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Does Economic Policy Uncertainty Matter for Environmental Degradation in Emerging Countries? Fresh Evidence from Fourier Bootstrap ARDL Estimation

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Abstract
In recent years, economic policy uncertainty has initiated a new discussion in environmental economics on the main drivers of environmental degradation. The main goal is to determine whether economic policy uncertainty leads to environmental damage or contributes to environmental quality. For this purpose, researchers commonly employ panel data analyses based on group estimation and use carbon emissions as a proxy for environmental indicators. However, by doing so they overlook country-specific estimations as well as underrepresent the ecological balance. To overcome these shortcomings, in this paper we employ two new approaches. First, we apply novel Fourier bootstrap autoregressive distributed lag estimation, which is the stronger estimation procedure in time-series analysis, to detect individual outcomes. Second, we use the ecological footprint as a proxy for environmental degradation, which reflects the natural balance more holistically and comprehensively than pollution indicators. In this context, our paper examines the impact of economic policy uncertainty on ecological footprint by using some control variables, such as economic growth and energy consumption. Our sample consists of seven emerging countries from 1965 to 2022. Fourier ARDL test results reveal a strong long-run relationship between ecological footprint and economic policy uncertainty, economic growth, and energy consumption for four emerging countries: India, Indonesia, Russia, and Türkiye. The estimations reveal that economic policy uncertainty in these countries contributes to environmental quality in the long run. In this context, it is important for policymakers to implement environmentally friendly growth strategies far from any uncertainty for the sake of sustainable economic development.

Keywords Economic policy uncertainty · Ecological footprint · Emerging countries · Fourier ARDL estimation

JEL Classification C32 · D80 · Q50

Extended author information available on the last page of the article

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Introduction

Does economic activity cause environmental degradation? For the past three decades environmental economics researchers have focused on this question. Many studies investigate the different types of nexus to reveal this relationship both theoretically and empirically, and those that are best known are based on the relationship between the environment and economic growth (Alper, et al., 2023; Jiang, 2024), energy consumption (Dradra & Abdennadher, 2024; Islam & Rahaman, 2024; Orach et al., 2024), and financial development (Dridi et al., 2024; Lang et al., 2024; Rahman et al., 2024). However, no consensus has been reached on these issues. Some argue that economic activities (e.g., economic growth, international trade, urbanization) harm environmental quality because greater consumption and production increase carbon dioxide (CO_2) emissions, especially in developing or underdeveloped countries with more flexible environmental policies (Vitenu-Sackey and Acheampong, 2022; Kızılkaya et al., 2024). Others emphasize that economic activity contributes to environmental quality, especially in developed countries, because technological and innovational progress helps to eliminate pollutant emissions (Benzerrouk et al., 2021). This dilemma encourages researchers to conduct more detailed investigations to determine the main/actual reasons for environmental degradation in terms of an economic and sustainability approach.

The basis of all these efforts in recent years is growing concern in the international community about global warming and climate change. As is well known, population growth increases demand for food and energy consumption worldwide; however, there is not enough environmentally friendly production capacity for satisfying all this demand in any country under current conditions. Increases in consumer demand cause greater deterioration in the environment or ecological balance by expanding greenhouse gas emissions and threatens ecological sustainability. Despite the efforts made to reduce greenhouse gas emissions, especially in a few developed countries (Ahmad et al., 2018), they make limited and insufficient contributions to ecological balance. According to the Emission Gas Report (2021) published by the United Nations Environment Program, the countries are not upholding their emissions reduction commitments in the framework of the Paris Agreement. Therefore, the goal of keeping global temperatures from increasing less than 2 °C above pre-industrial levels by the end of the century is not being achieved.

Globally, countries are still not making serious attempts to combat environmental degradation and climate change. Most populated and developed countries continue to prioritize economic growth in their policies (Doğanlar et al., 2024). In this context, consumption and production continue to play a determining role in environmental degradation, based with some fundamental parameters, such as economic growth, energy consumption, urbanization, and financial development, as shown by some recent papers. For example, Gyamfi et al. (2021) indicate that economic growth and coal consumption cause environmental degradation in seven emerging (E-7) countries. Khan et al. (2022) find that economic growth and international trade increase pollutant emissions in East Asian economies. Usman and Hammar (2021) find that technological innovation and population have worsened environmental degradation in the member countries of the Asia Pacific Economic Cooperation forum in the long

run. Chu et al. (2023) report that economic growth and energy consumption create environmental pollution in E-7 countries in both the short and long run. Finally, Guliyev (2024) states that financial development, industrialization, and globalization negatively affect environmental quality in European countries.

Recently, economic policy uncertainty (EPU) is also participated in these discussions. This is acceptable because of a great deal of economic, social, and political instability in the past few decades. EPU is directly linked to various macroeconomic indicators, such as economic growth (Sahinoz & Erdogan Cosar, 2018), investment (Chen et al., 2021), financial development (Phan et al., 2021), international trade (Tam, 2018), stock market returns (Kang & Ratti, 2013), and oil prices (Antonakakis et al., 2014). Specifically, EPU may influence investment and production decisions by firms and businesses (Bloom, 2009), technology and innovation capacity (Syed & Bouri, 2022), stock prices, expected cash flows or discount rates (Kang & Ratti, 2013), and tourism arrivals and revenue (Saint Akadiri et al., 2020). Following the Covid-19 pandemic, inflation rates rose in many countries, leading them to adjust their monetary policy. Political conflict, such as the Russian-Ukraine war and tensions between the US and Iran, added to price pressure for oil and food. These are only a few examples; however, every new source of instability creates more uncertainty at both the local and global scale.

In environmental matters, EPU is accepted as an important determinant of ecological balance, based on its role in economic activities. The main argument is that EPU has a negative impact on environmental quality (Adams et al., 2020; Adedoyin & Zakari, 2020; Anser et al., 2021a, b). According to this view, governments tend to implement weaker environmental policies during periods of EPU. This may lead to a further increase in energy consumption from fossil fuels and thus an increase in environmental destruction (Danish Ulucak & Khan, 2020). However, some scholars take the opposite view and argue that EPU can prevent environmental degradation in the long run (Aslan et al., 2024; Syed & Bouri, 2022). They believe that policy makers and firms may be motivated to seek and adopt new technological/innovative approaches in order to address growing environmental challenges during periods of economic uncertainty. This may decrease energy intensity and increase the use of clean energy. New investment decisions in renewable energy sources in this period can contribute to environmental quality as expected (Dunyo et al., 2024). They also claim that EPU can decrease production activities in emissions-producing sectors, and therefore this enables environmental quality to increase (Chen et al., 2021; Syed & Bouri, 2022). Finally, a few emphasize that EPU does not have any significant impact on the environment, and thus they do not show any transmission mechanism between these variables (Liu & Zhang, 2022).

The main goal of this paper is to investigate this newly developed nexus between EPU and environmental degradation empirically. Some studies have attempted to explain this relationship, but they commonly use panel data analyses based on group estimation (Anser et al., 2021a, b; Dao et al., 2024; Hussain et al., 2022; Li et al., 2024) or largely focus on pollutant emissions (mainly CO_2) as a proxy for environmental degradation (Wang et al., 2020; Vitenu-Sackey and Acheampong, 2022; Aslan et al., 2024). Panel data analyses can be advantageous in multicountry empirical models; however, they may present a significant obstacle in performing individual coun-

try analyses and obtaining country-specific results. But pollutant emissions, such as CO_2 emissions, are seen as only a subset of environmental degradation (Anser et al., 2021a, b); it may be insufficient to explain environmental balance and damage holistically and comprehensively. The studies that consider these two arguments are listed among the relevant literature in Appendix Tables 7 and 8.

By overcoming these shortcomings, we make three main contributions to the literature. First, we focus on time-series analyses with a Fourier bootstrap autoregressive distributed lag (ARDL) estimation in our empirical analyses and then determine country-specific outcomes on the nexus between EPU and environmental degradation. The Fourier bootstrap ARDL method is a newly developed estimation procedure that considers smooth structural changes and yields stronger/more reliable results than traditional cointegration estimations. It models structural breaks gradually and smoothly, and, therefore, it is not necessary to predetermine the break form and the number of breaks. The Fourier bootstrap ARDL model uses both integer and fractional frequency values in Fourier terms. In this way, it can capture both permanent and temporary structural breaks (Yilanci et al., 2020). The bootstrap ARDL test performs better than the asymptotic test in terms of power and size (McNown et al., 2018). In addition, it can employ regressors integrated with I(0) or I(1). Second, we use the ecological footprint as a proxy for environmental degradation, rather than pollutant emissions. The ecological footprint is an important parameter that reflects environmental degradation comprehensively and holistically (Anser et al., 2021a, b; Chu et al., 2023) and refers to the area required for a country to produce the resources it consumes and absorb the waste that it produces (Anser et al., 2021a, b). Finally, we consider the seven emerging countries (E-7), namely Brazil, China, Indonesia, India, Mexico, Russia, and Türkiye. Many studies on this issue overlook E-7 countries because they focus on developed countries (Adedoyin & Zakari, 2020; Balsalobre-Lorente et al., 2024; Jiang et al., 2019) and countries with the most emissions (Anser et al., 2021a, b; Villanthenkodath & Pal, 2024). A few attempts such as Xu et al. (2022) and Chu et al. (2023) focuses on this relationship for E-7 countries, however they performed group estimation based on panel analysis.

