Analyzing Energy Usage: An Index Decomposition Analysis and Econometrics Approach: Evidence from Türkiye

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Abstract

Understanding the drivers of energy consumption is essential for addressing global energy challenges. This study examines energy usage in Türkiye using Index Decomposition Analysis (IDA) and the Autoregressive Distributed Lag (ARDL) model. The IDA, applied to sectoral energy data for the industrial, service, and agricultural sectors from 1990 to 2023, reveals that production effect increased total energy consumption by nearly 87%, while structural changes reduced it by approximately 14%, and improvements in energy intensity reduced it by about 21%. The ARDL analysis, based on annual data from 1960 to 2023, confirms a long-run relationship among energy consumption per capita (EC pc), Gross Domestic Product per capita (GDP pc), carbon dioxide emissions per capita (CO_2 pc), and the share of renewable energy in total energy production. The results indicate an adjustment toward the long-run equilibrium, with approximately 46% of any deviation corrected each year, reflecting both short-run and long-run relationships. We also examine the Environmental Kuznets Curve (EKC) and Energy-Environmental Kuznets Curve (EEKC) hypotheses. Our results support an inverted U-shaped EEKC between EC pc and GDP pc, and an EKC between CO_2 pc and GDP pc. Ordinary least squares (OLS) is also used to assess data reliability and identify relationships among variables, as well as to estimate using the ARDL approach.

Keywords

Energy Usage, Energy Intensity, IDA, ARDL, Türkiye

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Introduction

The increasing demand for energy in Türkiye and global efforts to reduce greenhouse gas emissions (GHG) underscore the urgent need to understand the determinants of energy efficiency. Energy intensity, the amount of energy consumed per unit of economic output, is a central indicator for assessing energy efficiency and sustainable development.[1–3] Lowering energy intensity[5] is not only an economic objective but also a critical environmental strategy for mitigating climate change impacts such as global warming, GHG, biodiversity loss, and resource depletion.[4,5]

Concerns over resource sustainability are deeply rooted in economic thought. As early as 1798, Malthus warned of the pressure that population growth would place on finite resources. The Industrial Revolution intensified global energy demand, particularly for fossil fuels, and the 1973 oil crisis demonstrated the vulnerabilities of energy dependence. Since then, improving energy efficiency has become a central element of national energy strategies reinforced by international frameworks such as the Kyoto Protocol (1997) and the Paris Agreement (2015).[6] The World Energy Council identifies energy security, equity, and environmental impact as the three pillars of energy sustainability, emphasizing that efficiency improvements are essential for balancing supply and demand.

Energy consumption is a crucial driver of economic development, typically rising during industrialization and then declining as economies shift toward service-based sectors. This pattern is a concept adapted from Kuznets[7], who originally proposed an inverted U-shaped relationship between income inequality and economic development. In environmental economics, the EKC extends this framework to environmental pressures such as CO_2 emissions, suggesting that degradation increases with income at early stages of growth but decreases beyond a certain threshold as economies adopt cleaner technologies, stricter regulations, and less energy-intensive structures [1,8].[6] The EEKC applies the same structural logic specifically to energy consumption, linking rising and then declining energy consumption to the process of economic development.[9,10]

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5 Energy intensity (EI) is a metric used to assess the efficiency of energy usage within an economy. It is defined as the ratio of total primary energy consumption, including all forms of energy utilized in a country to GDP. For accurate computation, EI calculations should account for all primary energy sources, including unprocessed forms, before converting them into usable energy, such as electricity. While energy intensity and energy efficiency are related, they are distinct: EI measures the energy consumed per unit of output, whereas efficiency refers to producing the same output with less energy.

6 Structural change refers to the shift in economic activity from energy-intensive industries (e.g., manufacturing) toward less energy-intensive sectors, such as services. While certain services (e.g., transport, ICT, or large-scale commercial activities) can also require substantial energy, on average, the energy intensity of services remains lower than that of industry. Thus, the production effect, combined with a rising share of services, typically contributes to lower aggregate energy intensity.

We employ IDA using sectoral energy data from 1990 to 2023 to quantify the contributions of activity, structural change, and efficiency improvements to total energy consumption, applying the Logarithmic Mean Divisia Index (LMDI) method.[11–15]

We then use data from 1960 to 2023 to conduct OLS regressions that assess data reliability and establish baseline relationships among the variables. The EKC for CO_2 pc and the EEKC for EC pc on GDP pc are also examined. These regressions also help assess data reliability, establish baseline relationships, and address potential issues such as multicollinearity and autocorrelation, while incorporating a residual CO_2 pc as a proxy for unobserved environmental factors. Finally, we apply the ARDL and Error Correction Model (ECM) to investigate both the long-run equilibrium and short-run dynamics among EC pc, GDP pc, CO_2 pc, and renewable energy shares, after verifying the integration orders with unit root tests and bounds tests.[16–18]

Through IDA, we find that production effect increased energy use by nearly 87%, while structural shifts reduced consumption by around 14% and efficiency improvements by about 21%. The ARDL model indicates a stable long-run relationship among energy consumption pc, GDP pc, CO_2 emissions pc, and the share of renewable energy, with nearly 46% of deviations from equilibrium corrected each year. We also use OLS regressions prior to the ARDL estimation to assess data reliability, identify an inverted U-shaped EEKC for EC pc and GDP pc, and an EKC for CO_2 pc.

This study contributes to the literature by combining IDA and ARDL analysis in this study. We connect sectoral decomposition (activity, structure, intensity) with time-series evidence on energy use, income, CO_2, and renewable energy for Türkiye. We also test EKC and EEKC together. Bringing these elements together, we provide new evidence on the drivers of Türkiye's energy consumption and its links with income and emissions.

Türkiye is a suitable case for this analysis, as it is an emerging economy characterized by rapid industrialization, rising energy demand, and ambitious renewable energy goals. Its EU candidacy and strategic location between East and West enhance the importance of its energy policies and environmental performance in regional and global contexts. In addition, Türkiye is transitioning from an industry-based to a service-oriented economy while facing the challenge of balancing economic growth with climate commitments. These factors make it an ideal setting to examine the links between energy intensity, structural change, and environmental sustainability.

The remainder of the paper is organized as follows: Section 2 provides an overview of the Turkish economy and energy sector, focusing on greenhouse gas emissions in Türkiye. Section 3 reviews the literature on energy intensity, CO_2 pc, the EEKC and EKC, and IDA, highlighting their relevance to Türkiye. Section 4 describes the data sources, including their scope and limitations. Section 5 details the methodology employed, beginning with the IDA to quantify production, structural, and intensity effects, followed by the ARDL model to examine long-run and short-run relationships among energy consumption, GDP, CO_2, and renewable energy share, including diagnostic tests and the ECM capturing an annual adjustment rate of 46%. OLS regressions are then used to verify data reliability and provide preliminary associations. Section 6 presents the empirical results from the IDA, ARDL, and OLS analyses. Section 7 discusses the findings, compares them with existing literature, and considers policy implications. Finally, Section 8 concludes by summarizing the study's main contributions and outlining directions for future research.

An Overview of the Turkish Economy and Energy Sector

Türkiye, positioned between 36° and 42° north latitude and 26° and 45° east longitude, serves as a bridge between Europe and Asia. This strategic location influences its diverse energy consumption patterns due to the contrasting natural and socio-economic characteristics of the two regions. In 2023, Türkiye's population is approximately 85 million, with major urban centers such as Istanbul, Ankara, and İzmir housing the majority. The population is relatively young, with a median age of around 32 years, and about 75% reside in urban areas, driven by rural-to-urban migration in search of better employment, education, and living standards[7].[19]

Table 1: Descriptive Statistics of Türkiye

	1990	**2000**	**2010**	**2020**	**2023**	**Total Change % (1990-2023)**
Population (Million)	56.1	67.8	73.1	83.3	84.3	52.32
GDP (Current Billion US$)	148.7	277.9	777.4	717.1	1129.9	659
Energy Usage (Million TOE)	48.2	74.2	107.7	156.6	167.2	246
Energy Intensity (Million TOE/Current PPP GDP)	3.77	3.10	1.61	2.54	1.72	-54.4
CO_2 Emissions (MT CO_2)	151.6	229.9	316.8	412.8	432.1	184.9

Note: GDP stands for Gross Domestic Product, TOE stands for Ton of Oil Equivalent, PPP stands for Purchasing Power Parity, and MT stands for Million Ton. Data Sources: Turkish Statistical Institute (TSI), The State Planning Organization of Economic and Social Indicators of Türkiye (SPO), International Energy Agency (IEA)

Table 1 presents the descriptive statistics of Türkiye from 1990 to 2023. The population grew by about 52%, reflecting demographic expansion. GDP rose by

[7] https://www.tuik.gov.tr/Home/Index

nearly 660%, corresponding to an average annual real growth rate of 5.4%. Energy usage also increased by about 246%, with an average annual growth rate of 3.6%. In contrast, energy intensity declined by nearly 54%, indicating gains in energy efficiency. Meanwhile, CO_2 emissions increased by about 185%, at an average annual rate of 3.2%[8].[20]

Figure 1 shows the sectoral distribution of energy consumption in Türkiye from 1990 to 2022. The industry sector remained the largest share throughout the period. The residential sector gradually declined. The transport sector increased steadily, especially after the early 2000s. The services sector rose sharply around 2005 and then stayed relatively stable. The agricultural sector remained stable throughout the entire period.

