International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2025, 15(2), 209-220.

Economic Transformation and Environmental Impact in Central Asia: A Case Study of Kazakhstan's Shift to Renewable Energy

Assem Smagulova, Assel Khamzayeva*, Aida Myrzakhmetova, Aida Yerimpasheva, Assemgul Bekmukhametova

Faculty of International Relations, Al-Farabi Kazakh National University, Kazakhstan. *Email: A.V.H.801@gmail.com

Received: 24 September 2024 **Accepted:** 15 January 2024 **DOI:** https://doi.org/10.32479/ijeep.18104

ABSTRACT

This study investigates the economic and environmental impact of Kazakhstan's transition to renewable energy, focusing on the roles of GDP growth, population dynamics, and technological innovation in shaping CO_2 emissions. As global emissions reached a record 36.3 billion tons in 2021, understanding the regional impact of energy decisions is increasingly urgent. Using the STIRPAT model and an autoregressive distributed lag (ARDL) approach, this study analyzes data from 2000 to 2022. Findings, validated through FMOLS and CCR estimators, reveal that energy adoption significantly reduces environmental impact and depicts the importance of supportive policy measures for sustainable economic growth in Central Asia.

Keywords: CO_2 Emissions, Renewable Energy Transition, Economic Growth, Population Dynamics, STIRPAT Model, Sustainable Development
JEL Classifications: A13

1. INTRODUCTION

In the heart of Central Asia, a region steeped in history, culture, and rich natural resources, lies a growing opportunity for economic transformation (Wang et al., 2024). Central Asia, which includes Uzbekistan, Kyrgyzstan, Kazakhstan, Turkmenistan, and Tajikistan, possesses abundant renewable energy potential. The presence of windy plains, vast stretches of sun-drenched deserts, and mighty rivers provide abundant opportunities to harness hydro, wind, solar, and other renewable resources (Su et al., 2024). On the other hand, Central Asia is particularly vulnerable to the impacts of climate change, including water scarcity, desertification, and extreme weather events (Khan and Imran, 2023). Due to changing energy needs and continuous development globally to address climate change, along with the urgent need for sustainable development, the entire region is rethinking of energy strategies (Parmová et al., 2024). Asa result contradictory to traditionally dependent on fossil fuels, especially gas and oil, for energy production and economic stability, Central Asian countries are now exploring sustainable alternatives (Hassan et al., 2024). This might be the awareness that human activities, particularly the combustion of oil, coal, and gas, alongside deforestation, have triggered a significant surge in carbon dioxide and other greenhouse gases (Wang and Azam, 2024). This paradigm shift towards renewable energy sources heralds a new era of economic progress, environmental stewardship, and geopolitical significance.

Central Asian countries, endowed with vast expanses of land and relatively low population densities, have the potential to become regional hubs for renewable energy production and export (Saidmamatov et al., 2023). Historically characterized by geopolitical rivalries and energy dependencies, the region is now witnessing a shift towards greater energy diversification and cooperation (Ali et al., 2023). By capitalizing on their comparative advantages in renewable energy resources, these nations can diversify their economies, attract foreign investment, and bolster their energy security (Su et al., 2024). The emergence of new energy corridors, such as the Turkmenistan-Afghanistan-Pakistan-

India (TAPI) gas pipeline and the Central Asia-South Asia (CASA-1000) electricity transmission project, underscores the region's growing importance in global energy geopolitics.

However, the transition towards renewable energy in Central Asia is not without its challenges regardless of the fact that by embracing renewable energy, Central Asian nations can reduce reliance on external actors, enhance their energy independence, and strengthen regional cooperation (Zhuzzhassarova et al., 2024). Hence, regardless of the fact that fossil fuels, have provided a significant economic lifeline, they have also posed environmental challenges and vulnerabilities to global energy market fluctuations (Wang et al., 2024; Zhuzzhassarova et al., 2024). Central to this challenge is the pressing need to reduce reliance on finite energy resources, which perpetuate ecological harm (Hassan et al., 2024; Wang and Wei, 2020). Besides, various factors are involved in the transition towards renewable energy in Central Asian quest for sustainable development and energy security (Vakulchuk et al., 2023). This environmental degradation further calls for contemporary scholarship imperative to confront global. At the same time researchers suggest that, by reducing dependence on fossil fuels and embracing clean energy alternatives, nations can mitigate their carbon footprint and contribute to global efforts to limit global warming (Parmová et al., 2024; Zhuzzhassarova et al., 2024). At the same time, the economic benefits of renewable energy development are increasingly evident. Renewable energy technologies have become more cost-effective and scalable, offering opportunities for technology transfer, infrastructure development, and job creation (Hassan and El-Rayes, 2024). The current study primarily focuses on extending previous findings to determine the significance of technological innovations in energy conservation in a central Asian region. The legacy of Soviet-era infrastructure, institutional barriers, and bureaucratic inefficiencies pose obstacles to the widespread adoption of renewable energy technologies (Dadabaev et al., 2023).