Determining the relationship EPU and environmental sustainability in E-7 countries is crucial for the success of global climate policies. E-7 countries play a significant role in the global economy due to their production capacities, financial structures, and demographic dynamics. In this context, this study aims to address the research question of how EPU affects environmental degradation in E-7 countries, which are characterized by fragile economic structures. The lack of prior time-series investigations on this relationship in the existing literature highlights a significant research gap. The findings of this study will provide country-specific policy recommendations for E-7 nations, which hold a critical position in the global economy. To the best of our knowledge, this is the first study to examine the nexus between EPU and environmental degradation in the E-7 countries using Fourier ARDL estimation.

The rest of the paper is organized as follows. Section "Theoretical Background" introduces the theoretical background of the nexus between EPU and environmental degradation. Section "Emerging (E-7) Countries" presents the general perspectives

of environmental economies in E-7 countries. Section "Literature Review" consists of the data. Section "Data" describes the econometric methodology. Section "Econometric Methodology" discusses the empirical results. Section "Empirical Findings" is the conclusion and policy recommendations.

Theoretical Background

Since the introduction of EPU to the literature by Baker et al. (2016), an extensive body of research has been conducted on the environmental effects of economic policy uncertainty. In their study, the authors demonstrate that EPU leads to increased stock price volatility and a decline in investment and employment across specific sectors, including defense, healthcare, finance, and infrastructure. Building on this work, numerous subsequent studies have empirically examined the relationship between EPU and environmental degradation and quality.

Theoretically, EPU may affect environmental degradation/quality through various channels. This transmission mechanism is explained by scholars in various ways. For example, Wang et al. (2020) offer two main hypotheses about this issue: consumption and investment effects. In the consumption effect, EPU can slow production in pollution-intensive sectors and thereby contributes to environmental quality. In the investment effect, during periods of uncertainty, investment in green and renewable energy projects might be reduced. This leads to the use of traditional sources of energy in consumption and also causes environmental degradation. Jiang et al. (2019) distinguish direct policy adjustment effects from indirect economic demand effects. In direct policy adjustment effects, during periods of high uncertainty, governments focus their attention on core economic activities, rather than environmental policies, and this reduces environmental quality. However, in indirect economic demand effects, EPU can impact environmental degradation through different economic channels, such as the stock market and investment.

Almost all researchers refer to these two papers in explaining the relationship between EPU and environmental degradation. They also develop these approaches with their own arguments. Anser et al. (2021a, b) emphasize that high uncertainty may decrease investment in R&D, innovation, and renewable energy sources and cause environmental degradation. Similarly, Dunyo et al. (2024) assert that financial market fluctuations and economic downturns, which can lead to economic uncertainty, may hinder investment in green technology and, therefore, increase pollutant emissions. Finally, Chen et al. (2021) state that EPU can damage future expectations by investors and thus can reduce investment. This means that uncertainty can affect environmental quality via investment channels.

To further deepen the theoretical foundation and explain why EPU might have heterogeneous effects across countries, we incorporate the Environmental Kuznets Curve (EKC) and institutional theory frameworks. The EKC suggests a non-linear relationship between economic variables and environmental outcomes, often varying with a country's development stage. Applied to EPU, this implies that the impact of uncertainty may differ between emerging and developed countries. Emerging economies, often with less robust institutional structures, may experience more severe

negative effects of EPU on environmental quality due to limited capacity to absorb shocks. In contrast, developed countries may exhibit more resilience due to advanced policy frameworks and institutional mechanisms. Moreover, institutional theory emphasizes that institutional quality shapes the effect of economic policies and uncertainty. Strong institutions—characterized by effective governance, transparency, and rule of law—can mitigate the adverse effects of EPU by facilitating credible policymaking and enforcement. Weak institutions, however, may amplify the negative consequences of uncertainty, leading to greater environmental degradation.

Based on these arguments, we posit two hypotheses to evaluate the relationship between EPU and environmental degradation/quality, as follows:

Hypothesis 1 Higher EPU can hinder economic activity and, therefore, contributes to environmental quality in emerging countries.

Hypothesis 2 Higher EPU can lead producers to use more traditional production methods and, therefore, cause environmental degradation in emerging countries.

If we obtain a negative coefficient for EPU, then H1 is confirmed for emerging countries. In contrast, if the coefficient for EPU is positive, then H2 is confirmed for these countries. But if the coefficient lacks statistical significance, then neither hypothesis will be confirmed.

Emerging (E-7) Countries

The study focuses on the seven emerging countries (E-7) with the highest economic performance: Brazil, China, India, Indonesia, Mexico, Russia and Türkiye. E-7 countries have the potential to become developed countries because of their high economic growth and remarkable economic performance in recent years. However, this progress is accompanied by an important cost, environmental degradation. In the literature, E-7 countries are commonly characterized as having a fragile economic structure. They have large populations, which contribute to their economic growth; however, they also lack sufficient financial and technological capacities and need foreign investment to ensure their sustainable economic development. To deal with this issue, some emerging/developing countries maintain weak environmental policies in order to attract more foreign investment. But doing so can increase environmental destruction by causing ecological balance in these countries.

Figure 1 shows the trends in EPU and the ecological footprint for the seven countries from 1965 to 2022. It illustrates that all seven countries experienced high EPU after 2008, when the global financial crisis occurred. In addition, the figure demonstrates that ecological footprint indicators also rise after this period, especially in China, India, Indonesia, Russia, and Türkiye. These parallel trends lead us to pose an important question about the actual conditions in E-7 countries with respect to environmental policies: Is there any connection between EPU and ecological balance in the E-7 countries?



Fig. 1 Trends in EPU and the Ecological Footprint (EF) in the E-7 Countries

Literature Review

For the past three decades, researchers have intensively investigated the causes and consequences of environmental degradation. Following the environmental Kuznets curve hypothesis, many studies have analyzed the environmental impacts of economic activities through various channels. Some argue that economic activities are mainly responsible for environmental degradation or climate change, whereas others emphasize that these activities do not damage environmental quality based on different theoretical explanations. These discussions among researchers are ongoing and are prioritized in environmental economics (Doğanlar et al., 2022).

In recent years, this debate has been widened by adding EPU, which is a new driver of environmental degradation. Many studies explain this relationship mostly

using pollutant emissions (e.g., CO_2) and panel data analyses. For example, Jiang et al. (2019) examine the impact of EPU on CO_2 emissions in five sectors (the industrial, the residential, the transportation, the electric power, and the commercial) in the United States, using Granger causality in quantiles for monthly observations from January 1985 to August 2017. They find a unidirectional causal relationship from EPU to both total and sectorial CO_2 emissions. Adams et al. (2020) study the impact of the World Uncertainty Index (WUI; as a proxy for EPU) on CO_2 emissions in 10 resource-rich countries using pooled mean group ARDL (PMG-ARDL) estimation and the Dumitrescu-Hurlin panel causality test for the period 1996 to 2017. They reveal that the WUI increases CO_2 emissions in both the short and the long run and find a bidirectional relationship between the WUI and CO_2 emissions in these countries.

Adedoyin and Zakari (2020) analyze the impact of EPU on CO_2 emissions in the United Kingdom using ARDL bounds and Granger causality analyses for the period 1985 to 2017. ARDL estimations show that EPU reduces CO_2 emissions in the short run, whereas it has an increasing impact on CO_2 emissions in the long run. They also find unidirectional causality from CO_2 emissions to EPU there. Danish Ulucak and Khan (2020) investigate the impact of EPU on CO_2 emissions in the United States using dynamic ARDL estimation for the period 1985 to 2017 and reveal that EPU adversely affects environmental quality there. Wang et al. (2020) examine the impact of the WUI on CO_2 emissions in the United States using the ARDL model from 1960 to 2016 and find that the WUI is positively related to CO_2 emissions in the long run. Anser et al. (2021a, b) examine the impact of the WUI on CO_2 emissions in the ten countries with the highest carbon emissions using the PMG-ARDL estimation for the period 1990 to 2015. They claim that according to the WUI, CO_2 emissions are mitigated in the short run, but rise in the long run. Chen et al. (2021) investigate the impact of EPU on CO_2 emissions in 15 emerging and developed countries using fixed effects estimation for the period from 1997 to 2019 and conclude that higher EPU leads to lower CO_2 emissions in these countries. Syed and Bouri (2022) research the impact of EPU on CO_2 emissions in the United States using bootstrap ARDL estimation for monthly observations from 1985 to 2019 and find that EPU reduces CO_2 emissions in the short run, but increases emissions in the long run.