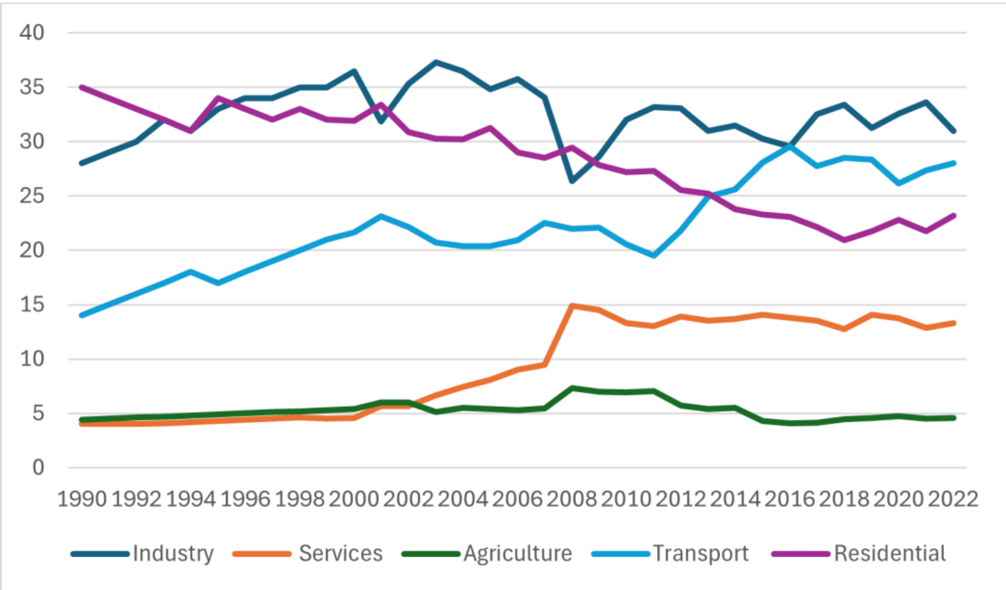

Figure 1: Total Final Energy Consumption by Sectors in Percentage

Data Source: TSI, SPO, IEA

Figure 2 presents the production trends in the industry, services, and agriculture sectors in Türkiye from 1990 to 2022. The service sector has shown a steady increase in production over time, indicating its growing importance in the economy. In contrast, the industry sector has experienced a gradual decline in its share of production, although it shows some fluctuations in recent years. The agricultural sector has maintained a relatively stable but decreasing trend, reflecting lower production compared to other sectors.

Figure 3 presents the trends in GDP pc, CO_2 pc, Human Development Index (HDI), EC pc, and energy intensity from 1960 to 2023. We normalized the values to 1990 as the base year because HDI data were only available starting from that

[8] The average annual growth rate of each variable is calculated using the compound annual growth rate formula. Due to inflation and currency instability, it is important to compute real GDP accurately, making nominal figures a more straightforward alternative for analysis.

year. This normalization allows for better comparison of the changes. GDP pc, CO_2 pc, HDI, and EC pc have generally increased over the years, reflecting economic growth, rising living standards, and higher energy demand. Meanwhile, energy intensity has followed a declining trend, suggesting improvements in energy efficiency or structural changes in the economy.

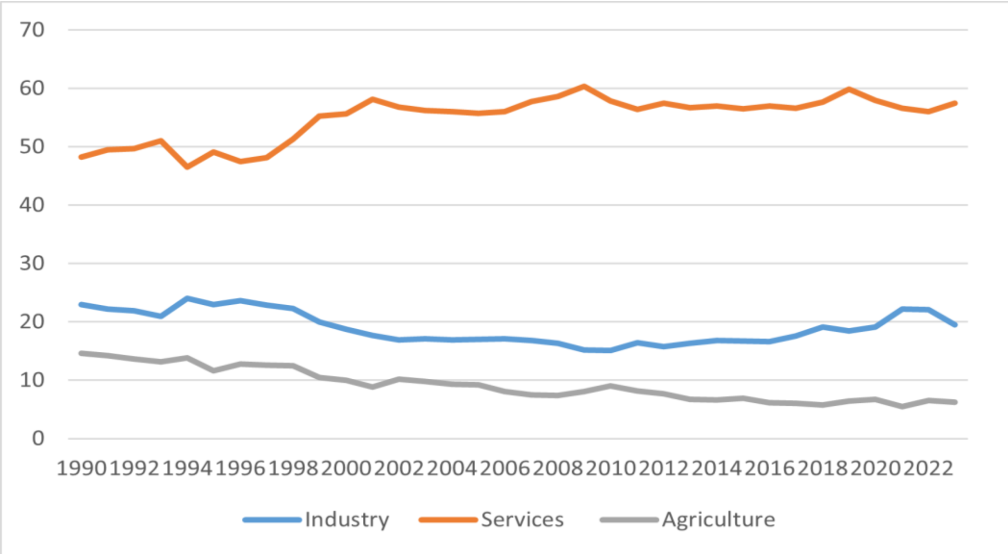

Figure 2: Total Production Shared by Sectors in Percentage

Note: We selected the industry, services, and agriculture sectors since they represent the main components of total production in the economy, allowing for a comparison of structural changes over time. Data Sources: World Development Indicator (WDI) and TSI

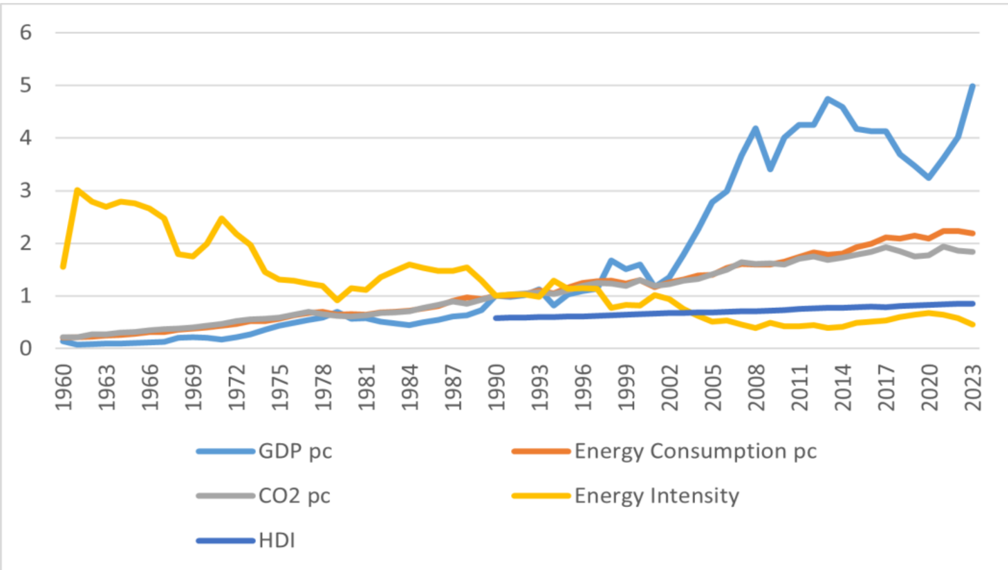

Figure 3: Changes in GDP pc, CO_2 pc, HDI, EC pc, and EI from 1960 to 2023

Note: The data is normalized to 1990 levels. Data sources: TSI, SPO, IEA, Central Bank of Türkiye (CBT), United Nations Development Program (UNDP), WDI

Türkiye's demographic growth and geographic position have influenced its energy consumption and economic development. The data indicate long-term economic growth, increasing energy consumption, and declining energy intensity, showing improvements in energy efficiency. At the same time, rising CO_2 highlights the continuing challenge of balancing economic growth with environmental concerns.

3. Literature Review

This literature review synthesizes research across five interconnected themes: (i) empirical patterns and determinants of energy usage and energy intensity, highlighting its role as a key indicator of energy efficiency and sustainability; (ii) IDA particularly the LMDI, as a method for disentangling the effects of activity, structural change, and efficiency improvements on energy use; (iii) EEKC and EKC hypotheses, which posit non-linear relationships between economic development, energy use, and environmental quality; (iv) applications of ARDL approach to capture the short and long-run dynamics between energy intensity and its economic, structural, and environmental drivers; and (v) evidence from Türkiye, shaped by the country's energy policies, structural transformation, and sectoral composition. These strands provide the conceptual and methodological foundation for investigating the determinants of energy usage and intensity.

3.1 Energy Usage and Energy Intensity

Energy intensity, defined as the amount of energy used per unit of GDP, is a main indicator for assessing energy efficiency and its relevance to development. Farrell[21] introduced the concept of energy efficiency, emphasizing the importance of maintaining or increasing output while reducing energy use. Subsequent studies have highlighted how technological progress, higher-quality fuels, and structural shifts toward less energy-intensive sectors, such as services, have contributed to declines in energy intensity, thereby easing growth constraints.[22,23]

Empirical studies indicate that the relationship between energy intensity and economic growth varies across stages of development. In high-income countries, growth is accompanied by relatively small increases in energy demand. In contrast, in emerging economies, growth is initially associated with rising energy use before intensity declines.[24] The rate of decline slows once per capita income surpasses a certain threshold.[25] A 1% reduction in energy intensity has been linked to a 0.5%–1.0% increase in GDP per capita growth, while a 1% increase in the share of renewable energy has been found to slightly reduce growth.[26] Historical patterns support this transition: in the 1970s, developing countries exhibited an elasticity of per capita energy use greater than 1, indicating rapid growth in consumption in tandem with income growth.[27] By contrast, recent evidence from 99 countries over four decades shows elasticity below one, indicating a general decline in energy intensity as economies expand.[28]

Several studies have examined the long-run dynamics of energy intensity. Csereklyei et al.[28] find a global pattern where energy use rises with income, but at a slower rate (elasticity of around 0.7), leading to a decline in intensity in most growing economies. They also identify unconditional and conditional convergence in energy intensity, with countries tending toward a common long-run path. At the microeconomic level, higher energy efficiency is associated with increased productivity. Firm-level evidence from 29 developing countries shows that lower energy intensity is associated with higher total-factor productivity (TFP), suggesting that efficiency gains support technological progress and industrial competitiveness.[4]

Over two centuries, Agovino et al.[3] decompose total energy intensity into traditional and modern components for Sweden, the Netherlands, Italy, and Spain. They identify a U-shaped pattern in overall intensity, with early declines driven by traditional energy use and later increases linked to the adoption of modern energy sources. Traditional energy steadily declines, while modern energy follows an inverted U-shape, highlighting the importance of distinguishing energy types in long-run analyses. Similarly, Galli[29] reports an inverted U-shaped relationship between energy intensity and income, suggesting that economic development, structural change, and technological innovation jointly drive long-term efficiency gains.

