions, and the use of green energy, ultimately enhancing environmental degradation. Second, EPU encourages producers to adopt conventional and environmentally harmful production methods, which increases carbon emissions [34]. The findings are in line with [24,62,63]. They showed that EPU increases environmental deterioration.

Additionally, findings demonstrate that FDI significantly influences CO_2 emissions over the long and short run. These findings confirm the pollution heaven hypothesis in Italy by demonstrating that a 1% intensification in FDI raises emissions levels by 0.0632% in the long run and 0.0022% in the short run. Similar outcomes are also described by [63] in the case of Pakistan, [64] for Malaysia, and [65] for the Chinese economy. They all discovered a positive connection between FDI and environmental degradation. Moreover, the outcomes reveal that GDP and CO_2 emissions are positively and significantly correlated. This finding reveals that a 1% rise in GDP results in increases in environmental deterioration by 1.165% and 0.723%, proving that growth positively impacts environmental deprivation in the long and short run. These outcomes are coherent with [51,59,66,67]. They revealed that GDP increases CO_2.

Furthermore, lagged ECT, which shows reasonable convergence towards long-run equilibrium at a speed of 27.42%, is significant and negative at the 1% level. Table 9, lower section, summarizes the diagnostic test performed to ensure the stability of the estimated model. In addition, we conducted Breusch–Pagan–Godfrey, ARCH, and Breusch–Godfrey LM tests to determine heteroscedasticity and serial correlation, respectively. The results reveal no problem of heteroscedasticity and serial correlation in our model. Moreover, the stability of parameters analyzed with the CUSUM and CUSUM Square indicates that the model is stable (Figure 4).

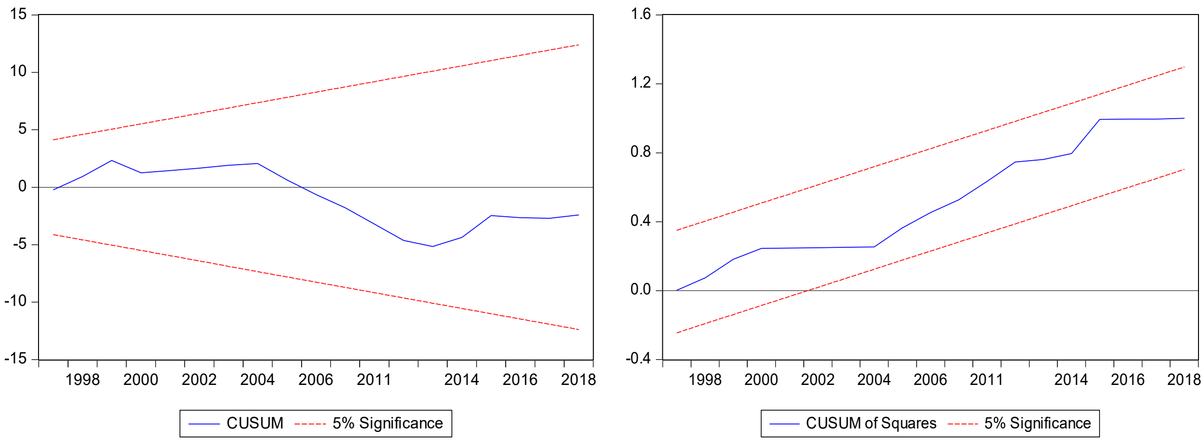

Figure 4. ARDL CUSUM and CUSUM of Squares.

4.4. NARDL Results

The results of the NARDL cointegration test are displayed in Table 10. The outcomes demonstrate that the estimated value of F-statistics surpasses the upper bounds critical value at 1% significance, suggesting that variables have a long-run cointegration. The anticipated long and short-run outcomes of the NARDL model are given in Tables 11 and 12, respectively. The findings demonstrate that the estimated coefficient of positive variations in GTI is negative and significant, suggesting that positive variations in GTI negatively impact environmental degradation. More precisely, any positive shocks in GTI decrease environmental degradation by 0.1436% and promote long-run environmental quality. It indicates that GTI has a significant role in decreasing environmental deterioration by reducing CO_2 emissions through the use of green sources of energy in production and consumption activities. This result is in line with the findings of [5]. Ref. [68] also asserted that GTI fosters environmental sustainability by lowering environmental damage.

Table 10. NARDL bounds test.