Vitenu-Sackey and Acheampong (2022) examine the impact of EPU on CO_2 emissions in 18 countries using different panel estimation techniques such as two-stage least squares (2SLS), generalized method of moments (GMM), and generalized least squares (GLS) for the period 2005 to 2018 and show that high EPU has negative impacts on environmental quality especially in countries with high pollution. Aslan et al. (2024) analyze the impact of EPU on CO_2 emissions in G-7 countries using the quantile regression method for the period 1995 to 2018 and find that EPU reduces CO_2 emissions at all quantile levels. Benlemlih and Yavaş (2024) investigate the impact of EPU on CO_2 emissions on firm-level using 6800 firm-year observations from 23 countries and found strong evidence that EPU increases firms' CO_2 emissions. Finally, Dunyo et al. (2024) research the impact of the WUI on CO_2 emissions in 58 countries using GLS estimation for the period 2000 to 2020 and show that EPU has a negative impact on environmental quality in these countries. Appendix Table 7 gives more detailed information about these studies.

However, a few studies consider the ecological footprint, which is a more comprehensive and holistic parameter than pollutant emissions in reflecting environmental degradation (Anser et al., 2021a, b; Chu et al., 2023). For example, Anser et al. (2021a, b) investigate the impact of EPU on the ecological footprint in five emerging countries using Westerlund cointegration and Dimitrescu-Hurlin panel causality analyses for the period 1995 to 2015; they find that EPU is responsible for more environmental damage in these countries. They also discover a unidirectional relationship from the ecological footprint to EPU. Hussain et al. (2022) research the impact of EPU on the ecological footprint in BRICS countries using Westerlund cointegration and pairwise causality analyses for the period 1992 to 2020 and reveal that EPU negatively impacts environmental quality in the long run. They also detect a unidirectional relationship from EPU to the ecological footprint.

Xu et al. (2022) analyze the impact of EPU on the ecological footprint in E-7 countries using Westerlund cointegration estimation for the period 1992 to 2020 and find that EPU damages the environmental balance in these countries. Chu et al. (2023) examine the impact of the WUI on the ecological footprint in E-7 countries using panel PMG-ARDL estimation for the period 1995 to 2018 and conclude that the WUI has a negative impact on environmental quality in the long run. Esmaeili et al. (2023) investigate the impact of EPU on the ecological footprint in 19 energy-intensive countries using Westerlund cointegration Dimitrescu-Hurlin panel causality analyses from 1997 to 2018. They find that EPU has a negative impact on the ecological footprint in the short run, but a positive impact in the long run. They also detect a bidirectional causal relationship between EPU and the ecological footprint in these countries. Shouchang et al. (2023) analyze the impact of EPU on the ecological footprint in G-10 countries using Westerlund cointegration and cross-sectional ARDL (CS-ARDL) estimations and conclude that EPU does not show an environmentally friendly process in these countries in both the short and long run. Balsalobre-Lorente et al. (2024) study the impact of EPU on the ecological footprint in G-20 countries using Westerlund cointegration and Konya bootstrap panel causality analyses for the period 1997 to 2018 and find that EPU has a positive impact on environmental quality in this countries. They do not detect any causal relationship between EPU and the ecological footprint in their empirical analysis.

Dao et al. (2024) analyze the impact of the WUI on the ecological footprint in 30 member countries of the Organization for Economic Cooperation and Development (OECD) using panel quantile regression and panel Granger causality procedures for the period 1990 to 2019 and conclude that the WUI shows ecological improvement in these countries. They also find a bidirectional causal relationship between the WUI and the ecological footprint. Li et al. (2024) explore the impact of the WUI on the ecological footprint in BRICS countries using Westerlund cointegration and pairwise causality procedures and show that the WUI has an increasing effect on environmental degradation in the long run. They also find a unidirectional causal relationship from the WUI to the ecological footprint in these countries. Sahoo et al. (2024) study the impact of the EPU on the ecological footprint in India using dynamic ARDL estimation for the period from 1990 to 2022 and concluded that EPU has a positive a significant effect on ecological footprint in India. Finally, Villanthenkodath and Pal (2024) also study the impact of the WUI on the ecological footprint in India

using dynamic ARDL estimation for the period 1990 to 2019 and reveal that the WUI increases environmental quality in both the short and long run. Appendix Table 8 gives more detailed information about these studies.

As mentioned above, the literature evaluating the nexus between EPU and environmental degradation/quality has two common elements: first, they employ panel data analyses based on group estimations, and, second, they largely use carbon emissions as a proxy for environmental degradation. A few studies—including Jiang et al. (2019), Adedoyin and Zakari (2020) and Wang et al. (2020)—focus on their motivations for time-series analyses, but they consider only developed countries using traditional time-series analyses and look at pollutant emissions, not the ecological footprint. This study fills this gap in the literature by looking at emerging countries, which are mostly neglected by researchers. In this context, we use a newly developed empirical methodology, using Fourier ARDL estimation, and the ecological footprint, which is seen as a more comprehensive parameter for measuring the environmental quality/ecological balance.

Data

The data for this study covers the period 1965–2022 for six of the seven emerging countries: Brazil, China, India, Indonesia, Mexico, and Türkiye. The period for Russia is 1992 to 2022 based on data availability. To investigate the nexus between EPU and the ecological footprint, we use the following empirical model specification with reference from Wang et al. (2020) and Anser et al. (2021a, b):

$$\ln\mathrm{EF}_t = a_0 + \beta_1 \ln\mathrm{EG}_t + \beta_2 \ln\mathrm{EC}_t + \beta_3 \ln\mathrm{EPU}_t + \varepsilon_t \tag{1}$$

The dependent variable, EF, the ecological footprint, is used as a proxy for environmental degradation/quality and ecological balance. It is a composite measure encompassing several components including carbon footprint, cropland, grazing land, fishing grounds, forest land, and built-up land. Among these, the carbon footprint often represents a significant portion, calculated by converting CO_2 emissions into the biologically productive area required for their absorption. The land use components quantify the area required to produce the resources consumed and to assimilate waste. It is important to acknowledge that the EF calculation relies on various assumptions, such as equivalence factors, yield factors, and carbon sequestration rates, which may introduce sensitivity into the measure. For instance, different assumptions regarding the sequestration capacity of forests or variations in agricultural yields can influence the estimated footprint substantially. Therefore, while EF provides a useful integrative environmental impact metric, its interpretation should consider these underlying methodological sensitivities.

EG and EC are control variables for economic growth and energy consumption, respectively, chosen because they are widely accepted main drivers of environmental degradation in the literature (Anser et al., 2021a, b). Finally, EPU is EPU, the main parameter in the study. Because of data constraints, we include the WUI as a proxy for EPU. The descriptive statistics of the variables are presented in Appendix Table 9.

Wang et al. (2020) emphasize that the WUI (or EPU) is also one of the main drivers of environmental degradation. For this purpose, we mainly focus on the impact of EPU on the ecological footprint in this paper. The variables are defined in Table 1.

The choice to use the WUI over country-specific EPU indices is motivated by several factors. First, the WUI provides a standardized measure of uncertainty across a wide range of countries, ensuring comparability in a cross-country analysis framework. Unlike country-specific EPU indices, which may differ in construction methodology and data availability, the WUI offers consistent coverage and longer time series data, allowing for more robust longitudinal studies. However, the use of WUI also presents limitations. It may not capture the nuances of country-specific policy environments and localized shocks as precisely as dedicated EPU indices. Additionally, the aggregation inherent in WUI can mask heterogeneity and specific policy uncertainty drivers unique to certain countries. Therefore, while WUI is suitable for broad comparative analyses, caution is needed in interpreting results at the individual country level.

In testing the theoretical hypotheses, we determine the two possible coefficients on the EPU parameters. If $\beta_3 < 0$, then H1 will be confirmed, which means that EPU contributes to environmental quality in emerging countries. But if $\beta_3 > 0$, H2 will be confirmed, which means that EPU causes environmental degradation in emerging countries. Finally, we expect to find that both control variables $(\beta_1 > 0, \beta_2 > 0)$ have detrimental effects, as in the literature.

Econometric Methodology

This study uses Fourier-based econometric approaches, which model structural breaks gradually and smoothly. In this way, we can perform analysis without the need to predetermine the number of breaks and the break form. The empirical procedures are carried out in three stages. First, we apply the Fourier Augmented Dickey-Fuller (ADF) unit-root method proposed by Christopoulos and Leon-Ledesma (2010) to examine the stationarity properties of the series. Because Fourier unit-root tests use a small number of parameters, we can avoid the power loss problem found in unit-root tests with too many dummy variables (Enders & Lee, 2012). Second, we employ the Fourier bootstrap ARDL technique to investigate the presence of cointegration and estimate the long-run coefficients. Finally, we perform the Fourier Toda-Yamamoto causality analysis (Nazlioglu et al., 2016) to determine the causality relationships between the variables. The flow chart of our econometric analyses is illustrated in Fig. 2.