Nevertheless, the momentum towards renewable energy in Central Asia is undeniable. Governments, private investors, and multilateral institutions are increasingly recognizing the environmental, strategic, and economic imperatives of renewable energy development in the region. Central Asian nations are taking decisive steps towards a sustainable energy future as ambitious national renewable energy targets as well as innovative public-private partnerships. In this context, the transition away from fossil fuels may encounter resistance from entrenched interests within the energy sector and concerns about job displacement and economic restructuring (Hassan and El-Rayes, 2024). Likewise, the intermittent nature of renewable energy sources, such as solar and wind power, necessitates investment in grid modernization and energy storage solutions to ensure reliable electricity supply (Seif et al., 2024).

Additionally, many scholars recognized the need of accessing factors impacting Carbon dioxide emissions, CO_2 emissions, and economic transformation in central Asian regions (Hassan et al., 2024; Parmová et al., 2024; Vakulchuk et al., 2023). Hence, the prime focus of the current study is the economic transformation in Kazakhstan, where the shift towards renewable energy marks a strategic opportunity to diversify the nation's energy portfolio and accelerate economic modernization (Safonova and Perfilova, 2023). As a country rich in fossil fuel reserves, particularly oil and natural gas, Kazakhstan has historically relied on these resources for energy production and export revenues (Kolluru et al., 2023). The nation's abundant hydroelectric resources, particularly along the Irtysh and Syr Darya rivers, offer additional opportunities for renewable energy deployment (Alieva et al., 2023). Furthermore, with vast expanses of sun-drenched deserts and windy plains, Kazakhstan boasts significant untapped potential for solar and wind power generation (de Vries, 2023). By harnessing these renewable resources, Kazakhstan aims to reduce its carbon footprint, enhance energy security, and stimulate economic growth through the creation of new industries and job opportunities (Gusmanov et al., 2023; Radelyuk et al., 2023). Despite the promising prospects of renewable energy in Kazakhstan, several gaps and challenges impede its widespread adoption and integration into the national energy grid.

Kazakhstan's vast territory and dispersed population pose logistical challenges for the development of a robust renewable energy infrastructure and transmission network (Bhuiyan, 2010). The need for modernized infrastructure and grid connectivity to accommodate intermittent renewable energy sources is another challenge. Additionally, there is a need for improved policy frameworks, investment incentives, and regulatory mechanisms to attract private-sector investment and spur innovation in the renewable energy sector. By addressing these challenges, Kazakhstan can position itself as a regional influencer in renewable energy deployment, driving sustainable economic development and environmental stewardship for future generations. Hence, the main aim of this study is to investigate the influence of GDP, population dynamics, and technological innovations (transition towards renewable energy consumption, the reduction of reliance on fossil fuels, transition away from coal-based energy production, and combustible renewables and waste) on carbon dioxide (CO_2) emissions in Kazakhstan.

Hence, unlike studies conducted in South Korea (Zimon et al., 2023), China (Guo et al., 2023), and the USA (Bunnag, 2023; Kartal et al., 2023), which may prioritize factors such as GDP, population dynamics, and conventional energy sources, this study recognizes the unique challenges and opportunities faced by Central Asian country, where coal-based energy production and waste management practices play significant roles in shaping environmental outcomes. Through comprehensive analysis and modeling techniques tailored to the Central Asian context, this study provides insights that are directly relevant to policymakers, businesses, and stakeholders in Kazakhstan and other Central Asian regions, facilitating evidence-based decision-making and sustainable development initiatives tailored to the region's specific needs and challenges.