Stern[23] argues that energy is a fundamental input in growth models and cannot be fully substituted by other factors, even when efficiency improves. Declines in energy intensity often reflect advances in fuel quality and technology, yet energy availability constrains long-term output. This view highlights the importance of focusing on total energy consumption rather than energy intensity.

3.2 Index Decomposition Analysis

IDA is a widely used methodology in empirical energy economics for examining the drivers of changes in energy consumption and intensity across countries, sectors, and periods. Developed as a top-down alternative to Structural Decomposition Analysis (SDA), it requires fewer data inputs and is well-suited for macroeconomic and sectoral studies where input–output tables are unavailable.[11,15,30–32]

A key advancement in IDA was the introduction of the LMDI method by Ang[11,12] and its further development by Ang and Goh[14], which has become widely used in the literature. LMDI is recognized for its properties of perfect decomposition (no residual term), path independence, aggregation consistency, and robustness in handling zero or negative values. These features make it a reliable tool for decomposing changes in energy consumption into output, structural, and efficiency components.[33]

Sun[34] developed early models for the complete decomposition of energy intensity, while Zhao et al.[35] reviewed over 100 studies and documented the shift from SDA to IDA, mainly due to the advantages of LMDI. Ang[14] Later, critics of the energy-to-GDP ratio as a proxy for efficiency proposed the Composite Energy Intensity (CEI) index as a more accurate measure, which requires disaggregated methods such as LMDI.

IDA and LMDI have been widely applied to study energy use and CO_2 emissions.[31,36] Wang et al.[37] applied the LMDI method to China's CO_2 from 1957 to 2000 and found industrial restructuring and output growth to be key drivers. Wu et al.[38] extended this analysis using panel data to capture provincial variation, highlighting the importance of both structural and efficiency effects. Wang et al.[39] examined China's industrial sector and reported that efficiency improvements increasingly outweighed structural effects over time.

3.3 Environmental Kuznets and Energy–Economic Kuznets Curves

The EKC suggests that pollution rises with income in the early stages of development but declines as regulations strengthen, technologies advance, and demand for cleaner production increases.[8] Empirical evidence is mixed: some studies confirm the pattern in OECD and middle-income countries, where renewable adoption is growing, while others find no turning point in developing economies constrained by technological or institutional factors.[40–43] Critics contend that EKC analyses often suffer from methodological shortcomings, placing excessive emphasis on income and neglecting structural and institutional determinants.[1,44,45]

The EEKC posits an inverted U-shaped relationship between energy consumption and GDP, where energy use rises in the early stages of development, peaks, and then declines as efficiency improves, cleaner technologies are adopted, and economies shift toward less energy-intensive sectors. Empirical findings are mixed: some high-income or resource-rich countries experience declining energy intensity after reaching a certain income threshold, while others, particularly those undergoing structural transition, show no clear turning point.[9,10,46]

3. 4 Autoregressive Distributed Lag Model

The ARDL model, developed by Pesaran et al.[16] is widely applied to study long-run and short-run terms. Unlike traditional cointegration methods, such as those of Engle & Granger[47] or Johansen[48], ARDL can accommodate variables with mixed integration orders without requiring pre-testing for stationarity.[17,49] Through its error correction model, the ARDL framework distinguishes between long-run equilibrium and short-run adjustments, while also estimating the speed of convergence.[18,50]

Numerous studies have employed the ARDL framework to investigate the relationships between energy, growth, and the environment, confirming its robustness across diverse contexts.[51,52,3,53,54] Beyond the energy-growth nexus, ARDL has been applied in diverse fields, including foreign direct investment and trade[55], infrastructure[56], tourism[57], health expenditure[58], immigration[59], and monetary policy[60].

3.5 Evidence from Türkiye

In Türkiye, studies applying IDA have examined the sectoral drivers of energy use and CO_2 emissions. Ataman[32] demonstrates that efficiency gains and structural shifts from industry to services led to a reduction in energy intensity after the 1990s, although rising economic activity remained the dominant factor driving demand growth. Özdemir[61] decomposes electricity-related CO_2 emissions and finds that improvements in efficiency partly offset the impact of industrial expansion, while structural change played a more limited role. These findings highlight the significance of efficiency and structural dynamics in shaping Türkiye's energy trajectory, providing a foundation for further analysis that integrates IDA with econometric approaches.

ARDL-based studies in Türkiye examined long-run relationships between energy consumption, economic growth, and environmental indicators. Halicioglu[52] analyzed residential energy demand and found that income and prices had a greater impact on consumption in the long run than in the short run. Ozturk and Acaravci[42] reported a long-run relationship between CO_2 emissions, energy use, and GDP, with bidirectional causality between energy consumption and income. Adebayo et al.[62] included renewable energy in the analysis and found that renewables reduced emissions but did not change total energy demand.

Evidence for the EKC in Türkiye is mixed. Bilgili et al.[43] found an inverted U-shaped relationship when renewable energy was included, indicating that clean energy adoption reduced emissions at higher income levels. Akbostancı et al.[41] and Tutulmaz[63] identified N-shaped or monotonically increasing patterns for CO_2 emissions, challenging the general validity of the EKC. Halicioglu[52] showed that income alone did not generate environmental improvements without supportive policies and technological progress.

We observe that, despite a growing body of literature on energy intensity, IDA, and environmental-economic linkages in Türkiye, several important gaps remain. Most existing studies focus either on decomposition analysis or on econometric modeling, but few integrate both approaches to provide a comprehensive understanding of the sectoral and macro-level drivers of energy use. We also note that while the ARDL model has been widely applied to analyze energy consumption and emissions, many studies neglect the role of renewable energy shares or fail to explicitly test the EEKC hypothesis. In our study, we bridge these gaps by combining the LMDI-based Index IDA with the ARDL-ECM framework, allowing us to evaluate both the structural components and dynamic relationships that drive energy usage. By including renewable energy, testing the EEKC and EKC hypotheses, and applying robustness checks, we offer a more nuanced and policy-relevant contribution to the literature on Türkiye's energy environment growth nexus.

4 Data

We compiled annual data for Türkiye from multiple sources, covering the period from 1960 to 2023. The dataset includes economic, energy, environmental, and socio-demographic indicators for econometric and decomposition analyses. We provide a summary statistics table in Appendix Section A.

We obtained macroeconomic indicators from TSI and CBT, including GDP in current USD.[9],[10] We also collected sectoral GDP data for agriculture, industry, and service sectors (excluding construction, taxes, and subsidies) from TSI, the Turkish Ministry of Energy and Natural Resources (TME)[11], and the SPO to ensure consistency across structural components. GDP data are gotten PPP adjusted values from CBT.

We retrieved sectoral energy consumption data (agriculture, industry, transport, residential, and commercial), measured in kilotons of oil equivalent (ktoe), from the IEA. We also obtained complementary indicators such as energy consumption pc (kWh) and total energy usage (TWh) from Our World in Data (OWID)[12]. To ensure metric consistency across datasets, we standardized all energy consumption data using the following conversion factors:

$$1\text{ktoe} = 11{,}630{,}000\text{kWh}, \qquad 1\text{ktoe} = 41.868\text{TJ}$$

We sourced renewable energy share data from OWID, capturing the share of renewables in total primary energy production. This share includes hydropower, solar, wind, geothermal, bioenergy, and marine sources, calculated using the substitution method. We obtained CO_2 data, both total (in million tons) and per capita (in tons), from OWID.

Due to methodological inconsistencies in published energy intensity metrics, we used the data from OWID, but also computed energy intensity directly as:

$$Energy\ intensity = \frac{Primary\ Energy\ Consumption}{GDP}$$

[9] https://www.tuik.gov.tr/Home/Index
[10] https://www.tcmb.gov.tr/
[11] https://www.enerji.gov.tr/homepage
[12] https://ourworldindata.org/energy/country/Türkiye

We retrieved population data from the World Bank (WB)[13]. We also included the HDI from the UNDP to provide a broader socio-economic context.[14], which reflects quality-of-life factors that influence energy demand and environmental outcomes.

5 Methodology

We adopt an integrated approach combining decomposition and econometric methods to analyze energy usage in Türkiye. First, we apply the LMDI method within the IDA framework to examine how sectoral shifts and changes in energy usage across industries, services, and agriculture have affected overall energy consumption between 1990 and 2023. Second, we estimate a baseline OLS model to explore the relationships among energy consumption, economic growth, CO_2 emissions, and the share of renewable energy, using diagnostic tests to verify data consistency. Third, we employ the ARDL model to analyze both the long-run equilibrium and short-run dynamics among key variables, using annual data from 1960 to 2023. Finally, we test the EKC and EEKC hypotheses to assess whether Türkiye's energy and environmental trends follow nonlinear income effects.