Table 1 Variable definitions

Symbol	Variable	Measurement	Source
EF	Ecological Footprint	Global hectares per capita	Global Footprint Network
EG	Economic Growth	Per capita (constant 2015 US$)	World Development Indicator
EC	Energy Consumption	Per capita (gigajoule)	BP Statistical Review
EPU	Economic Policy Uncertainty	Index (World Uncertainty Index)	FRED Economic Data

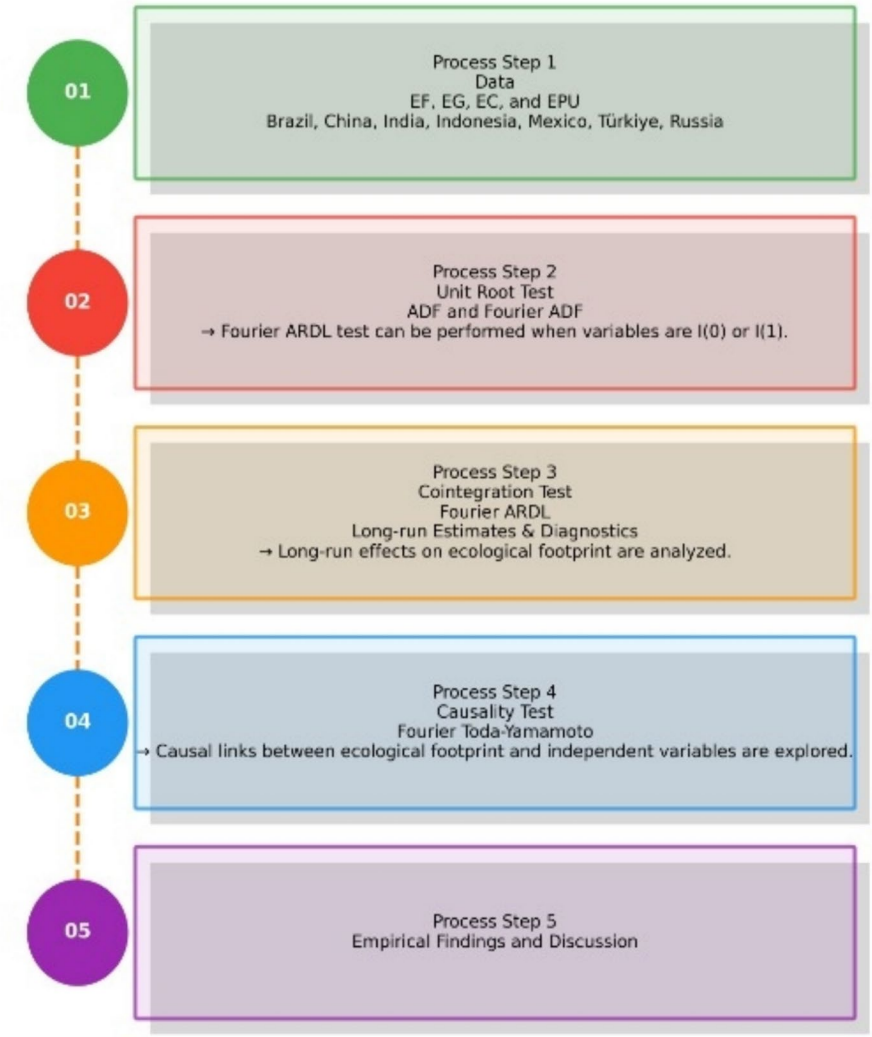


Fig. 2 Flow Chart of the econometric analyses

Fourier ADF Unit-Root Test

When structural breaks are not taken into account in the estimation process, the results of unit-root test can be misleading. Christopoulos and Leon-Ledesma (2010) expand the ADF test to consider smooth breaks using the Fourier approximation. A stochastic variable y_t with a time-varying deterministic component $d(t)$ and $\nu_t \sim N(0, \sigma)$ can be expressed as follows:

$$y_t = d(t) + \nu_t \tag{2}$$

Christopoulos and Leon-Ledesma (2010) use the Fourier series in Eq. (3) for $d(t)$:

$$d(t) = \gamma_0 + \gamma_1 \sin\left(\frac{2\pi kt}{T}\right) + \gamma_2 \cos\left(\frac{2\pi kt}{T}\right) \tag{3}$$

where k is the frequency in the Fourier function, t is the trend, and T is the sample size. The appropriate frequency value (k^*) is determined in the first stage of the Fourier ADF test. Accordingly, Eq. (3) is estimated using the ordinary least squares (OLS) method for each integer value of k, $1 \leq k \leq 5$, and the k value that minimizes the sum of the squares residuals is used as k^*. Then, the OLS residuals of the model are calculated:

$$\widehat{v}_t = y_t - \widehat{\gamma}_0 + \widehat{\gamma}_1 \sin\left(\frac{2\pi k^* t}{T}\right) + \widehat{\gamma}_2 \cos\left(\frac{2\pi k^* t}{T}\right) \tag{4}$$

In the next stage of the test procedure, a unit-root test is performed for the residuals obtained, with the standard ADF regression as follows:

$$\Delta\nu_t = \alpha_1 \nu_{t-1} + \sum_{j=1}^{p} \beta_j \Delta\nu_{t-j} + u_t \tag{5}$$

which tests the null hypothesis ($H_0 : \alpha_1 = 0$), showing the existence of a unit root. In the final stage of the Fourier ADF test, we investigate the existence of unknown (smooth) breaks in the data generation process of y_t using the null hypothesis ($H_0 : \gamma_1 = \gamma_2 = 0$). The *F*-statistic is used to test the null hypothesis.

Fourier Bootstrap ARDL Test

The ARDL bounds test by Pesaran et al. (2001) can be performed when the variables in the model are I(0) or I(1). The ARDL technique can effectively give an estimate even if the sample size is small. In addition, the choice of the appropriate lag length in the ARDL approach is effective at solving the possible endogeneity problem. Equation (6) shows the short- and long-term interactions among the variables in the ARDL model.

$$\begin{aligned}\Delta \mathrm{lnEF_t} = {} & a_0 + \textstyle\sum_{k=1}^{p} \theta_k \Delta \mathrm{lnEF_{t-k}} + \sum_{k=0}^{p} \partial_k \Delta \mathrm{lnEG_{t-k}} + \sum_{k=0}^{p} \gamma_k \Delta \mathrm{lnEC_{t-k}} \\ & + \textstyle\sum_{k=0}^{p} \vartheta_k \Delta \mathrm{lnEPU_{t-k}} + \varphi_1 \mathrm{lnEF}_{t-1} + \varphi_2 \mathrm{lnEG}_{t-1} + \varphi_3 \mathrm{lnEC}_{t-1} + \varphi_4 \mathrm{lnEPU}_{t-1} + \varepsilon_t\end{aligned} \tag{6}$$

where *p* signifies the lag order determined by the Akaike information criterion (AIC). The constant is a_0, and the long-run coefficients of explanatory variables are φ_1, φ_2, φ_3, and φ_4. The conventional ARDL test uses the F-test or *t*-test for testing the null hypothesis ($H_{0A} : \varphi_1 = \varphi_2 = \varphi_3 = \varphi_4 = 0$). When the test statistics obtained in the ARDL procedure are evaluated, they are compared to the lower bounds, defined as I(0), and the upper bounds, defined as I(1). If the test statistic exceeds the critical values of the upper bounds, the null hypothesis is rejected, indicating the presence

of a cointegration relationship. However, when the test statistic is between the upper and lower bounds, no decision can be made regarding the existence or absence of a cointegration relationship. McNown et al. (2018) calculate the bootstrap critical values to eliminate this problem. In addition to the *F*-statistics and *t*-statistics used in the ARDL test, they recommend an additional test statistic for the lagged values of the independent variables. Three test statistics are used in the bootstrap ARDL test, as follows.

$$\begin{aligned} &F_A - test \rightarrow H_{0A} : \varphi_1 = \varphi_2 = \varphi_3 = \varphi_4 = 0 \\ &t - test \rightarrow H_{0B} : \varphi_1 = 0 \\ &F_B - test \rightarrow H_{0C} : \varphi_2 = \varphi_3 = \varphi_4 = 0 \end{aligned}$$

The values of F_A, t, and F_B portray two different situations. First, when F_A, t, and F_B are all significant, cointegration is judged to exist. Second, if any of the F_A, t, and F_B statistics are insignificant, then no cointegration is found.

The traditional cointegration tests may have biased results because they fail to consider structural breaks in the estimation process. Cointegration tests using dummy variables only capture the dynamics of sudden changes (e.g. Gregory & Hansen, 1996; Hatemi-j, 2008; Maki, 2012). These tests assume that the number of breaks is known a priori and that the breaks take place at a particular point. On the other hand, Fourier-based cointegration tests (e.g. Banerjee et al., 2017; Tsong et al., 2016; Yilanci et al., 2020) address gradual and smooth structural breaks. The Fourier approach allows for an unknown number of structural breaks in the deterministic components of a series (Kızılkaya et al., 2024). Solarin (2019) proposes a bootstrap ARDL cointegration test with a Fourier function to allow for nonlinear breaks. The Fourier bootstrap ARDL test is based on the bootstrap ARDL procedure by McNown et al. (2018). This approach outperforms the traditional ARDL method in terms of power characteristics when multiple explanatory variables are available (McNown et al., 2018).