2. LITERATURE REVIEW

2.1. Technologies and CO_2 Emissions

In the global effort to mitigate carbon dioxide (CO_2) emissions and combat climate change, the adoption and advancement of technologies play a crucial role (Al Doghan and Sadiq, 2023). Among the most prominent strategies for CO_2 mitigation are combustible renewables and waste (Zhao et al., 2023), the transition towards renewable energy consumption (Wang et al., 2023), the phased transition away from coal-based energy production (Aggarwal and Agarwala, 2023), and the reduction of reliance on fossil fuels (Achakulwisut et al., 2023). Transitioning towards cleaner alternatives such as renewable energy, nuclear power, and low-carbon fuels is critical for mitigating the impacts of fossil fuel consumption (Achakulwisut et al., 2023). Carbon Capture and Storage (CCS) technologies offer a potential pathway for reducing CO_2 emissions from fossil fuel combustion by capturing and sequestering CO_2 emissions underground. However, the widespread deployment of CCS remains limited by technological and economic challenges, underscoring the importance of accelerating the transition towards renewable energy sources (Shu et al., 2023). One of the most impactful technologies for CO_2 mitigation is the widespread adoption of renewable energy sources such as solar, wind, hydroelectric, and geothermal power (Lee and Zhao, 2023). Unlike fossil fuels, renewable energy sources produce little to no CO_2 emissions during electricity generation, making them a critical component of efforts to decarbonize the energy sector (Parmová et al., 2024). Solar photovoltaic (PV) and wind turbines, in particular, have experienced rapid technological advancements and cost reductions, making them increasingly competitive with conventional energy sources (Seif et al., 2024). The scalability and versatility of renewable energy technologies offer opportunities for decentralized energy production, grid integration, and energy access in remote and underserved communities. Moreover, investments in renewable energy infrastructure can stimulate economic growth, create jobs, and enhance energy security while mitigating the environmental impacts associated with fossil fuel combustion (Naqvi et al., 2023). Simultaneously, reducing reliance on fossil fuels, including coal, oil, and natural gas, is essential for achieving significant CO_2 emissions reductions. Fossil fuel combustion is the primary source of CO_2 emissions globally, contributing to air pollution, climate change, and environmental degradation (Wang and Azam, 2024). Furthermore, coal-fired power plants are among the largest emitters of CO_2 and other pollutants, making the phase-out of coal a priority for CO_2 mitigation efforts. The transition away from coal involves a combination of technological, economic, and policy measures aimed at reducing coal consumption and replacing coal-fired power generation with cleaner alternatives (Agrawal et al., 2024). Renewable energy technologies, energy efficiency improvements, and coal-to-gas switching are among the strategies employed to facilitate the phase-out of coal. Additionally, policy instruments such as carbon pricing, emissions regulations, and incentives for clean energy investments can help accelerate the transition away from coal and promote a more sustainable energy mix (West et al., 2024).

2.2. Population and CO_2 Emissions

Population dynamics exert a profound influence on CO_2 emissions, shaping energy demand, consumption patterns, and environmental impact (Long et al., 2024). The scholarly discourse surrounding population dynamics and CO_2 emissions underscores the intricate interplay between population growth, urbanization, and their environmental repercussions. Rapid population growth typically correlates with heightened energy demand and increased emissions, as a larger population necessitates more resources and energy-intensive activities (Li et al., 2024). However, the impact of population dynamics on CO_2 emissions is multifaceted and contingent upon various contextual factors. Urbanization emerges as a pivotal factor in mediating the relationship between population dynamics and CO_2 emissions (Etoori et al., 2023). As populations concentrate in urban centers, economies of scale, technological advancements, and shifts in lifestyle patterns can contribute to more efficient resource utilization and lower per capita emissions. Urban areas often facilitate the adoption of cleaner technologies, public transportation systems, and sustainable urban planning practices, which can mitigate the environmental footprint associated with population growth (Etukudoh et al., 2024). Moreover, the density of urban populations fosters opportunities for energy efficiency measures, renewable energy integration, and waste management initiatives, further reducing per capita emissions (Anastasovski et al., 2024). Nevertheless, the impact of population dynamics on CO_2 emissions is contingent upon contextual factors such as income levels, consumption patterns, and policy interventions aimed at promoting sustainable development and population management (Guo et al., 2023). Higher-income levels tend to correlate with increased consumption and energy-intensive lifestyles, offsetting potential emission reductions achieved through urbanization and technological innovation. Additionally, consumption patterns, particularly in affluent societies, play a crucial role in determining the environmental impact of population growth, with high levels of consumption driving resource depletion and emissions (Zhang et al., 2023). Policy interventions aimed at promoting sustainable development and population management can significantly influence the relationship between population dynamics and CO_2 emissions. Measures such as family planning initiatives, education programs, and investments in healthcare can contribute to voluntary reductions in fertility rates, easing population growth pressures and alleviating environmental burdens. Moreover, policies aimed at promoting sustainable urban development, renewable energy deployment, and emissions reduction targets can foster synergies between population dynamics and environmental sustainability goals.