5.1 Index Decomposition Analysis

Decomposition techniques in energy analysis are generally classified as SDA and IDA. SDA helps separate direct and indirect energy use but requires detailed input-output tables, which are often unavailable.[31] IDA is more flexible and can be applied to data at different levels of aggregation, making it suitable for time-series analysis.[64]

Within IDA, the two main approaches are the Divisia Index (DI) and the Laspeyres Index (LI). The LMDI, a form of the DI, is widely used because it achieves complete decomposition without residuals, handles zero and negative values, and ensures consistent aggregation across different levels of analysis.[11,12] Its path independence also makes it useful for studying policy-driven changes in energy demand, such as taxes or subsidies.[14]

For this study, we applied the LMDI method to examine changes in energy usage across Türkiye's major sectors (industry, services, and agriculture) from 1990 to 2023.[15] The LMDI's path independence and consistent aggregation

[13] https://data.worldbank.org/indicator/

[14] https://hdr.undp.org/en/content/human-development-index-hdi

[15] We focus on industry, services, and agriculture because they represent the core sectors of economic activity and together account for nearly all energy use in Türkiye. Analyzing these three sectors captures the main structural shifts in the economy while maintaining a simple and tractable framework.

properties allow for a detailed breakdown of sectoral contributions to overall energy intensity trends. Total energy consumption can be expressed as[16]:

$$E_t = \sum_i Y_t \frac{Y_{i,t}}{Y_t}\frac{E_{i,t}}{Y_{i,t}} = \sum_i Y_t S_{i,t} I_{i,t} \tag{1}$$

where E_t is the total energy consumption in year t, $E_{i,t}$ is the energy consumption in sector i in year t, Y_t is total production in year t, and $Y_{i,t}$ is the production of sector i in year t. $S_{i,t}$ and $I_{i,t}$ represent the sectoral production share ($S_{i,t} = Y_{i,t}/Y_t$) and sectoral energy intensity ($I_{i,t} = E_{i,t}/Y_{i,t}$), respectively.

The change in total energy consumption (ΔE_{tot}) between a base year (0) and year t can be decomposed as follows:

$$\Delta E\text{tot} = Et - E0 = \Delta E\text{out} + \Delta E\text{str} + \Delta E\text{int} \tag{2}$$

where the output effect (ΔE_{out}), structural effect (ΔE_{str}), and intensity effect (ΔE_{int}) are defined as:

$$\Delta E\text{out} = \sum_i W_{i,t}\, ln(\frac{Y_t}{Y_0}) \tag{3}$$

$$\Delta E\text{str} = \sum_i W_{i,t}\, ln(\frac{S_{i,t}}{S_{i,0}}) \tag{4}$$

$$\Delta E\text{int} = \sum_i W_{i,t}\, ln(\frac{I_{i,t}}{I_{i,0}}) \tag{5}$$

These effects collectively describe the overall change in energy consumption (ΔE_{tot}):

$$\Delta E\text{tot} = \sum_i W_{i,t}\, ln(\frac{Y_t}{Y_0}\frac{S_{i,t}}{S_{i,0}}\frac{I_{i,t}}{I_{i,0}}) \tag{6}$$

where W_{it} is the LMDI weighting matrix, given by:[17]

$$W_{i,t} = \mathrm{L}(E_{i,t}, E_{i,0}) = \frac{(E_{i,t} - E_{i,0})}{ln(E_{i,t}) - ln(E_{i,0})} \tag{7}$$

This framework decomposes total energy consumption into the contributions of output, sectoral structure, and energy intensity over time. A detailed derivation of the IDA is provided in Appendix B.

5.2 OLS Analysis

[16] In our analysis, we use the formula (Equation 1) developed by Ang[11,12] to combine multiple factors when examining relationships between variables. This method captures how these factors jointly influence the outcomes.

[17] The logarithmic mean function $L(x,y)$ is defined for $x \neq y$ and $x,y > 0$ as: $\mathrm{L}(x,y) = \frac{x-y}{ln(x) - ln(y)}$

We estimate an OLS model (log-log) to examine the relationship between energy consumption, GDP, renewable energy, and CO_2 emissions, following Galli[29], Agovino et al.[3], and Makuteniene et al.[10]. While our main estimation method is the ARDL approach, the OLS model is used as a robustness check for our econometric analysis and data.

$$\ln(EC_{pc}) = \beta_0 + \beta_1 ln(GDP_{pc})_t + \beta_2 ln(GDP_{pc}^2)_t + \beta_3 ln(Renew)_t + \beta_4 ln(CO_{2_{pc}})_t + \varepsilon_t \quad (8)$$

where EC_{pc} is energy consumption per capita, GDP_{pc} is GDP per capita, Renew is the ratio of renewable energy to total energy production, and $CO_{2_{pc}}$ is CO_2 emissions per capita. All variables are expressed in natural logarithms to facilitate the measurement of elasticities and mitigate heteroskedasticity. The squared GDP term tests for a possible non-linear relationship between income and energy use. The error term ε_t is assumed to have zero mean and constant variance.

Although equation (8) is our baseline model, we apply several transformations and diagnostic tests (explained in later sections) to ensure it meets the assumptions of the classical linear regression model.

To ensure the reliability of our OLS estimates, we applied:

- Variance Inflation Factors (VIF) test for multicollinearity.
- The Breusch–Pagan test for heteroskedasticity. However, we use robust standard errors while running a regression.
- Durbin–Watson statistics for first-order autocorrelation. We applied Prais–Winsten estimation to test for serial correlation.

5.3 ARDL Analysis

We used the ARDL approach to analyze both short-run dynamics and long-run relationships among the variables. ARDL can handle variables with different integration orders and selects the optimal lag structure using the Akaike Information Criterion (AIC).[3,18,29,50]

Let us write the equation for our ARDL model as follows:

$$\ln(EC_{pc})_t = \beta_0 + \beta_1 ln(GDP_{pc})_t + \beta_2 ln(GDP_{pc}^2)_t + \beta_3 ln(Renew)_t + \beta_4 ln(CO_{2_{pc}})_t + \varepsilon_t \quad (9)$$

In the ARDL model, β_0 represents the intercept, and β_i is the slope coefficient of a linear time trend. All variables are expressed in natural logarithms unless otherwise specified. The error term ε_t is assumed to be identically and independently distributed (i.i.d.) with zero mean and constant variance.

Estimating the coefficients in equation 9 can give misleading results if the variables are nonstationary. Non-stationary in $\ln(EC_{pc})$ and its regressors can carry over to the residuals ε_t, causing spurious regression even when no real long-run relationship exists. However, equation 9 is valid if the variables are cointegrated. Even if $\ln((EC_{pc})_t$ and its regressors are integrated of order one, I(1), the model represents a meaningful long-run relationship if there is a linear combination of them that produces stationary residuals ε_t, integrated of order zero, I(0).[18] If cointegration holds, the variables share a common trend, and short-run deviations from equilibrium are temporary. Without cointegration, regression inference may be invalid because of non-stationarity and omitted short-run dynamics.

The ARDL model is particularly useful because it accommodates variables with different orders of integration, enabling us to test both short-term and long-term relationships between the variables. If a long-run relationship is found, the ECM will be used to capture the speed of adjustment toward equilibrium after short-term deviations.

5.3.1 Unit Root Test

We first conduct unit root tests to examine whether each series is stationary, using the Augmented Dickey-Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tets. If a series is non-stationary, the model is adjusted accordingly. In time-series analysis, variables must be either stationary or cointegrated; otherwise, regression results may be spurious. A stationary series has constant statistical properties, such as a zero mean and constant variance, whereas a non-stationary series exhibits persistent trends that must be addressed in the modeling process.

5.3.2 ARDL Cointegration Procedure

We employ the ARDL bounds test to examine the long-run relationship among the variables. This test is suitable when variables are a mix of I(0) and I(1). It involves estimating an ARDL model with lagged terms of the dependent and independent variables and then applying F-tests to the lagged independent variables.

The rules of the decision are:

- If the F-statistics are above the upper bound (I(1)), we reject the null hypothesis and conclude there is a long-run relationship.
- If it is below the lower bound (I(0)), we fail to reject the null hypothesis, meaning no cointegration, and we estimate only the short-run relationship.

- If it lies between the bounds, the result is inconclusive.

If cointegration is found, the variables share a long-run relationship, meaning they move together over time despite short-term fluctuations.[18]

5.3.3 Error Correction Model

The ECM is employed when a long-run relationship exists among the variables. It captures the speed of adjustment toward equilibrium after short-term shocks. The ECM expresses the variables in differences while including an error correction term, which helps remove trends that could otherwise distort the regression results.

We specify the ECM model in Equation 10 as follows:

$$\Delta\ln(EC_{pc})_t = \beta_0 + \beta_1\Delta(GDP_{pc})_t + \beta_2\Delta(GDP^2_{pc})_t + \beta_3\Delta(Renew_{pc})_t + \beta_4\Delta(CO_{2_{pc}})_t + \sum_i^p \gamma_i\Delta\ln(EC_{pc})t - I + \sum_i^q \rho_i\Delta(GDP_{pc})_{t-i} + \sum_{i=0}^r \delta_i\Delta(Renew_{pc})_{t-i} + \sum_{i=0}^s \theta_i\Delta(CO_{2_{pc}})_t + \epsilon_t \quad (10)$$

where Δ represents the first difference of each variable, capturing the short-run dynamics. The lagged terms $\Delta\ln(EC)_{t-i}$, $\Delta\ln(GDPpc)_{t-i}$, $\Delta\ln(CO_2pc)_{t-i}$, and Δ(Renewable)$_{t-i}$ are included to capture the influence of past values on current values. The ARDL model allows for different lag lengths for each variable (p,q,r,s), which will be determined based on model selection criteria. The disturbance term $\varepsilon_t \sim$ is i.i.d.

5.3.3 Model Diagnostics and Specification Tests

After estimating the ARDL model, we conduct several diagnostic tests to verify model specification, autocorrelation, and heteroskedasticity.