The cointegration relation among the ecological footprint (EF), economic growth (GDP), energy consumption (EC), and economic policy uncertainty (EPU) is discussed using the Fourier bootstrap ARDL test, as follows:

$$\begin{aligned} &\Delta \ln \mathrm{EF}_{\mathrm{t}} = a_0 + \sum_{k=1}^{p} \theta_{\mathrm{k}} \Delta \ln \mathrm{EF}_{\mathrm{t-k}} + \sum_{k=0}^{p} \partial_{\mathrm{k}} \Delta \ln \mathrm{EG}_{\mathrm{t-k}} + \sum_{k=0}^{p} \gamma_{\mathrm{k}} \Delta \ln \mathrm{EC}_{\mathrm{t-k}} \\ &+ \sum_{k=0}^{p} \vartheta_{\mathrm{k}} \Delta \ln \mathrm{EPU}_{\mathrm{t-k}} + \varphi_1 \ln \mathrm{EF}_{t-1} + \varphi_2 \ln \mathrm{EG}_{t-1} + \varphi_3 \ln \mathrm{EC}_{t-1} + \varphi_4 \ln \mathrm{EPU}_{t-1} \\ &+ \varphi_5 \sin\left(\frac{2\pi kt}{T}\right) + \varphi_6 \cos\left(\frac{2\pi kt}{T}\right) + \mathrm{e}_{\mathrm{t}} \end{aligned} \tag{7}$$

where φ_5 and φ_6 are amplitude and displacement, respectively. Yilanci et al. (2020) use fractional frequency values to take into account structural breaks with the Fourier approach. This method estimates Eq. (7) using all the values of k in the interval k=[0.1, …, 5]. Christopoulos and Leon-Ledesma (2011) indicate that integer frequency shows temporary structural breaks, whereas fractional frequency values imply permanent structural breaks.

Fourier Causality Test

Granger (1969) suggests the use of stationary series in the causality procedure. Toda and Yamamoto (1995) allow series with different integration orders to be included in causality analysis. Hacker and Hatemi-j (2006) recommend leveraged bootstrap distribution to decrease size distortion. However, these causality tests do not take structural breaks into consideration. The Fourier Toda-Yamamoto test (Nazlioglu et al., 2016) allows structural breaks (gradual and smooth changes) in causality analysis. This test is based on the Toda and Yamamoto (1995) causality test procedure. In the Toda-Yamamoto approach, the VAR $(\mathrm{p}+\mathrm{d})$ model is estimated as follows:

$$\mathrm{y_t} = \delta + \beta_1 \mathrm{y_{t-1}} + \cdots + \beta_{\mathrm{p+d}} \mathrm{y_{t-(p+d)}} + \epsilon_\mathrm{t} \tag{8}$$

where p is the optimal order of the vector autoregressive (VAR) model, d is the maximum integration order, and ϵ_t represents white-noise residuals. Nazlioglu et al. (2016) describe the VAR $(\mathrm{p}+\mathrm{d})$ model as in Eq. (9) by relaxing the assumption that the intercept term δ is constant over time to consider structural breaks in the Toda-Yamamoto procedure:

$$\mathrm{y_t} = \delta_0 + \beta_1 \mathrm{y_{t-1}} + \cdots + \beta_{\mathrm{p+d}} \mathrm{y_{t-(p+d)}} + \epsilon_\mathrm{t} \tag{9}$$

In Eq. (9), the intercept term δ_0 denotes any structural breaks in $\mathrm{y_t}$. The model considered in the Fourier Toda-Yamamoto test is defined as follows:

$$y_t = \delta_0 + \gamma_1 \mathrm{sin}\left(\frac{2\pi \mathrm{kt}}{\mathrm{T}}\right) + \gamma_2 \mathrm{cos}\left(\frac{2\pi \mathrm{kt}}{\mathrm{T}}\right) + \beta_1 \gamma_{t-1} + \cdots + \beta_{p+d} y_{t-(p+d)} + \varepsilon_t \tag{10}$$

In the Fourier Toda-Yamamoto test, the null hypothesis of noncausality $(\mathrm{H_0} : \beta_1 = \cdots = \beta_\mathrm{p} = 0)$ is tested using Wald statistics.

Empirical Findings

Unit-Root Test Results

In order to determine the appropriate estimating technique in time series analyses, we need to investigate the stationarity properties of the variables. Therefore, we employ traditional ADF and Fourier ADF unit-root tests at level and first difference. The ADF and Fourier ADF unit-root test results are presented in Table 2.

The absence of a nonlinear trend in the series is tested using the *F*-statistics. Because using Fourier tests in the absence of nonlinearity can cause a significant loss of power (Enders & Lee, 2012). Enders and Lee (2012) propose using traditional unit-root tests if the process is linear. Therefore, in this study, we analyze the Fourier ADF results when the Fourier trigonometric terms are significant, as well as the ADF results when these terms are not significant. The unit-root test findings show that *F*-statistics obtained at the I(0) level are greater than the critical values (except

Table 2 Fourier ADF Unit-root test results

Countries	Variables	I(0)			I(1)			Decision
		ADF	FADF	*F*-Statistic	ADF	FADF	*F*-Statistic	
Brazil	EF	−3.298**	−2.531 (1)	18.96*	−6.550*	−6.181 (3)*	3.39	I(1)
	EG	−3.101**	−2.170 (1)	16.09*	−4.587*	−5.569 (2)*	8.08*	I(1)
	EC	−5.511*	−1.927 (1)	23.48*	−4.416*	−3.016 (2)***	7.83*	I(1)
	EPU	−2.273	−4.189 (1)**	17.95*	−8.321*	−6.232 (5)*	0.66	I(0)
China	EF	−0.048	−0.844 (1)	50.43*	−4.573*	−5.131 (2)*	2.74	I(1)
	EG	−0.891	−0.180 (1)	56.13*	−4.905*	−5.961 (1)*	6.71**	I(1)
	EC	−0.741	−1.148 (1)	36.70*	−4.107*	−2.838 (2)	3.58	I(1)
	EPU	−2.746***	−5.580 (3)*	4.98**	−8.287*	−8.649 (4)*	0.41	I(0)
India	EF	−0.345	−1.824 (1)	50.94*	−8.572*	−9.186 (3)*	1.47	I(1)
	EG	2.682	−0.125 (1)	50.97*	−7.258*	−5.835 (1)*	5.67**	I(1)
	EC	0.451	−0.152 (1)	47.91*	−8.331*	−8.966 (3)*	1.53	I(1)
	EPU	−3.878*	−4.756 (1)	10.32*	−10.794*	−8.105 (5)*	0.98	I(0)
Indonesia	EF	1.037	−1.182 (1)	81.06*	−5.698*	−6.682 (1)*	1.11	I(1)
	EG	−0.860	−0.632 (1)	34.33*	−5.886*	−6.441 (3)*	3.26	I(1)
	EC	−2.621***	−0.307 (1)	51.53*	−2.836***	−3.945 (1)**	3.26	I(1)
	EPU	−4.064*	−5.026 (1)*	8.89*	−6.035*	−7.258 (5)*	1.38	I(0)
Mexico	EF	−1.939	−3.379 (1)	75.09*	−11.869*	−12.43 (1)*	0.55	I(1)
	EG	−2.694***	−1.874 (1)	26.89*	−6.509*	−6.908 (5)*	1.97	I(1)
	EC	−3.399**	−1.044 (1)	35.96*	−5.405*	−6.276 (1)*	4.84***	I(1)
	EPU	−4.085*	−5.426 (1)*	12.59*	−7.604*	−8.054 (5)*	0.42	I(0)
Russia	EF	−3.696*	−2.945 (1)	5.87**	−6.490*	−3.953 (3)*	1.05	I(1)
	EG	−0.096	−0.977 (1)	63.98*	−3.313**	−3.989 (1)**	6.44**	I(1)
	EC	−2.224	−3.942 (1)**	16.29*	−4.404*	−5.278 (1)*	3.59	I(0)
	EPU	−4.143*	−4.385 (3)*	2.94	−4.413*	−7.200 (3)*	1.66	I(0)
Türkiye	EF	−1.388	−2.245 (1)	36.10*	−11.426*	−7.630 (3)*	0.42	I(1)

Table 2 (continued)

Countries	Variables	I(0)			I(1)			Decision
		ADF	FADF	*F*-Statistic	ADF	FADF	*F*-Statistic	
	EG	0.498	−0.286 (1)	33.93*	−7.368*	−5.037 (1)*	1.09	I(1)
	EC	−3.315**	−0.859 (1)	36.46*	−7.590*	−8.540 (3)*	2.92	I(1)
	EPU	−4.019*	−6.565 (1)*	6.57**	−2.763***	−2.380 (5)	0.19	I(0)

The suitable frequencies are reported within the parentheses. *, ** and *** demonstrate statistical significance at the 1%, 5% and 10% level, respectively

for EPU in Russia). However, most of the *F*-statistics obtained at the I(1) level are insignificant. According to the ADF and Fourier ADF unit-root test results, all series have different stationarity properties at I(0) or I(1). For all countries, EF and EG are stationary at their first difference, I(1), and EPU is stationary at level, I(0). However, EC is stationary at the first difference for all countries except Russia. In summary, the dependent variable EF is obtained as I(1), and the independent variables are obtained as I(0) or I(1).