F-Statistics		H_0: No Level of Relationship		
		Significance	**I(0)**	**I(1)**
F-statistics	6.2916 ***	10%	1.92	2.89
K	4	5%	2.17	3.21
		2.50%	2.43	3.51
		1%	2.73	3.9

Note: *** indicates a statistically significant level at 2.5%.

Table 11. NARDL long-run estimates.

Variables	Coefficients	Std. Error	t-Stat.	Probability
LNGTI-Positive	−0.1436 ***	0.0432	−3.3257	0.0060
LNGTI-Negative	0.2307 ***	0.0422	5.4646	0.0001
LNEPU-Positive	0.0208 **	0.0068	3.0533	0.0100
LNEPU-Negative	0.0390 ***	0.0066	5.9039	0.0001
LNFDI-Positive	0.0464 ***	0.0103	4.4911	0.0007
LFDI-Negative	0.0497 ***	0.0076	6.5429	0.0000
LNGDP	1.8594 ***	1.2704	14.6358	0.0000
Constant	−16.1723	1.2014	−13.4617	0.0000

Note: ** and *** denote statistically significant levels at 5% and 1%, respectively.

Table 12. NARDL short-run estimates and diagnostics tests.

Variables	Coeff.	Std. Err.	t-Stat.	*p*-Values
LNGTI-Positive	−0.0269	0.0192	−1.4009	0.1866
LNGTI-Negative	0.1033 ***	0.0262	3.9374	0.0020
LNEPU-Positive	0.0102 **	0.0034	2.9878	0.0113
LNEPU-Negative	−0.0050	0.0025	−1.9948	0.0693
LNFDI-Positive	0.0051	0.0052	0.9878	0.3427
LNFDI-Negative	−0.0034 *	0.0018	−1.9077	0.0806
LNGDP	1.6736 ***	0.0770	21.7296	0.0000
Coint. Eq(−1)	−0.1381 ***	0.1172	−9.7146	0.0000
		Diagnostics Tests		
		χ^2	*p*-value	
Normality	2.2809		0.3197	
Serial-Corre.	2.7029		0.1152	
Hetero.	0.7868		0.7163	
ARCH	0.0127		0.9109	
CUSUM	Stability Confirmed			
CUSUM-sq	Stability Confirmed			

Note: ***, ** and * denote statistically significant levels at 1%, 5%, and 10%, respectively.

On the contrary, GTI increases CO_2 emissions by 0.2307% in response to any negative shock. The asymmetry connection between GTI and emissions is confirmed by the fact that any increase or decrease in GTI has a different influence on CO_2 emissions. However, regarding the magnitude, the statistics illustrate that negative shocks in GTI affect emissions growth more than positive shocks, which have approximately half the effect. These findings notify that GTI is essential for sustainable growth, and its positive effects can be reduced if GTI falls. Similar findings are also highlighted by [27,69]. They reported that GTI reduces carbon emissions.

Furthermore, in the short-run direction, the connection between both factors remains the same, but the significance level changes. The findings show that CO_2 emissions are not significantly affected by any positive shock to GTI. In contrast, negative shocks in GTI influence CO_2 emissions, which indicates that negative growth in GTI results in a rise of CO_2 by 0.1033%. This outcome confirms the asymmetric impact of GTI on CO_2 emissions because the estimated coefficients of positive and negative shocks are noticeably different. Moreover, we also performed a Wald test to confirm the long-run asymmetric influence of GTI on CO_2 emissions. The findings are given in Table 13. The results demonstrate that GTI and CO_2 emissions have a significant asymmetric association.

Table 13. Long-run asymmetries results.

Variables	F-Stat.	*p*-Values	Decision
LNGTI	24.977 ***	0.000	GTI and CO_2 have an asymmetric relationship
LNEPU	5.751 **	0.030	EPU and CO_2 have an asymmetric relationship
LNFDI	0.537	0.537	FDI and CO_2 have no asymmetric relationship

Note: ** and *** denote statistically significant levels at 5% and 1%, respectively.

Additionally, the asymmetries brought on by GTI are investigated using dynamic multiplier modifications, plotted in Figure 5. Black lines in different patterns, dotted and solid, represent the nonlinear adjustments of CO_2 emissions to positive and negative changes in GTI. The asymmetric pattern of red lines indicates the difference between positive and negative shocks.