- **Autocorrelation Test:** The Breusch-Godfrey test is conducted to ensure that there is no serial correlation in the residuals.
- **Heteroskedasticity Test:** Breusch–Pagan/Cook–Weisberg test is performed to check for any heteroskedasticity in the residuals.
- **Stability of the Model:** The CUSUM and CUSUMSQ tests are used to test the stability of the regression coefficients over time.

These diagnostic tests are essential for verifying the robustness of the ARDL model, ensuring that the results can be interpreted more accurately.

5.4 Analyzing the EEKC and the EKC

To examine whether Türkiye follows the EEKC and EKC hypotheses, we analyze the sign and significance of the GDP coefficients, focusing on the income levels at which energy consumption and CO_2 emissions reach their respective peaks.

We begin by analyzing energy consumption as a function of GDP to test for the EEKC relationship, formulated as:

$$\ln(EC_{pc}) = \beta_0 + \beta_1 ln(GDP_{pc})_t + \beta_2 ln(GDP_{pc}^2)_t + \epsilon_t \qquad (11)$$

where, $\ln(EC_{pc})$ is the natural logarithm of energy consumption pc, $\ln(GDPpc)_t$ is the natural logarithm of GDP pc , ϵ_t (i.i.d) with $\epsilon_t \sim N(0,\sigma^2)$.

The turning point of GDP, where energy consumption reaches its maximum, is given by:

$$GDP_{pc}^* = \frac{\partial ln(EC_{pc})}{\partial ln(GDP)_{pc}} = -\frac{\beta_1}{2\beta_2} \qquad (12)$$

- If $\beta_2 < 0$, the relationship is inverted U-shaped, indicating that energy consumption first increases with economic growth and then decreases after a certain GDP threshold, supporting the EEKC hypothesis.

- If $\beta_2 > 0$, the relationship is U-shaped, indicating no EKC relationship.

Thus, if $\beta_2 < 0$, our findings would support the EEKC hypothesis, suggesting that economic growth initially drives higher energy consumption, but beyond a certain GDP threshold, energy consumption declines as economies transition to more efficient energy use.

Next, we test for a similar relationship between GDP and CO_2 emissions, hypothesizing that energy consumption leads to higher CO_2 emissions. We propose the following equation:

$$\ln(CO_{2_{pc}}) = \alpha_0 + \alpha_1 ln(GDP_{pc})_t + \alpha_2 ln(GDP_{pc}^2)_t + \epsilon_t \qquad (13)$$

where, $\ln(CO_{2_{pc}})$ is the natural logarithm of CO_2 pc, ϵ_t is the new stochastic disturbance term.

The turning point for CO_2 pc where emissions reach their maximum is given by:

$$ln(CO_{2_{pc}}))^* = \frac{\partial ln(CO_{2_{pc}})}{\partial ln(CO_{2_{pc}})} = -\frac{\alpha_1}{2\alpha_2} \qquad (14)$$

- If $\alpha_2 < 0$, the relationship between GDP and CO_2 emissions is inverted U-shaped, indicating that higher GDP initially leads to more emissions, but after a certain threshold, emissions begin to decrease.

- If $\alpha_2 > 0$, the relationship is U-shaped, suggesting no EKC relationship for CO_2 pc.

By testing both equations, we assess the EEKC and EKC hypotheses for EC pc and CO_2 pc in Türkiye. Energy consumption is considered a primary driver of CO_2 emissions. The results show that economic growth initially increases energy consumption and emissions, but beyond a certain GDP per capita level, it leads to declines due to technological progress and more efficient energy use.

6. Results

Our results are presented in the IDA, where we examine the contributions of different components to changes in energy consumption, and the regression analysis, which includes the OLS estimations, the EEKC and EKC tests, and the ARDL model.

6.1 Index Decomposition Analysis Results

IDA reveals the impact of production, structural, and intensity effects on total energy use in Türkiye.

Table 2: Index Decomposition Analysis' Results

Period	Change of Energy Consumption	Production Effect	Structural Effect	Intensity Effect
1990-1994	2628	3003	-526	151
1995-1999	-4588	211	-3649	-1150
2000-2004	-3075	2083	-1907	-3251
2005-2009	4541	5629	-1979	891
2010-2014	7704	10495	889	-3680
2015-2019	4924	5014	843	-933
2020-2023	-2127	1554	-748	-2933
1990-2023	10007	27992	-7079	-10905

Note: Values are in kilotons of oil equivalent (ktoe). Data Source: TSO, SPO, WDI, OWID, IEA

Table 2 presents the changes in energy consumption across five-year periods from 1990 to 2023. Over this period, growth in production contributed to an increase of around 28,000 ktoe in energy consumption. In contrast, the structural effect reduced energy use by about 7,000 ktoe, while the intensity effect lowered it by roughly 11,000 ktoe. Overall, the combined influence of these three factors resulted in a net increase of around 10,000 ktoe in total energy consumption, indicating that the production effect outweighed the reductions from structural changes and improvements in energy intensity in Türkiye.

Figure 4 shows the percentage contributions of the production, structural, and intensity effects on energy consumption from 1990 to 2023. The production effect contributed to about an 87% increase in energy consumption, reflecting growth in economic activity and output. The structural effect contributed to a decrease of approximately 14%, indicating a shift toward less energy-intensive industries and services. The intensity effect contributed to a decrease of approximately 21%, primarily due to improvements in energy efficiency and technology.

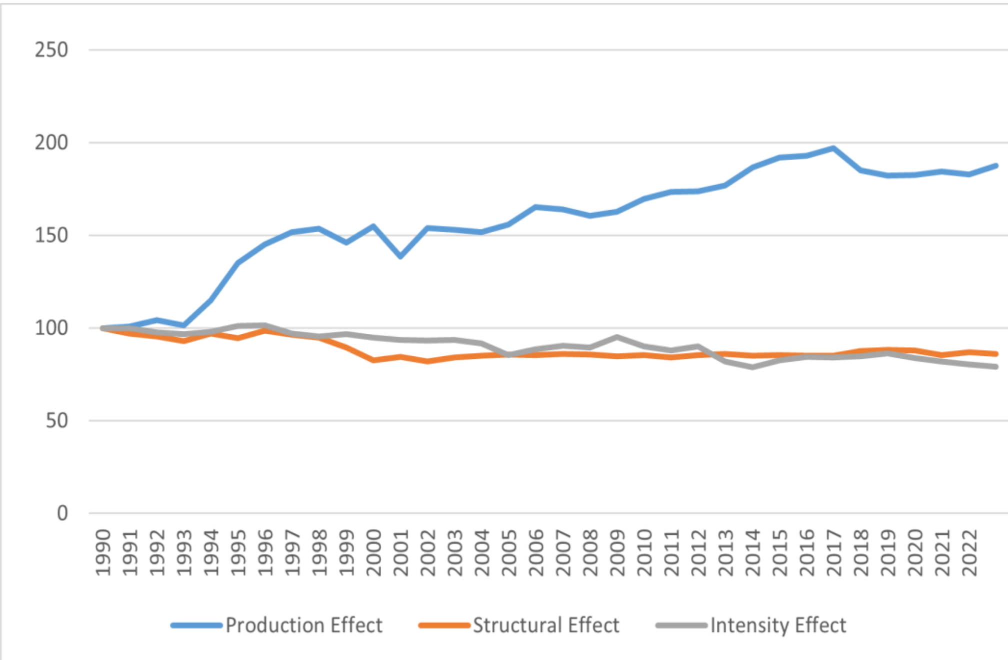

Figure 4: Decomposition of Energy Consumption Changes Over Time

Data Sources: TSI, SOP, IEA, CBT, UNDP

Together, the structural and intensity effects offset part of the increase in energy consumption driven by production growth. Their combined impact reduced energy consumption by about 35% compared to a scenario where structure and intensity remained unchanged. Without these improvements, energy use would have been nearly one-third higher. This highlights the role of efficiency gains and shifts toward less energy-intensive sectors in limiting energy consumption.

6. 2 OLS Results

We first estimate an OLS model to provide a linear specification of the relationship between energy consumption, income, carbon emissions, and the share of renewable energy. This serves as a benchmark for comparison with subsequent estimation results.

Table 3 presents the OLS estimation results. All explanatory variables are statistically significant. The natural logarithms of GDP pc and its squared term, the renewable energy share, and CO_2 pc exhibit strong associations with energy consumption. Robust standard errors are reported in parentheses.

Table 3: OLS Estimation Results (Log-Transformed)

Variables	Model 1	Model 2	Model 3	Model 4
GDP pc	0.532***	1.206***	1.176***	0.198***
	(0.015)	(0.143)	(0.133)	(0.092)
GDP pc²		-0.045***	-0.044***	-0.009*
		(0.009)	(0.008)	(0.005)
Renewable Share			0.260***	0.135***
			(0.065)	(0.031)
Resid CO_2 pc				0.934***
				(0.049)
Constant	5.005***	2.524***	2.104***	6.986
	(0.119)	(0.535)	(0.481)	(0.375)
Observations	64	64	64	64
R-squared	0.958	0.967	0.974	0.996
F-statistic	1208	830.30	628.45	3261.72
VIF	1.00	163.422	109.434	137.394
Durbin–Watson	2.266	2.254	2.215	1.142

Notes: All variables are expressed in natural logarithms. The dependent variable is log EC pc. Models (1) through (4) progressively introduce GDP pc, its squared term, the renewable energy ratio, and CO_2 pc. Robust standard errors are reported in parentheses. Formal heteroskedasticity test results are not reported, as robust estimators were used throughout to ensure valid inference regardless of variance structure. VIF indicates multicollinearity, with higher values suggesting potential collinearity problems. The Durbin–Watson statistic tests for autocorrelation in the residuals *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Data Source: TSI, SPO, OWID, WDI, IEA

Although the models exhibit high explanatory power, with R-squared values ranging from 0.96 to 0.99, the diagnostics raise concerns. The VIFs in columns (2) and (4) exceed conventional thresholds, indicating multicollinearity among regressors. The Durbin–Watson statistics are also well below 2, suggesting positive autocorrelation in the residuals.