Cointegration Test Results

Following a unit-root analysis, we investigate the long-run relationship between the series using the Fourier bootstrap ARDL approach. Almost all traditional cointegration tests require all variables to be stationary at the first difference. Because our variables are stationary at both level and the first difference, it is appropriate to use the ARDL-based techniques, instead of traditional cointegration tests. According to the Fourier bootstrap ARDL test, the null hypothesis is rejected if the estimated F_A, t, and F_B statistics are greater than the critical values. In this case, the variables are cointegrated. The Fourier bootstrap ARDL bounds test results are given in Table 3.

Our cointegration test findings show that the null hypothesis is rejected for India, Indonesia, Russia, and Türkiye. This means that a long-run relationship exists in these countries between the ecological footprint and economic growth, energy consumption, and EPU. In contrast, Brazil, China, and Mexico have no cointegration relationship in their series because at least one of the test statistics is lower than the critical value. The results on the long-run estimation based on the Fourier bootstrap ARDL model are reported in Table 4.

As stated earlier, EPU is the main focus of this investigation, and our results indicate that EPU does not damage the ecological footprint in emerging countries, namely, India, Russia, and Türkiye. However, its contribution is quite limited because the EPU coefficients are low. Accordingly, a 1% increase in EPU leads to a decrease of 0.02%, 0.04%, and 0.02% in the ecological footprint in India, Russia, and Türkiye, respectively. We do not have any statistically significant coefficients on the EPU for Indonesia, thus EPU does not explain the ecological footprint there.

These findings confirm H1 theoretically, which means that EPU contributes to environmental quality in emerging countries. This contribution can be largely explained by the slowdown in economic activity. Accordingly, higher EPU can prevent deci-

Table 3 Cointegration analysis results

Countries	Frequency	AIC	Statistics	Values	Bootstrap Critical Values			Decision
					10%	5%	1%	
			F_A	2.422	4.484	5.391	7.175	
Brazil	3.4	−4.371	T	−1.971	−3.576	−4.015	−4.798	No Cointegration
			F_B	1.108	4.583	5.725	8.257	
			F_A	1.845	3.854	4.609	6.579	
China	3.9	−4.569	T	−2.464***	−2.216	−2.649	−3.537	No Cointegration
			F_B	2.394	3.549	4.504	6.522	
			F_A	4.027***	3.209	4.061	6.309	
India	2.8	−4.943	T	−3.096**	−2.180	−2.572	−3.530	Cointegration
			F_B	5.369**	3.539	4.599	7.686	
			F_A	6.374**	5.263	6.236	8.374	
Indonesia	0.8	−4.291	T	−4.796**	−3.886	−4.268	−5.138	Cointegration
			F_B	6.383**	4.197	5.336	8.115	
			F_A	3.869***	3.822	4.550	6.597	
Mexico	5	−2.588	T	−0.684	−3.135	−3.487	−4.218	No Cointegration
			F_B	4.286***	4.020	4.910	7.264	
			F_A	8.419**	6.132	7.595	11.829	
Russia	1.6	−4.600	T	−4.943**	−3.767	−4.285	−5.486	Cointegration
			F_B	5.564***	5.440	7.098	11.522	
			F_A	5.626**	4.121	5.153	7.615	
Türkiye	1.7	−3.593	T	−4.576*	−2.873	−3.314	−4.186	Cointegration
			F_B	7.170**	4.541	5.751	8.819	

*, ** and *** demonstrate statistical significance at the 1%, 5% and 10% level, respectively

Table 4 The long-run coefficients

Countries	EG		EC		EPU	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
India	0.291*	6.962	0.049	1.012	−0.017**	−2.129
Indonesia	0.263**	2.356	0.147**	2.029	−0.005	−0.901
Russia	0.072**	2.255	0.586*	6.020	−0.040*	−7.827
Türkiye	0.158**	2.072	0.162*	4.109	−0.018***	−1.894

*, ** and *** demonstrate statistical significance at the 1%, 5% and 10% level, respectively

sions on investment and production processes in emerging countries, which reduces environmentally harmful actions, such as releasing toxic gases and consuming excessive natural resources, but, at the same time, a great sacrifice will be made in economic growth policies. From an economic significance perspective, the magnitude of these effects, although statistically significant, is relatively modest. For instance, a 1% increase in EPU corresponds to a 0.02% to 0.04% reduction in the ecological footprint across these countries, indicating limited but meaningful practical impact. While these elasticities might seem small, even marginal improvements in environmental quality can be relevant when aggregated over time and large populations, particularly in emerging economies facing rapid development challenges. Moreover, in policy terms, these findings suggest that moderate increases in economic policy uncertainty can temporarily suppress environmentally harmful economic activities,

but such benefits come at the cost of slower economic growth. Policymakers should therefore weigh the trade-offs between uncertainty-driven environmental benefits and the negative implications for economic expansion. This nuanced understanding emphasizes the importance of managing policy uncertainty to balance environmental and economic objectives effectively. Our findings are consistent with the long-run outcomes by Chu et al. (2023); Esmaeili et al. (2023); Balsalobre-Lorente et al. (2024), and Dao et al. (2024), who apply different panel estimation techniques on group estimations for various country groups and find that EPU increases environmental quality in the long run.

However, we detect devastating effects by the control variables on environmental sustainability in emerging countries. First, economic growth has positive and statistically significant coefficients for all countries; this means that economic growth is mainly responsible for environmental degradation in the long run. A 1% increase in economic growth causes an increase in the ecological footprint of 0.29%, 0.26%, 0.07%, and 0.16% in India, Indonesia, Russia, and Türkiye, respectively. E-7 countries have a gap between investment and savings and, therefore, are highly dependent on foreign capital. In order to attract foreign capital, they have environmental policies that are weaker than those in developed countries. Although this policy may seem appropriate for economic growth, it has negative consequences in the form of environmental destruction. Wang et al. (2020) and Anser et al. (2021a, b) obtain similar findings on this issue, confirming that economic growth causes environmental degradation in the long run. Second, energy consumption has positive and statistically significant coefficients for three emerging countries. A 1% rise in energy consumption increases the ecological footprint by 0.15% in Indonesia, 0.59% in Russia, and 0.16% in Türkiye in the long run. The renewable energy investment and production capacities of these countries are quite weak compared to those in developed countries. They need financial sources for green technology and investment. For this reason, these countries continue to use nonrenewable energy sources in their consumption and production activities. These inevitably damage the natural balance and environmental sustainability. Adams et al. (2020) and Anser et al. (2021a, b) obtain similar results in their empirical analysis. They find that consumption of nonrenewable energy has detrimental impacts on environmental sustainability in the long run.

These findings give us some information about countries. First, Russia has the highest coefficient on EPU. The political and military strategies that Russia pursues internationally are not approved by Western countries, and that is why sanctions have long been imposed on its economy. This inevitably creates uncertainty in its economy and complicates investment policies in the public and private sectors. Second, Türkiye has also a high coefficient on after Russia. Incompatible economic policies, especially in the past decade, have created uncertainty in the country and caused investment to be abandoned. High inflation and a low growth rate continue to be the most important source of this uncertainty. Finally, India has mostly suffered because of international geopolitical risks, such as the Russia-Ukraine war, the Israel-Hamas war, and rising oil prices. These risks create high inflation in this crowded country and, therefore, lead to more uncertainty in economic conditions. Overall, this country-specific uncertainty causes a slowdown in economic activities in these emerging

countries. Thus, it reduces production from environmentally harmful industries and thus environmental destruction. Indonesia has no significant impact on this issue.

Table 5 reports the results of diagnostic tests to investigate the ARDL model validity. LM and ARCH tests indicate the absence of autocorrelation and heteroskedasticity, respectively. The Jarque–Bera normality test shows a normal distribution, and the Ramsey Reset test confirms the correct model specification. CUSUM and CUSUMsq graphs are presented in Fig. 3. CUSUM and CUSUMsq tests imply that the models are stable. Accordingly, the diagnostic test results confirm the robustness of the Fourier ARDL model.

Causality Test Results

Following the Fourier bootstrap ARDL procedure, we also apply the Fourier Toda-Yamamoto causality technique to determine the causal relationship between the series. Table 6 shows the causality relationships in the E-7 countries among the ecological footprint and economic growth, energy consumption, and EPU.