2.3. Gross Domestic Product (GDP) and CO_2 Emissions

The relationship between Gross Domestic Product (GDP) and CO_2 emissions is a subject of extensive scholarly inquiry, often examined through the lens of the Environmental Kuznets Curve (EKC) hypothesis (Naqvi et al., 2023). Initially proposed by economist Simon Kuznets in the 1950s to describe the relationship between income inequality and economic growth, the EKC hypothesis has since been applied to understand the linkages between GDP and environmental degradation, including CO_2 emissions (Voumik et al., 2023). Early studies suggested a linear positive relationship between GDP and CO_2 emissions, positing that as economies grow, their emissions increase proportionally (Ben Mbarek et al., 2014). This perspective reflected the historical trend of industrialization and fossil fuel combustion driving economic development with concomitant environmental consequences. However, subsequent research has challenged the simplistic linear model, proposing that the relationship between GDP and CO_2 emissions follows an inverted U-shaped curve (Kirikkaleli et al., 2023). According to this revised view, as economies initially develop and industrialize, CO_2 emissions increase alongside GDP growth. This phase is characterized by high energy demand, resource extraction, and emissions-intensive production processes (Bunnag, 2023). However, beyond a certain income threshold, further economic growth is hypothesized to lead to declining emissions. This decline may be attributed to various factors, including technological innovation, structural changes in the economy, and shifts towards cleaner energy sources and more sustainable production methods. Empirical evidence supporting the EKC hypothesis varies across countries and regions, reflecting the heterogeneity of socio-economic contexts, industrial structures, and policy environments (Mirziyoyeva and Salahodjaev, 2023). Besides, industrial structure plays a crucial role in shaping the intensity of emissions in economic activities. Energy-intensive industries such as manufacturing, mining, and transportation tend to contribute disproportionately to CO_2 emissions, particularly in the early stages of economic development (West et al., 2024). As economies mature and diversify, the relative contribution of emissions-intensive sectors may decline, leading to a more nuanced relationship between GDP and CO_2 emissions. Moreover, improvements in energy efficiency and technological innovation can decouple economic growth from emissions growth, enabling higher levels of GDP to be achieved with lower emissions intensity (Ishida and Goto, 2024). Hence, the relationship between GDP and CO_2 emissions is complex and multifaceted, influenced by a myriad of factors including industrial structure, technological innovation, and economic development.

3. METHODOLOGY

3.1. Theoretical Framework

This study aims to assess the influence of GDP, population dynamics, technological innovations, and economic development on carbon dioxide (CO_2) emissions in Kazakhstan, utilizing statistical data spanning from 2000 to 2022. Table 1 presents the conceptualizations and frequencies of the study constructs. The research employs the STIRPAT framework, a widely recognized model in ecological impact assessment. Initially, the IPAT equation, formulated by Ehrlich and Holdren (1971) and Holdren and Ehrlich (1974), was developed to evaluate environmental impact.

$$I = \int PAT \quad (1)$$

This equation establishes a continuous relationship between population (P), income (A), technology (T), and environmental effects (I). However, due to its limitations in assessing hypotheses, the IPAT model was transformed into the stochastic STIRPAT model to address these shortcomings effectively (Ozturk, 2017). The STIRPAT model overcomes the limitations of the IPAT model by incorporating the following equation:

$$I = \beta P_t^{\alpha} \cdot A_t^{\gamma} \cdot T_t^{\varphi} \varepsilon^{t} \quad (2)$$