Table 4: OLS Estimation Results (Mean-Centered Approach)

Variables	**(Model 1)**	**(Model 2)**	**(Model 3)**	**(Model 4)**
	OLS	OLS	OLS	OLS
GDP pc	0.532***	0.516***	0.491***	0.516***
	(0.015)	(0.014)	(0.014)	(0.005)
GDP pc²		-0.045***	-0.044***	-0.009*
		(0.009)	(0.008)	(0.005)
Renew			0.260***	0.135***
			(0.065)	(0.031)
Resid CO_2 pc				0.934***
				(0.049)
Constant	0.000	0.069***	0.069***	0.013
	(0.018)	(0.021)	(0.018)	(0.010)
Observations	64	64	64	64
R-squared	0.958	0.967	0.974	0.996
F-statistic	1260	830	628.45	3261.72
VIF	1.00	1.09	1.28	1.42
Durbin–Watson	2.266	2.254	2.215	2.225

Notes: All variables are log-transformed and mean-centered. Each column presents a sequential model specification for explaining EC pc. Model (1) includes log GDP pc; Model (2) adds GDP pc squared term; Model (3) includes the renewable energy ratio; and Model (4) introduces Residual CO_2, derived from a separate regression of CO_2 on exogenous variables and used here as a proxy for unobserved environmental degradation. This approach isolates the portion of CO_2 not explained by economic and energy variables, allowing the model to capture latent environmental influences without introducing endogeneity. Durbin-Watson statistics are based on Prais-Winsten estimation. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Data sources: TSI, SPO, WDI, IEA

Table 4 reports the OLS estimates using log-transformed and mean-centered variables to reduce multicollinearity. CO_2 pc are included in Model 4 as residuals from a separate regression to capture unobserved factors related to energy consumption. GDP pc, its squared term, and the renewable energy ratio are statistically significant across specifications. The R-squared values range from 0.958 in Model 1 to 0.996 in Model 4. Robust standard errors are provided. Mean-centering reduces collinearity between GDP pc and its squared term, as shown by the lower VIF values (1.00–1.42). The Durbin–Watson statistics (2.215–2.266) from the Prais–Winsten estimation indicate no autocorrelation.

Table 5: OLS Estimates for the EEKC and EKC Hypotheses

	Model 1	**Model 2**	**Model 3**	**Model 4**
GDP pc	1.206*** (0.143)	0.516*** (0.014)	1.063*** (0.142)	0.321*** (0.007)
GDP pc^2	-0.045*** (0.009)	-0.045*** (0.009)	-0.038*** (0.009)	-0.001 (0.006)
Constant	2.524*** (0.535)	0.069*** (0.021)	-5.010*** (0.540)	0.001 (0.015)
Observations	64	64	64	64
R-squared	0.967	0.967	0.967	0.969

Notes: This table presents OLS regression results testing the EEKC and EKC hypotheses using GDP pc and its squared term as explanatory variables. Models (1) and (3) use log-transformed variables, while Models (2) and (4) apply mean centering. The dependent variable is EC pc in Models (1) and (2), and CO_2 pc in Models (3) and (4). Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.; Data sources: TSI, SPO, WDI, IEA

In Table 4, Model 1, GDP pc has a positive and significant effect on EC pc (0.532). In Model 2, adding the squared GDP pc term slightly increases the coefficient on GDP per capita to 0.516, while the squared term is negative and significant (−0.045), indicating a non-linear relationship. This pattern persists in Models 3 and 4, although the GDP pc coefficients decline slightly as additional controls are added. The renewable energy ratio, included in Model 3, is positive and significant (0.260) and remains significant in Model 4 (0.135), suggesting a mild rebound effect where renewable adoption lowers marginal energy costs and indirectly stimulates consumption[65].[18]

[18]The rebound effect refers to a behavioral or economic response in which improvements in energy efficiency or access to low-cost renewable energy lead to increased overall energy consumption, thereby offsetting some of the anticipated environmental benefits. We reference this concept as a potential explanatory mechanism discussed in recent literature. For instance, Oliver et al. (2024) examine the *"solar rebound"* effect under net metering schemes and show that reduced marginal energy costs can induce higher total energy use. Although direct empirical evidence for such an effect in Türkiye is lacking, the framework remains conceptually relevant for understanding how expanded renewable capacity might alter energy consumption patterns.

6.3 EEKC and EKC Results

We tested the EEKC hypothesis (Energy usage–GDP pc relationship) and the EKC hypothesis (CO_2 pc–GDP pc relationship) to examine their respective relationships.

Table 5 presents the OLS estimation results for testing the EEKC (EC pc-GDP pc) and EKC (CO_2 pc–GDP pc) hypotheses. Columns (1) and (2) use EC pc as the dependent variable, while Columns (3) and (4) use CO_2 pc. Models (1) and (3) apply log-transformed variables, whereas Models (2) and (4) use mean-centered regressors to reduce multicollinearity and improve the interpretation of coefficients. In each specification, GDP pc and its squared term are included to assess potential non-linear effects of income on energy use and environmental outcomes.

Across all four models, the coefficient on GDP pc is positive and significant, indicating that economic growth is associated with higher energy use and emissions. The squared term is negative and statistically significant in Models (1) through (3), supporting the existence of an inverted U-shaped relationship, consistent with the EEKC and EKC hypotheses. This suggests that beyond a certain income threshold, further economic growth may lead to reductions in energy use or CO_2 emissions.

6.4 ARDL Results

For our time series analysis, we employed the ARDL approach. We first conducted unit root tests to assess the stationarity of the data. Subsequently, we applied the bounds test to examine the presence of cointegration among the variables. Finally, we estimated the ECM to examine the short-run relationships and the adjustment of variables toward the long-run equilibrium.

6.4.1 Unit Root Test Result

In time series analysis, variables must be either stationary or cointegrated. A stationary series has constant statistical properties, such as mean and variance. A non-stationary series, by contrast, does not maintain these properties, which can produce spurious results and lead to misleading conclusions.

Hypotheses:

- **H_0**: The time series has a unit root.
- **H_1**: H_0 is not true.

This explanation is therefore offered as a plausible, though not conclusive, channel warranting further empirical study.

Table 6 presents the ADF unit root test and KPSS results for each variable at both levels and in first differences, using both intercept and trend-intercept specifications. At levels, most test statistics are above the 5% critical value, indicating non-stationarity. After the first difference, all variables have test statistics below the critical values (in absolute terms), confirming that they are stationary in their differences. Thus, all variables are integrated in order one, I(1).

Table 6: Unit Root Test Results

Variable	ADF Intercept (Level)	ADF Trend and Intercept (Level)	ADF Intercept (First Difference)	ADF Trend and Intercept (First Difference)	KPSS Level (p-values)	KPSS Trend (p-values)
EC pc	-3.525	-2.209	-4.440	-5.410	0.612	0.231
GDP pc	-1.689	-2.446	-5.181	-5.281	0.721	0.508
GDP pc	-1.080	-2.503	-4.990	-4.990	0.693	0.401
Renew	-2.526	-3.686	-7.705	-7.677	0.559	0.226
CO_2 pc	-3.887	-2.550	-5.146	-6.007	0.679	0.247

Note: The table reports Augmented Dickey–Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test statistics under both level and first-difference forms, with intercept and trend specifications. The ADF test examines the null hypothesis of a unit root (non-stationarity), whereas the KPSS test assumes stationarity under the null. All variables become stationary after first differencing, indicating they are integrated of order one, I(1). The results from both tests are consistent, as the ADF rejects non-stationarity and the KPSS fails to reject stationarity at first differences. Dickey–Fuller Critical Values: 1% = -3.565, 5% = -2.921, 10% = -2.596. P-values are shown in the table for the KPSS test. Data Sources: TSI, SPO, WDI, IEA

This finding supports the use of the ARDL framework, which is valid when variables are integrated of order zero (I(0)) or order one (I(1)). Since all variables become stationary after first differencing, it is appropriate to apply the bounds testing procedure to examine potential long-run cointegration relationships among them.

6.4.2 Bound Test Results

Cointegration among time series variables indicates a stable long-run relationship despite short-run fluctuations. Although individual series may be non-stationary, their linear combination can be stationary, showing that the variables move together over time.

If cointegration is not present, relationships are only short-term, and any long-run link is spurious, making an unrestricted ARDL suitable for capturing short-run dynamics. If cointegration is confirmed, the ARDL can be extended with an ECM to estimate both long-run relationships and short-run adjustments.

Hypotheses:

- H_0: No long-run relationship (no cointegration).
- H_1: H_0 is not true.