Table 5 Diagnostic tests

Tests	India	Indonesia	Russia	Türkiye
LM	0.968 (0.387)	0.605 (0.551)	1.074 (0.381)	0.118 (0.888)
ARCH	1.381 (0.245)	0.059 (0.807)	0.056 (0.813)	0.398 (0.530)
Ramsey Reset	2.207 (0.121)	0.026 (0.870)	0.329 (0.578)	0.734 (0.396)
JB-Stats	0.347 (0.840)	2.159 (0.339)	2.147 (0.341)	0.697 (0.705)
CUSUM	S	S	S	S
CUSUMsq	S	S	S	S

The *p*-values are reported within the parentheses

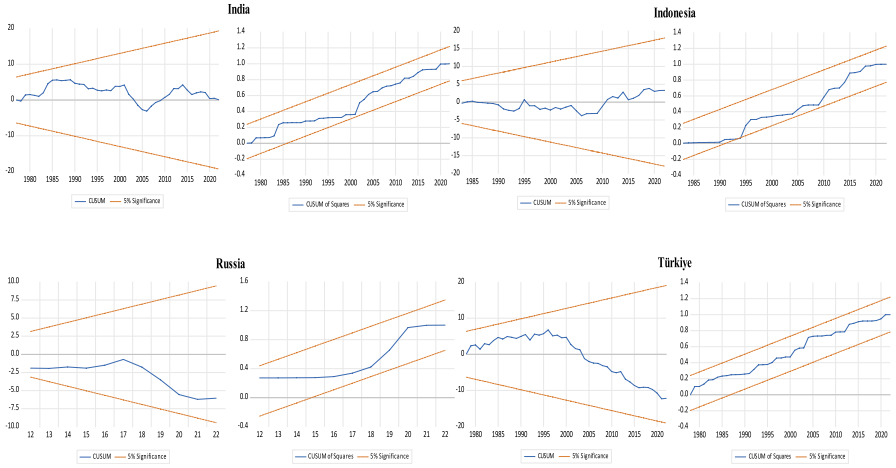


Fig. 3 CUSUM and CUSUMsq graphs

Table 6 Causality analysis results

Countries	Causality path	WALD Statistic	p-values	Causality path	WALD Statistic	*p*-values
Brazil	EG → EF	0.225 (3)	0.974	EF → EG	4.109 (3)	0.275
	EC → EF	0.969 (3)	0.816	EF → EC	7.544 (3)***	0.075
	EPU → EF	4.722 (3)	0.203	EF → EPU	8.414 (3)**	0.048
China	EG → EF	1.986 (2)	0.582	EF → EG	2.202 (2)	0.533
	EC → EF	17.377 (1)*	0.003	EF → EC	0.137 (1)	0.986
	EPU → EF	0.012 (1)	0.913	EF → EPU	0.839 (1)	0.365
India	EG → EF	4.728 (3)**	0.035	EF → EG	0.740 (3)	0.396
	EC → EF	3.679 (1)***	0.065	EF → EC	0.435 (1)	0.508
	EPU → EF	2.819(1)***	0.097	EF → EPU	0.548 (1)	0.459
Indonesia	EG → EF	1.125 (1)	0.751	EF → EG	10.116 (1)**	0.030
	EC → EF	3.485 (1)	0.330	EF → EC	5.007 (1)	0.195
	EPU → EF	0.896 (1)	0.345	EF → EPU	0.265 (1)	0.607
Mexico	EG → EF	3.447 (1)	0.190	EF → EG	0.187 (1)	0.901
	EC → EF	2.687 (2)	0.274	EF → EC	6.644 (2)**	0.047
	EPU → EF	0.321 (1)	0.561	EF → EPU	0.189 (1)	0.660
Russia	EG → EF	1.906 (1)	0.401	EF → EG	11.003 (1)**	0.012
	EC → EF	12.519 (1)*	0.002	EF → EC	1.883 (1)	0.188
	EPU → EF	1.160 (1)	0.286	EF → EPU	2.127 (1)	0.160
Türkiye	EG → EF	0.647 (1)	0.427	EF → EG	4.605 (1)**	0.037
	EC → EF	0.077 (1)	0.787	EF → EC	0.871 (1)	0.355
	EPU → EF	8.981 (1)**	0.048	EF → EPU	3.098 (1)	0.380

Values in parentheses are suitable frequencies. *, ** and *** demonstrate statistical significance at the 1%, 5% and 10% level, respectively

The null hypothesis is rejected if the MWALD statistic is larger than the critical value that is calculated by the bootstrap method, showing a causality relation between the series. Based on this information, we find unidirectional causality from economic growth to the ecological footprint only in India, whereas unidirectional causality runs from the ecological footprint to economic growth in Indonesia, Russia, and Türkiye. Next, we find unidirectional causality from energy consumption to the ecological footprint in China, India, and Russia, but unidirectional causality from the ecological footprint to energy consumption in Brazil and Mexico. We also detect unidirectional causality from EPU to the ecological footprint in India and Türkiye and from the ecological footprint to EPU in Brazil.

The causality results provide key insights for policy in emerging countries. In India, economic growth drives environmental degradation, suggesting the need for sustainable growth strategies and stronger environmental regulations. Conversely, in Indonesia, Russia, and Türkiye, environmental degradation affects economic performance, highlighting the importance of environmental restoration and resource management. Causality from energy consumption to ecological footprint in China, India, and Russia underscores the urgency of investing in renewable energy and improving energy efficiency. Additionally, the effect of Economic Policy Uncertainty (EPU) on the ecological footprint in India and Türkiye indicates that reducing policy uncer-

tainty can encourage green investments and sustainable production. Overall, these findings call for coordinated policies that integrate economic growth with environmental protection by promoting renewables, enhancing policy stability, and addressing the feedback between economy and environment.

Conclusion and Policy Recommendations

In the past quarter century, all countries have experienced at least one type of instability, such as war, pandemic, social conflict, and economic and financial crises, and now, they all face a new global threat: climate change. Researchers in different fields have made intensive efforts to explain (and also warn about) the role that human activity plays in environmental sustainability and ecological balance. Some important international organizations, such as the United Nations, also contribute these efforts with their conferences, meetings, and reports. However, these attempts all seem to be insufficient. As the population continues to increase, ecological balance is harmed, and the climate crisis continues to deepen.

Every day, the world faces new sources of instability, which inevitably creates risks and uncertainty for every country's economy. So how does uncertainty affect environmental sustainability? This is the question that needs to be answered and is also the main motivation for this study. To explain this relationship, we focus on emerging countries, which have experienced great economic and financial instability in recent years, and analyze the impact of EPU on environmental sustainability in them. For this reason, we also consider economic growth and energy consumption as control variables because they are the main drivers of environmental sustainability. We conduct analyses with novel Fourier bootstrap ARDL estimation because it has stronger estimation procedures in time series to determine the individual outcomes. Our sample consists of seven emerging countries—Brazil, China, India, Indonesia, Mexico, Russia, and Türkiye—from 1965 to 2022.

The Fourier ARDL test results reveal a strong long-run relationship between the ecological footprint and EPU, economic growth, and energy consumption in four of the seven emerging countries: India, Indonesia, Russia, and Türkiye. The long-run coefficient estimations reveal that EPU increases environmental quality in the long run. This contribution can be largely explained by the slowdown in economic activity in these countries. Higher EPU can negatively affect the decisions by investors and businesses, and, therefore, they can postpone or stop the investment and production processes in these countries. Slowing economic activity mean less use of fossil fuels and less environmental destruction in these countries, where traditional production processes are prevalent. This can be considered a good result in environmental terms, but it is not a desirable outcome in terms of economic growth and development. Thus, these countries need policies that will ensure environmental sustainability without harming their economic activity.

Our results also identify positive coefficients for economic growth and consumption of nonrenewable energy in emerging countries. This is completely consistent with the literature, which largely indicates that these parameters are the main drivers of environmental degradation. This is the result of their insistence on enforcing weak environmental regulations. Emerging countries continue to use traditional methods in their production processes, preferring them over environmentally friendly practices. Finally, we also apply the Fourier Toda-Yamamoto causality technique to identify the causal relationship between the series. The results are mostly consistent with the long-run estimations from the Fourier ARDL procedure.

This study offers some important policy recommendations for emerging economies. First, E-7 countries should avoid practices that harm environmental sustainability when they deal with risks and uncertainty in their economic conditions. In other words, the administrative policies should simultaneously reduce economic policy uncertainty and promote both sustainable economic growth and environmental protection. Second, E-7 countries should enhance the effectiveness of environmental policies, particularly those promoting green technology and renewable energy investments, to mitigate the potential environmental damage associated with economic growth and energy consumption. Third, they need to seek greater cooperation on climate change and environmental sustainability with international organizations, such as the United Nations and the World Bank. Finally, they need to implement more effective macroeconomic policies to guard against local and global uncertainty.

The primary limitation of this study is the lack of clear findings for certain E-7 countries, namely Brazil, China, and Mexico. These countries have significant roles in global production, trade, and financial markets, making it crucial to better understand the relationship between Economic Policy Uncertainty (EPU) and environmental sustainability for effective global policy design. Future research should conduct more comprehensive analyses involving these nations. Additionally, this study faces potential endogeneity issues, particularly due to the bidirectional causality detected between EPU and the ecological footprint in some countries. Such endogeneity may bias the results and should be addressed through advanced econometric techniques in future studies. Moreover, our analysis relies on a specific measure of EPU; however, alternative EPU indices or uncertainty proxies may yield different results. Hence, sensitivity analyses with diverse EPU measures are recommended to ensure robustness. In this context, while this study uses the World Uncertainty Index (WUI) as a global measure, future research could enhance robustness by combining WUI with country-specific uncertainty indices to better capture national dynamics. Finally, we suggest that future research utilize firm-level data or sectoral analyses to capture heterogeneous effects within countries more accurately. This micro-level approach can provide deeper insights into how economic policy uncertainty influences environmental outcomes across different industries and firms.