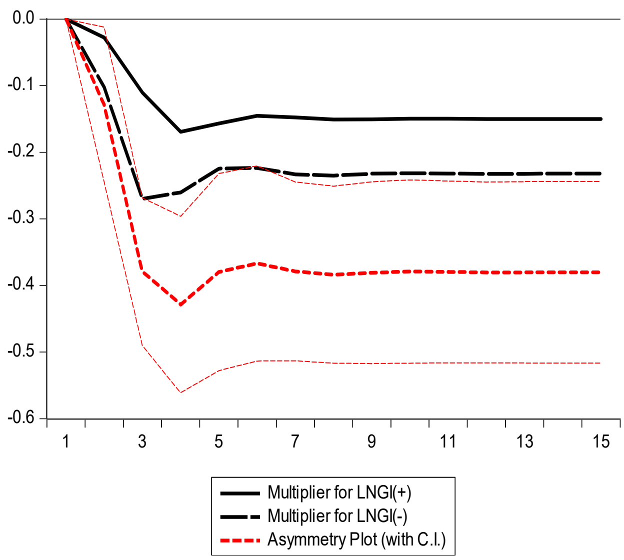

Figure 5. The dynamic multiplier for LNGTI.

Furthermore, findings demonstrate that positive shocks to EPU substantially affect CO_2 emissions, suggesting that a rise in EPU (positive shock) enhances environmental degradation by 0.0208% in the long run. This outcome is logical and supports that EPU may impact the quality of the environment by influencing economic activities, including investment, stock market, and commerce. This result is consistent with [23]. Similarly, when the policy is ambiguous, policies meant to protect environmental quality are not implemented well, leading to continued environmental harm by economic agents. [70] have proven the terrible influence of policy uncertainty on the environment in Chile. Negative shocks to EPU also positively influence carbon emissions with an estimated value of 0.0390%. This result explains that negative shocks in EPU enhance CO_2 emissions.

When the EPU level decreases, individuals and businesses start investing and producing again, and consumer demand rises. These factors increase the utilization of energy and, consequently, the level of emissions. However, short-run outcomes demonstrate that positive changes in EPU significantly enhance CO_2 emissions by 0.0102%, whereas negative shocks do not significantly impact CO_2 emissions to EPU. Furthermore, the results of the Wald test given in Table 13 and the dynamic multiplier graph of EPU shown in Figure 6 further support this asymmetric link between EPU and environmental degradation. In the case of FDI, outcomes explain that a positive shock to FDI (rise in FDI) enhances the emissions level by 0.0464% in the long run, while any decline in FDI (negative changes in FDI) also raises CO_2 emissions. However, the level of the negative shocks in FDI on CO_2 emissions is more remarkable than the negative.

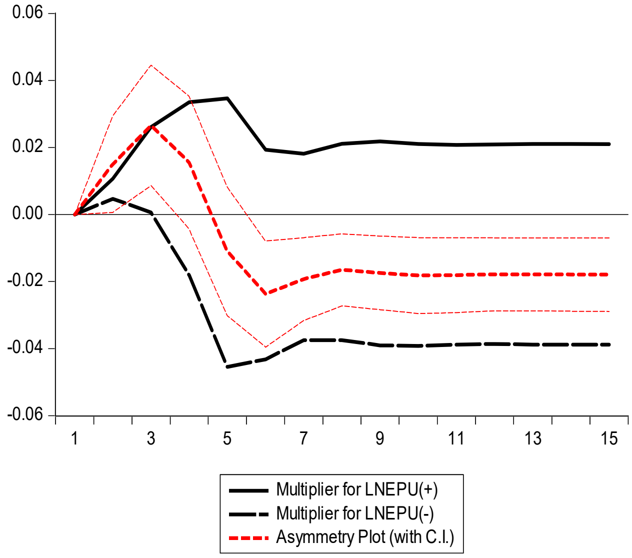

Figure 6. The dynamic multiplier for LNEPU.

Conversely, the short-run outcomes explain that (positive shock) rise in FDI does not significantly impact CO_2 emissions, whereas (negative shock) a decline in FDI enhances CO_2 emissions. These results confirm the pollution heaven hypothesis by showing that positive and negative changes in FDI considerably enhance environmental degradation. Similar outcomes are also identified by [48,71,72]. They indicated that the rise and decline in FDI harm the environment by increasing CO_2 emissions. Furthermore, the findings of the Wald test given in Table 13 for determining the asymmetric effects of FDI on CO_2 emissions do not confirm the asymmetry also shown in FDI dynamic multiplier graph (Figure 7). Proceedings to statistics of GDP, both long- and short-run results demonstrate that GDP increases CO_2 emissions. Our outcomes are coherent with [22,48,50].