Table 7: Bounds Test Results

Variables (Model)	AIC lags	F-statistic	t-stat	Result
EC pc - GDP pc, GDP pc^2, CO_2 pc, Renew	1	23.475	-9.258	Conclusive
Critical Values from Pesaran, Shin & Smith and Gregory & Hansen				
Significance Level	10%	5%	2.5%	1%
Lower I(0) – Upper I(1)(ADF)	2.26–3.35	2.62–3.79	2.96–4.18	3.41–4.68
Lower I(0) – Upper I(1)(G&H)	3.19 -3.73	3.87-4.46	N\A	5.60-6.193

Note: This table presents the results of the ARDL bounds testing procedure, with all variables expressed in natural logarithms. The computed F-statistics (23.475) exceeds the upper bound critical values at the 1%, 2.5%, 5%, and 10% significance levels, based on the Pesaran, Shin, and Smith (2001) critical value bounds. This provides strong evidence in favor of a long-run cointegrating relationship. Additionally, the highly significant t-statistic (–9.258) supports the presence of a stable adjustment mechanism toward long-run equilibrium. In addition, critical values are extracted from table in Gregory and Hansen (1996, p. 109) (G&H) Data Sources**:** TSI, SPO, WDI, IEA

Table 7 reports the results of the ARDL bounds test for cointegration among energy consumption, GDP pc, squared GDP pc, CO_2 pc, and the renewable energy ratio. The model, selected based on the Akaike Information Criterion (AIC) with one lag, yields an F-statistic of 23.475, which exceeds the upper critical bounds at all significance levels, and a t-statistic of 9.258, both indicating the rejection of the null hypothesis of no long-run relationship. These results confirm the existence of a conclusive long-run equilibrium relationship among the variables.

6.4.3 ARDL Model Diagnostic Evaluation

Before interpreting the ARDL model results, diagnostic tests were conducted to assess serial correlation and heteroskedasticity. The Breusch–Godfrey LM test was used to detect serial correlation, and the Breusch–Pagan/Cook–Weisberg test was used to evaluate heteroskedasticity.

Table 8 reports the diagnostic test results for the estimated ARDL model. The Breusch–Godfrey LM test reveals evidence of first-order serial correlation, as the p-value (0.0089) rejects the null hypothesis of no autocorrelation at the 1% significance level. The Breusch–Pagan/Cook–Weisberg test, applied to detect heteroskedasticity, shows that the null hypothesis of homoskedastic residuals cannot be rejected, indicating no evidence of heteroskedasticity. Stability was further assessed using the CUSUM and CUSUM of squares (CUSUMSQ) tests, which are shown in Appendix C.

Table 8: ARDL Diagnostic Test Results

Breusch–Godfrey LM Test for Autocorrelation				
Indicators	**Lags (p)**	$\chi 2$	**df**	*p*-value
Values	1	6.852	1	0.0089
Breusch–Pagan/Cook–Weisberg Test for Heteroskedasticity				
Indicators	**Variable**	$\chi 2$	**df**	*p*-value
Assumption: Normal errors	Fitted values	0.29	1	0.589

Note: This table presents post-estimation diagnostic tests for the ARDL model. The Breusch–Godfrey LM test is used to assess serial correlation in the residuals. The result indicates the presence of first-order autocorrelation, as the null hypothesis of no autocorrelation is rejected. Meanwhile, the Breusch–Pagan/Cook–Weisberg test is applied to detect heteroskedasticity. The p-value suggests that the null hypothesis of homoscedastic residuals cannot be rejected, indicating no evidence of heteroskedasticity. Data Source: TSI, WDI, SPO, IEA

6.4.4 Error Correction Model Result

Following the confirmation of a long-run relationship among the variables through cointegration analysis, the ECM is employed to capture both the short-run and long-run dynamics of energy consumption per capita. The ECM framework enables analysis of how deviations from the long-run equilibrium are corrected over time and how explanatory variables influence energy use across different time horizons.

Table 9 presents the estimation results from the ECM derived from the ARDL model. The error correction term, represented by the lagged dependent variable L.ln(EC pc), is negative and statistically significant (–0.456), indicating that approximately 46% of any deviation from the long run equilibrium is corrected in the following period.

Table 9: Error Correction Model Result

Variables	Adjustment Term	Long-run Coefficient	Short-run Coefficient
lnGDP pc		0.130** (0.063)	
lnGDP pc²		-0.006 (0.005)	
lnCO₂ pc		0.965*** (0.105)	
lnRenew		0.137*** (0.052)	
L.lnEC pc	-0.456*** (0.096)		
D.lnGDP pc			0.017 (0.143)
LD.lnGDP pc			0.379*** (0.126)
D.lnGDP pc²			-0.001 (0.011)
LD.lnGDP pc²			-0.024*** (0.008)
D.lnCO₂ pc			0.370*** (0.119)
LD.lnCO₂ pc			0.235** (0.112)
D.lnRenew			0.379 (0.276)
LD.lnRenew			0.302 (0.236)
Constant			6.674*** (1.344)
Observations	63	63	63
R-Squared	0.756	0.756	0.756

Note: This table presents the estimation results of the Error Correction Model (ECM) derived from the ARDL framework. The lagged dependent variable (L.lnECpc) represents the adjustment term and is statistically significant and negative, confirming convergence toward long-run equilibrium. Long-run relationships are identified through the level terms, while short-run dynamics are captured by first differences and their lags. The model demonstrates a good fit with an R^2 of 0.756, and *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Data Sources: TSI, SPO, CBT

The long-run coefficients indicate how energy consumption responds to changes in the explanatory variables over the long term. Specifically, lnCO_2 pc (0.965***) and lnRenew (0.137***) have significant positive effects, implying that higher carbon emissions and a greater share of renewable energy are both associated with higher long-run energy consumption. The lnGDP pc coefficient (0.130**) is positive and significant, while the squared term lnGDP pc^2 (-0.006) is negative but insignificant, suggesting no strong evidence of nonlinearity in the long-run relationship.

The short-run coefficients capture short-term dynamics through first-differenced variables and their lags. The results show that lagged GDP growth (LD.lnGDP pc = 0.379***) and contemporaneous changes in carbon emissions (D.lnCO_2 pc = 0.370***) both have significant positive effects on short-term energy consumption. However, the coefficients for renewable energy variables in the short term are statistically insignificant, indicating that adjustments to renewable energy may take longer to influence energy consumption behavior.

Overall, the model demonstrates a strong fit with an R^2 of 0.756, meaning that approximately 76% of the variation in energy consumption is explained by the included variables. The statistical significance of the adjustment term further validates the convergence toward the long-run equilibrium.

7 Discussion

This study examines the relationship between EC pc, GDP pc, and environmental factors in Türkiye from 1960 to 2023. The IDA results indicate that improvements in energy intensity and structural changes were the primary factors contributing to the reduction in energy consumption. Between 1990 and 2023, the intensity effect reduced total energy use by about 21%. Structural changes, mainly the shift from manufacturing to services, contributed to an additional 14% reduction. These findings are consistent with global evidence that efficiency gains are a key driver of declining energy intensity in developing economies, aligning with previous results for Türkiye.[32,61] Our estimated structural effect is slightly larger than in earlier studies, likely due to the longer period and the inclusion of more recent data.

The regression analysis highlights the relationships among EC pc, GDP pc, renewable energy share, and CO_2 pc. In the baseline OLS model, a 1% rise in GDP pc is associated with a 0.516% increase in energy use, while the squared GDP term is negative and significant, supporting an inverted U-shaped pattern consistent with the EEKC. The positive coefficient for renewable energy share suggests that renewable deployment has complemented rather than substituted for energy demand, consistent with Dercon[66], who argued that in low- and middle-income countries, renewable capacity often supplements rather than displaces fossil-based systems.

ARDL and ECM provide additional evidence on long-run relationships. The ECM coefficient (–0.456) implies that about 46% of any deviation from long-run equilibrium is corrected annually, indicating moderate adjustment. In the long run, CO_2 prices have a positive and significant effect on energy use, underscoring the dependence on fossil fuels. GDP per capita also has a positive effect, suggesting that economic growth continues to drive energy demand, even with efficiency gains. Similar patterns have been observed in other middle-income economies undergoing structural transformation, though our smaller coefficient likely reflects Türkiye's efficiency improvements and sectoral diversification [42, 67]

Several limitations should be acknowledged. First, sectoral data for the IDA are available only from 1990, restricting the decomposition period compared to the econometric analysis (1960–2023). Second, historical data may be influenced by changes in statistical methods and sector classifications. Third, CO_2 emissions per capita were used as the main environmental indicator, while other pollutants (e.g., methane, nitrous oxide, particulate matter) and broader measures (e.g., ecological footprint, air quality indices) were excluded due to data limitations. Fourth, renewable and non-renewable energy use were not consistently available throughout the full period; therefore, total energy use was analyzed with the renewable share computed separately, limiting the ability to distinguish the effects of different energy sources. Finally, the use of annual data smooths short-term fluctuations; higher-frequency data could better capture short-run adjustments and policy shocks.

Overall, the results indicate that efficiency improvements and structural shifts have reduced Türkiye's energy intensity, while economic growth and CO_2 emissions remain key long-term drivers of energy demand. This study builds on earlier work by integrating IDA, OLS, and ARDL approaches to provide complementary insights into the drivers of energy use. The findings on efficiency improvements suggest that targeted energy policies and the adoption of new technologies have been effective in improving efficiency. Future research should distinguish between renewable and non-renewable sources, incorporate additional environmental indicators, and employ higher-frequency data to capture short-run responses and policy impacts.

8 Conclusion

This study employed an integrated framework, combining IDA and ARDL methods, to examine the drivers of energy consumption in Türkiye. The IDA results show that energy intensity improvements reduced total energy use by about 21%, while structural shifts away from energy-intensive sectors contributed a further 14% reduction. In contrast, production growth increased energy consumption by approximately 87%.

The OLS estimates provide evidence of both the EKC and EEKC relationships. GDP pc has a positive and significant effect on energy consumption, while the squared GDP term is negative and significant, supporting an inverted U-shaped pattern. Similar non-linear effects are observed between CO_2 pc, and GDP pc. The ARDL analysis confirms a long-run cointegrating relationship among EC pc, GDP pc, CO_2 pc, and renewable energy share. The ECM indicates that about 46% of deviations from the long-run equilibrium are corrected per year. In the long run, GDP per capita and CO_2 per capita both have positive and significant effects on energy consumption, while the renewable energy share also contributes positively, indicating that renewable energy has so far added to, rather than replaced, fossil fuel use.