Appendix 1

Table 7 Literature review: Economic policy uncertainty vs. Environmental quality nexus (CO_2)

				Results			
Author(s)	Period & Sample	Variables	Method	EKC	Causality	Coefficient Signs	
						Short-Run	Long-Run
Jiang et al. (2019)	1985:M1-2017:M8 United States	CO_2, EPU	- Granger Causality	-	EPU → CO_2	-	-
Adams et al. (2020)	1996–2017 Ten Resource Rich Countries	CO_2, WUI, EG, EN, GPR	- PMG-ARDL Modeling - D–H Panel Causality	Valid	WUI ↔ CO_2	WUI (+)	WUI (+)
Adedoyin and Zakari (2020)	1985–2017 United Kingdom	CO_2, EPU, EG, EN	- ARDL Bounds Test	Valid	CO_2 → EPU	EPU (-)	EPU (+)
Danish Ulucak and Khan (2020)	1985–2017 United States	CO_2, EPU, EG, EI	- Dynamic ARDL Estimation	Valid	-	-	EPU (+)
Wang et al. (2020)	1960–2016 United States	CO_2, WUI, EG, EP	- ARDL Bounds Test - Granger Causality	-	-	-	WUI (+)
Anser et al., (2021a, b)	1990–2015 Top Ten Carbon Emitter Countries	CO_2, WUI, EG, EN, POP	- PMG-ARDL Modeling	Valid	-	WUI (-)	WUI (+)
Chen et al. (2021)	1997–2019 15 Countries	CO_2, EPU, EG, FDI	- Fixed Effect Estimation	-	-	-	EPU (-)
Syed and Bouri (2022)	1985:M1-2019:M12 United States	CO_2, EPU, REN, TRA, IP	- Bootstrap ARD Estimation	Valid	-	EPU (+)	EPU (-)
Vitenu-Sackey and Acheampong (2022)	2005–2018 18 Countries	CO_2, EPU, EG, EI, REN, URB, FDI, PAT, R&D	- 2SLS - GLS - GMM	Valid	-	-	EPU (-)
Aslan et al. (2024)	1995–2018 G7 Countries	CO_2, EPU, EG, REN, URB, TEC	- Panel Quantile Estimation	Valid	-	-	EPU (-)
Dunyo et al. (2024)	2000–2020 58 Countries	CO_2, EPU, EG, EI, REN, URB, FDI, PAT, R&D	- Generalized Least Square	Valid	-	-	EPU (-)

Abbreviations: *CO_2* Carbon dioxide emissions, *EG* Economic growth, *EI* Energy intensity, *EN* Energy consumption, *EP* Energy price, *EPU* Economic policy uncertainty, *FDI* Foreign direct investment, *GPR* Geopolitical risk, *IP* Industrial production, *PAT* Registered patents, *POP* Population, *R&D* Research & Development, *TEC* Technology, *TRA* Trade openness, *URB* Urbanization, *WUI* World uncertainty index. (+): Positive impact, (-): Negative impact, (N): Insignificant impact

Table 8 Literature review: economic policy uncertainty vs. environmental quality nexus (EF)

				Results			
Author(s)	Period & Sample	Variables	Method	EKC	Causality	Coefficient Signs	
						Short-Run	Long-Run
Anser et al. (2021a, b)	1995–2015 5 Emerging Countries	EF, EPU, EG, EN, REN, POP, GPR	- Westerlund Cointegration - D–H Panel Causality	-	EF → EPU	-	EPU (+)
Hussain et al. (2022)	1992–2020 BRICS Countries	EF, EPU, EG, REN, POP, ERT	- Westerlund Cointegration - Pair-Wise Causality	-	EPU → EF	-	EPU (+)
Xu et al. (2022)	1992–2020 E-7 Countries	EF, EPU, EG, ES, NRR	- Westerlund Cointegration - DOLS and FMOLS	Invalid	-	-	EPU (+)
Chu et al. (2023)	1995–2018 E-7 Countries	EF/CO_2, WUI, EG, EN, ECI, GPR	- Westerlund Cointegration - PMG-ARDL Modeling	Valid	-	WUI (+)	WUI (-)
Esmaeili et al. (2023)	1997–2018 19 Countries	EF, EPU, TRA, NRR, LE, SW	- Westerlund Cointegration - D–H Panel Causality	-	EF ↔ EPU	EPU (+)	EPU (-)
Shouchang et al. (2023)	1995–2018 G-10 Countries	EF, EPU, EG, ES, NRR, TFP	- Westerlund Cointegration - CS-ARDL Modeling	-	-	EPU (+)	EPU (+)
Balsalobre-Lorente et al. (2024)	1997–2018 G-20 Countries	EF/CO_2/CF, EPU, EG, REN, ECI, GPR	- Westerlund Cointegration - Konya Bootstrap Causality	Valid	-	-	EPU (-)
Dao et al. (2024)	1990–2019 30 OECD Countries	EF/BIO, WUI, EG, TRA, NRR, NRD, ERT	- Panel Quantile Regression - Panel Granger Causality	Valid	EF ↔ WUI	-	WUI (-)
Li et al. (2024)	2000–2021 BRICS Countries	EF, WUI, EG, EN, REN, GPR	- Westerlund Cointegration - Pair-Wise Causality	-	EPU → EF	WUI (N)	WUI (+)

Table 8 (continued)

Author(s)	Period & Sample	Variables	Method	Results			
				EKC	Causality	Coefficient Signs	
						Short-Run	Long-Run
Sahoo et al. (2024)	1990–2022 India	EF, EPU, EG, REN, NRR, TOR	- Dynamic ARDL Estimation	-	-	EPU (N)	EPU (+)
Villanthenkodath and Pal (2024)	1990–2019 India	EF/CO_2, WUI, EG, REN, NRR, GPR, LCF	- Dynamic ARDL Estimation	-	-	WUI (-)	WUI (-)

Abbreviations: *BIO* Bio capacity, CO_2 Carbon dioxide emissions, *CF* Carbon footprint, *ECI* Economic complexity, *EF* Ecological footprint, *EG* Economic growth, *EN* Energy consumption, *EPU* Economic policy uncertainty, *ERT* Environment-related technologies, *ES* Energy structure, *GPR* Geopolitical risk, *LCF* Load capacity factor, *LE* Life expectancy, *NRD* Natural resources rents diversification, *NRR* Natural resources rents, *POP* Population, *REN* Renewable energy consumption, *SW* Social welfare, *TFP* Total factor productivity, *TOR* Tourism development, *TRA* Trade openness, *WUI* World uncertainty index. (+): Positive impact, (-): Negative impact

Table 9 Descriptive statistics

Variables	Stat	Brazil	China	India	Indonesia	Mexico	Russia	Türkiye
EF	Maximum	1.120	1.286	0.079	0.521	1.428	1.928	1.246
	Minimum	0.811	-0.212	-0.646	0.075	0.650	1.561	0.515
	Skewness	-0.860	0.298	0.388	0.641	0.291	0.112	-0.114
	Kurtosis	2.858	1.697	1.821	2.176	3.052	3.741	1.932
	Jarque–Bera (p-value)	0.027	0.084	0.090	0.060	0.662	0.679	0.237
EG	Maximum	9.129	9.355	7.645	8.312	9.244	9.235	9.551
	Minimum	7.918	5.370	5.755	6.346	8.532	8.415	7.929
	Skewness	-1.088	0.149	0.488	-0.124	-0.941	-0.439	0.312
	Kurtosis	3.686	1.641	1.888	1.939	2.844	1.591	2.041
	Jarque–Bera (p-value)	0.002	0.096	0.071	0.238	0.013	0.168	0.205
EC	Maximum	4.144	4.717	3.247	3.569	4.258	5.445	1.948
	Minimum	2.455	1.945	1.495	1.028	3.207	5.139	-1.111
	Skewness	-1.076	0.018	0.086	-0.526	-1.128	0.024	-0.386
	Kurtosis	3.405	1.919	1.718	1.910	2.986	2.852	2.081
	Jarque–Bera (p-value)	0.003	0.243	0.132	0.062	0.002	0.984	0.175
EPU	Maximum	0.086	-0.975	-0.595	-0.600	-0.414	-0.737	-0.326
	Minimum	-4.605	-4.605	-4.605	-4.776	-4.605	-3.176	-9.210
	Skewness	-0.406	-0.581	-0.760	-1.269	-0.816	-0.714	-2.914
	Kurtosis	2.495	2.570	4.113	4.042	3.320	3.329	11.453
	Jarque–Bera (*p*-value)	0.331	0.156	0.014	0.000	0.035	0.250	0.000

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