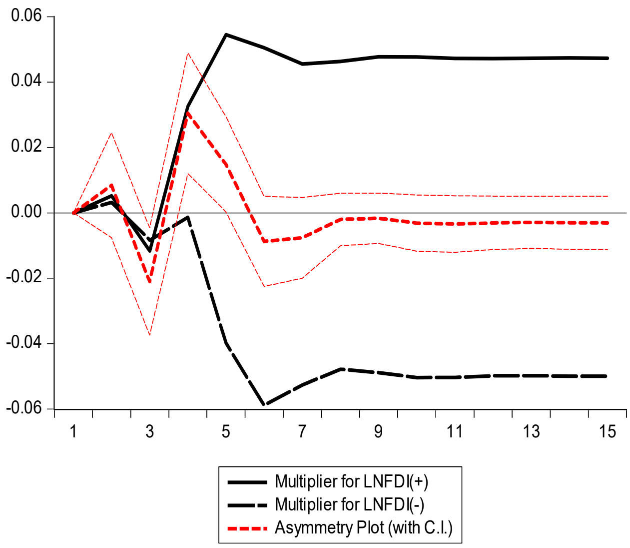

Figure 7. The dynamic multiplier for LNFDI.

Additionally, the lagged ECT is also negative and significant, suggesting a speed of adjustment is 13.18%, which indicates that if any shock appears in the short-run will converge toward long-run equilibrium at a speed of approximately 13% annually. The findings of numerous diagnostic tests, including the Breusch–Pagan–Godfrey, ARCH, and Breusch–Godfrey LM tests, are reported in the lower portion of Table 12. The findings demonstrate that our model is reliable and does not have autocorrelation or heteroskedasticity issues. Furthermore, the model's parameters shown by CUSUM and CUSUM Square appear stable in Figure 8.

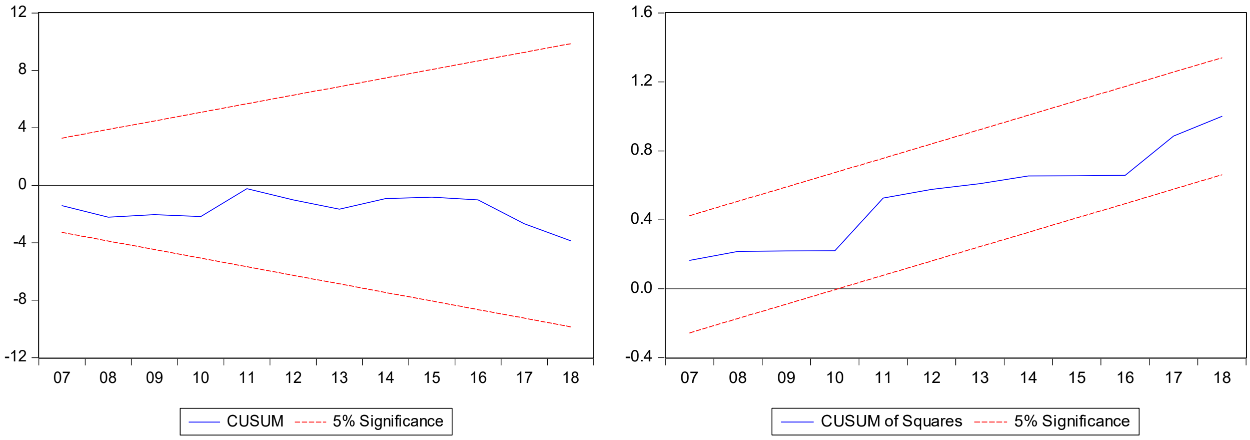

Figure 8. NARDL CUSUM and CUSUM of Square.

5. Robustness Analysis

The current study also applied the dynamic ordinary least square (DOLS) and fully modified ordinary least square (FMOLS) models to examine the robustness of the ARDL results. Tables 14 and 15 present the outcomes of the (DOLS) and (FMOLS), respectively. The findings of both models are compatible with the outcomes of ARDL estimations. For instance, GTI and EPU negatively influence CO_2 emissions, which is persistent with findings of ARDL estimations. As a result, findings of long-run ARDL and NARDL coincide with those of (DOLS) and (FMOLS).

Table 14. Dynamic ordinary least square results.