Overall, the results indicate that Türkiye has achieved significant efficiency gains and structural changes, which have helped moderate its energy intensity. Yet economic growth and emissions remain key long-run drivers of energy demand. Reconciling growth with environmental goals will require continued efforts to improve efficiency, accelerate the shift toward less energy-intensive activities, and expand renewable deployment in ways that directly replace fossil fuels.

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Appendix

Appendix A: Summary Table

Table 10: Descriptive Statistics of Main Variables (1960–2023)

Variable	Mean	Std. Dev.	Min	Max
Energy Consumption pc (kWh)	11,238	6,357	2,105	23,108
GDP pc ($)	4,342	4,207	194.08	13,243
Renewable Energy Ratio (%)	11.86	2.98	7.48	19.01
CO_2 pc (tons)	2.82	1.45	0.59	5.22
Energy Intensity (MJ/$)	4.62	2.72	1.47	11.38
HDI	0.710	0.087	0.579	0.856
Population(million)	56.8	17.2	78.3	85.3

Note: This table summarizes the key descriptive statistics for the variables used in the analysis from 1960–2023. It includes the number of observations, mean values, standard deviations, and the minimum and maximum values for each variable. Data Sources: TSI, SPO, WDI, IEA

Appendix B

Derivation of the LMDI Additive Decomposition Method

Total energy consumption in year t is expressed as:

$$E_t = \sum_i E_{i,t} = \sum_i Y_t S_{i,t} I_{i,t} = \sum_i Y_t \frac{Y_{i,t}}{Y_t} \frac{E_{i,t}}{Y_{i,t}}$$

where $S_{i,t} = \frac{Y_{i,t}}{Y_t}$ and $I_{i,t} = \frac{E_{i,t}}{Y_{i,t}}$, E_t is enery consumption, Y_t is GDP, $S_{i,t}$ is a structural change, $I_{i,t}$ is intensity

The change in energy consumption between the base year 0 and year t is:

$$\Delta E = E_t - E_0$$

The change is decomposed into three effects:

$$Et = \Delta E\text{out} + \Delta E\text{str} + \Delta E\text{int}$$

The LMDI method starts by expressing the sectoral ratio of energy consumption:

$$\frac{E_{i,t}}{E_{i,0}} = \frac{Y_t}{Y_o}\frac{S_{i,t}}{S_{i,O}}\frac{I_{i,t}}{I_{i,o}}$$

Taking the natural logarithm of both sides

$$\ln(\frac{E_{i,t}}{E_{i,0}}) = ln(\frac{Y_t}{Y_o}) + \ln(\frac{S_{i,t}}{S_{i,O}}) + ln(\frac{I_{i,t}}{I_{i,o}})$$

The logarithmic means is used to define the weighting matrix: $W_{i,t}$

$$L(x,y) = \begin{cases}\dfrac{y - x}{lny - lnx}, & x \neq y, \quad x,y > 0\end{cases}$$

$$W_{i,t} = \mathrm{L}(E_{i,t}, E_{i,0}) = \frac{(E_{i,t} - E_{i,0})}{ln(E_{i,t}) - ln(E_{i,0})}$$

Using this weighting matrix, each effect is defined:

$$\Delta E\mathrm{out} = \sum_i W_{i,t}\, ln(\frac{Y_t}{Y_0})$$

$$\Delta E\mathrm{str} = \sum_i W_{i,t}\, ln(\frac{S_{i,t}}{S_{i,0}})$$

$$\Delta c = \sum_i W_{i,t}\, ln(\frac{I_{i,t}}{I_{i,0}})$$

To complete the expression is:

$$\Delta E = \sum_i W_{i,t}\, ln(\frac{Y_t}{Y_0}\frac{S_{i,t}}{S_{i,0}}\frac{I_{i,t}}{I_{i,0}})$$

This framework helps decompose total energy consumption into the contributions of output, sectoral structure, and energy intensity over time.

Alternatively, the generalized LMDI structure can be written as:

$$\Delta \mathrm{F} = \sum_i L(f_{i,t}, f_{i,0}).\,[ln(\frac{x_{i,t}}{x_{i,0}}) + ln(\frac{y_{i,t}}{y_{i,0}}) + ln(\frac{z_{i,t}}{z_{i,0}})]$$

with F = $\sum_i f_i = \sum_i x_i y_i z_i$

where F = E, x = Y, y = S, z = I, and F is the Cumulative Distribution Function and f is the Probability Distribution Function.

Note: Special cases for zero values: If $E_{i,t} = E_{i,0} = 0$, $W_i = 0$, If only one of $E_{i,t}, E_{i,0} = 0$, then the corresponding term is excluded from the summation.

Appendix C

ARDL Model Stability Diagnostics

The stability of the ARDL model parameters is examined using the CUSUM and CUSUM of Squares (CUSUMSQ) tests. These plots are commonly used to detect parameter instability over time. If the plotted lines remain within the 5% significance bounds, the null hypothesis of stable coefficients cannot be rejected.

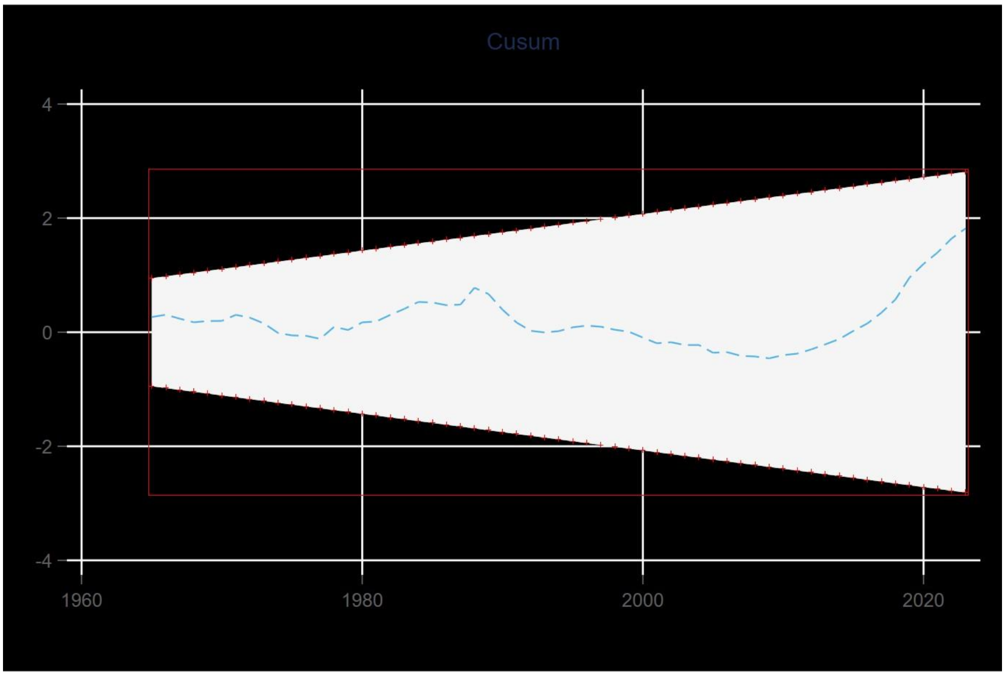

Figure 5: CUSUM Stability Test

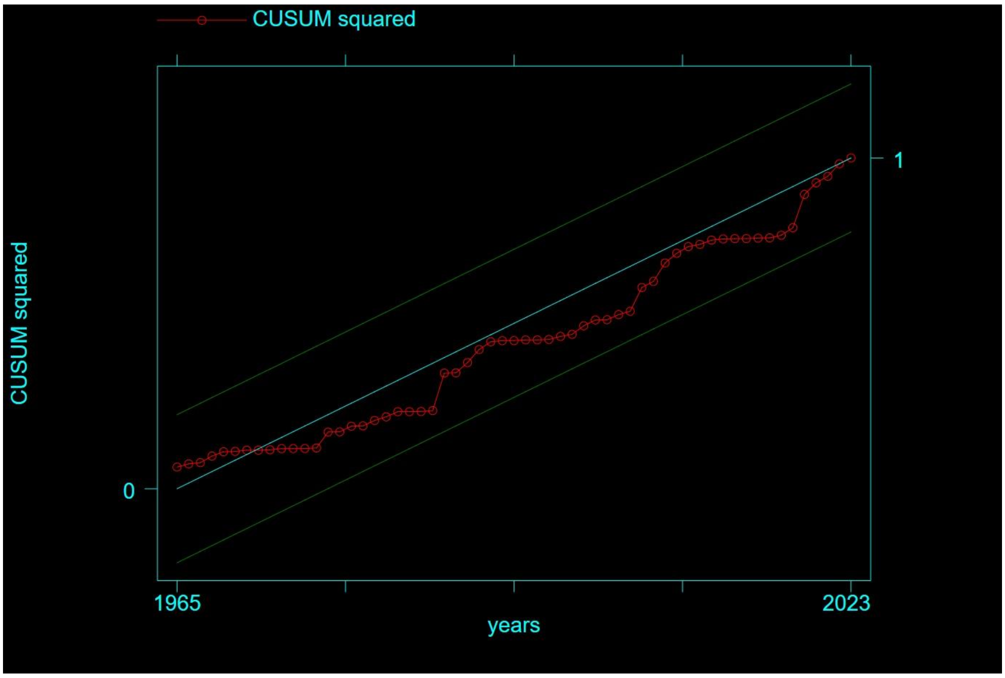

Figure 6: CUSUM of Squares Stability Test