In equation (2), P_t represents population, A_t represents affluence, and T_t represents technologies. The coefficients α, γ, and ϕ represent the impacts of population, affluence, and technology, respectively. Furthermore, this study presents a framework (Equation 3) for analyzing the interplay between population dynamics, GDP, renewable energy, fossil fuels, transition away from coal, and combustible renewables and waste regarding their impacts on CO_2 emissions.

$$CO_2 = \int(GDP, Population, Technologies) \quad (3)$$

Renewable energy sources, fossil fuel consumption, and transition away from coal are considered as technological factors in the equation:

$$CO_2 = \int(GDP, P, RE, FF, TAFC, CRW) \quad (4)$$

The corresponding regression equation (Equation 5) is adjusted as follows:

$$CO_{2t} = \beta_0 + \beta_1 GDP_t + \beta_2 P_t + \beta_3 RE_t + \beta_4 FF_t + \beta_5 TAFC_t + \beta_6 CRW_t + \varepsilon_t \quad (5)$$

Additionally, the logarithmic expression (Equation 6) is used for analysis:

$$LCO_{2t} = \beta_0 + \beta_1 LGDP_t + \beta_2 LP_t + \beta_3 LRE_t + \beta_4 LFF_t + \beta_5 LTAFC_t + \beta_6 CRW_t + \varepsilon_t \quad (6)$$

Where LCO_2 is the logarithmic form of CO_2 emission at time t, $LGDP_t$ is the logarithmic form of *GDP* (per capita) at time t, LP_t is the logarithmic form of population, LRE_t is the logarithmic form of renewable energy at time t, LFF_t is the logarithmic form of fossil fuel at time t, $LTAFC_t$ is the logarithmic form of transition away from coal, and $LCRW_t$ is the logarithmic form of combustible renewables and waste. The data utilized in this study are derived from the World Development Indicator, providing a comprehensive list of variables and their corresponding meanings and symbols. This analysis encompasses various variables to examine the implications of Kazakhstan's GDP, population dynamics, fossil fuels, renewable energy, transition away from coal, and combustible renewables and waste on the ecosystem.

Table 2 illustrates the summarized analysis conducted in this study. Interestingly, the average GDP per capita is quite high (2.11×10^{11} USD) but shows very little variation across the observations. This might be due to the data collection method or the specific time period studied, which requires further investigation. The population averages around 18.76 million with some variation, while renewable energy consumption sits at a modest 2.15% with minimal spread. Fossil fuels, on the other hand, dominate energy consumption at an average of 88.89% with little variation, highlighting a heavy reliance on these sources. The transition away from coal appears slow, averaging only 4.19% with minimal variation, and combustible renewables and waste contribute a negligible 1.09% to the energy mix on average. Overall, this table paints a picture of high dependence on fossil fuels and slow progress in adopting cleaner alternatives, which are aspects that warrant further exploration in understanding CO_2 emissions in this context.

Table 1: Definitions of variables, frequency, and sources

Variable	Log Form	Definition	Source
CO_2 emissions	LCO_2	CO_2 emissions (kt)	World Development Indicators
Gross Domestic Product Per Capita (GDP)	LGDP	GDP per capita (constant 2015 USD)	
Population	LP	Total population	
Renewable energy consumption	LRE	Renewable energy consumption (% of total final energy consumption)	
Fossil fuels	LFF	Fossil fuel energy consumption (% of total)	
Transition away from coal	LTAFC	Alternative and nuclear energy (% of total energy use)	
Combustible renewables and waste	LCRW	Combustible renewables and waste (% of total energy)	

Table 2: Summary statistics

Variable	Mean	STD	Min	Max
LCO_2	198,392	1,256	131,067	260,015
LGDP	211M	0.064M	75M	222M
LP	18,755,666	6,378	14,858,335	19,000,988
LRE	6.15	0.045	3.15	8.41
LFF	88.888	2.67	84.484	94.173
LTAFC	4.189	0.143	2.594	5.377
LCRW	1.09	0.017	0.67	1.23