Variables	Coeff.	Std. Err.	t-Stat.	*p*-Values
LNGTI	−0.2335 ***	0.0521	−4.4806	0.0005
LNEPU	−0.0859 **	0.0345	−2.4901	0.0260
LNFDI	0.0603 *	0.0325	1.8558	0.0847
LNGDP	0.8695 ***	0.1290	6.7427	0.0000
Constant	−5.8680 ***	1.2320	−4.7630	0.0003

Note: *, ** and *** demonstrate significant levels at 10%, 5%, and 1%, respectively.

Table 15. Fully modified ordinary least square.

Variables	Coeff.	Std. Err.	t-Stat.	*p*-Values
LNGTI	−0.1429 ***	0.0308	−4.6367	0.0000
LNEPU	−0.0409 ***	0.0123	−3.3198	0.0020
LNFDI	0.0210 *	0.0106	1.9751	0.0554
LNGDP	1.0080 ***	0.1255	8.0309	0.0000
Constant	−7.6756 ***	1.1378	−6.7459	0.0000

Note: * and *** demonstrate significant levels at 10 and 1%, respectively.

6. Conclusions

The present study examined the symmetric and asymmetric impacts of EPU, GTI, FDI, and GDP on CO_2 from 1970 to 2018 in Italy. We employed linear and non-linear ARDL techniques to scrutinize long- and short-run correlations between the study's variables. The symmetric and asymmetric bounds tests provide evidence of long-run relationships among variables. Additionally, empirical findings of the ARDL model reveal that GTI negatively influences CO_2 emissions under the symmetrical framework. This result implies that a rise in GTI reduces environmental damage, encouraging sustainable growth in Italy. Conversely, GTI harms the environment by raising emissions in the short run. Furthermore, in the case of EPU, long-run outcomes demonstrate that the influence of EPU on CO_2 emissions is negative and significant, suggesting that rising EPU reduces CO_2 emissions.

However, EPU enhances environmental issues over the short run, indicating that it hastens environmental deterioration. Furthermore, we see that FDI has a favorable effect on CO_2 emissions both in the long and short run, establishing the pollution haven hypothesis in Italy. Finally, the non-linear ARDL approach outcomes show that GTI and EPU have considerable asymmetric effects on CO_2 emissions in the long and short run. According to findings, GTI positive shocks significantly lower CO_2 emissions, whereas GTI negative shocks considerably increase CO_2. Furthermore, the results demonstrate that positive shocks to EPU favorably influence CO_2 emissions, while negative shocks to EPU similarly affect CO_2 emissions.

Based on the study's findings, we propose some important policy implications to enhance the quality of the environment. First, the results demonstrate that positive shocks in GTI lower CO_2 emissions and promote sustainability. However, the effects of negative shocks in GTI on environmental quality are more harmful, as a decline in green technology innovations led to higher emissions with greater intensity. This result suggests that the emissions-reducing effects of using green technologies are less significant than the effects of a negative shock on increasing emissions. Therefore, the authorities should prevent a decline in the use of green technologies. Furthermore, increased research and development expenditures in green technology innovations could promote environmental innovation, resulting in more efficiency and lower environmental degradation.

Additionally, authorities should encourage investors to acquire and protect patents about environmental protection, and more specifically, innovation concerning renewable energy should be encouraged. In contrast, a green energy strategy should reduce non-renewable energy sources and substitute them with renewable energy (wind, solar, hydro, and nuclear power) in the overall energy mix. Finally, the government should reform and execute green growth policies and initiatives to achieve carbon neutrality targets.

The outcomes show that EPU promotes environmental deprivation by enhancing carbon dioxide emissions. Therefore, the authorities should consider the possible influence of EPU when making economic policies, especially environmentally friendly policies, because a decrease in EPU is preferred for environmental protection. It is advised that the government should promote clear and stable policies to encourage investment in clean energy sectors. It would help to reduce CO_2 emissions and diminish environmental deterioration. Authorities should also take deliberate measures to mitigate policy-related economic uncertainty. Stable economic policies will boost stable growth and promote environmental quality.

Additionally, the findings support the claim that both positive and negative FDI shocks have a negative effect on Italy's environmental quality. Therefore, it is recommended that the authorities adopt stringent environmental regulations and entry requirements for FDI rather than allowing it at the expense of ecological deterioration. Moreover, the government must adopt tools such as tax rebates, feed-in tariffs, subsidies, and incentives to encourage and motivate green investments in the country. This action will help to boost their productivity without harming the environment. Furthermore, governments should reward foreign companies that use green technologies in their manufacturing processes by lowering taxes and offering green subsidies. On the other side, it is suggested that high tariffs should be imposed on foreign companies in the host country that utilize cheap and dirty technologies in their production processes.

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