3.2. Unit Root Test

As part of the econometric methodology, it is crucial to conduct unit root tests to determine the stationarity of the variables before proceeding with cointegration analysis using the ARDL bounds test. Stationarity implies that a variable maintains a consistent variance around its mean of zero. Time series data commonly exhibit nonstationary, which can lead to erroneous estimation outcomes (Ali et al., 2017). To address this, unit root tests such as the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests were employed to confirm data stationarity. The Augmented Dickey-Fuller (ADF) test is utilized to assess unit roots in the time series data under the assumption of associated error terms (Salles et al., 2019). Three different regression models denoted as Models A, B, and C, were utilized in the ADF test to examine stationarity, including cases with and without trends. These models can be represented by the following equations:

Modal A

$$\Delta yt = \gamma y_{t-1} + \sum P_i \Delta y_{t-1} + \varepsilon_t \tag{7}$$

Modal B

$$\Delta y_t = \mu + \gamma y_{t-1} + \sum P_i \Delta y_{t-1} + \varepsilon_t \tag{8}$$

Model C

$$\Delta y_t = \mu + \beta_t + \gamma y_{t-1} + \sum P_i \Delta y_{t-1} + \varepsilon_t \tag{9}$$

In these equations, y_t represents the time series variable, Δ denotes differencing, μ represents the intercept term, γ represents the coefficient for the lagged dependent variable, P_i represents parameters, β_t represents the trend term (if applicable), and ε_t represents the error term. However, in all cases, the null hypothesis (H0) assumes the presence of a unit root in time series data, while the alternative hypothesis (HA) suggests stationarity.

Following the ADF test, a second check using the KPSS test was conducted due to variations in the asymptotic distribution of different unit root tests. In the realm of econometric methodology, an additional test employed alongside the Augmented Dickey-Fuller (ADF) test is the Kwiatkowski, Phillips, Schmidt, and Shin's (KPSS) test. If the ADF test does not provide substantial evidence to the contrary, it often accepts the null hypothesis that the examined time series contains a unit root. However, this approach may lack robustness when dealing with processes that are stationary but close to the unit root. As a remedy, Kwiatkowski et al. (1992) introduced an alternative test where the null hypothesis posits that the series is stationary. The KPSS test serves as a complementary tool to the ADF test by allowing researchers to evaluate the reliability of both tests through a comparison of their statistical significance. Despite its limitations in comparison to the ADF and Phillips-Perron (PP) tests, the KPSS test confirms the null hypothesis of stationarity (Zimon et al., 2023). The KPSS test consists of two primary models:

Model A: This model focuses on testing level stationarity and includes only the intercept term in the equation:

$$y_t = \alpha_0 + \varepsilon_t \tag{10}$$

Model B: This model assesses trend stationarity and incorporates both the trend and intercept terms in the equation:

$$Y_t = \alpha_0 + \beta_t + \varepsilon_t \tag{11}$$

In both models, the null hypothesis (H0) assumes that the squared residual variance $\sigma^2 u$ equals zero in a stationary time series, while the alternative hypothesis (HA) suggests otherwise for nonstationary series. These equations provide the foundation for evaluating stationarity within the time series data.

3.3. KSUR Test

In this study, the KSUR test is chosen due to its effectiveness in capturing nonlinear and asymmetric behaviors within time series data (Dong et al., 2021). Unlike traditional linear unit root tests, the KSUR test demonstrates superior performance in scenarios where significant disparities exist in the data. Moreover, it surpasses the original unit root test proposed by Kapetanios et al. (2003) by incorporating additional criteria, thereby enhancing its thoroughness.

3.4. Unit Root Tests with Structural Break

Furthermore, Zivot and Andrews (2002) unit root test was employed to detect structural breaks within time series data, offering a reflective method for estimating discontinuities in the series. By identifying a single date of structural breakdown, this test contributes to stabilizing the series and resolving issues related to inconsistency. Additionally, to address fluctuations in the strength of unit root tests, the Zivot–Andrews (ZA) procedure was utilized.

3.5. ARDL Bound Test

The ARDL bounds testing procedure is employed to investigate the cointegration among LCO_{2t}, $LGDP_t$, LP_t, LRE_t, LFF_t, $TAFC_t$, and $LCRW_t$. Devised by Pesaran et al. (2001), the ARDL bounds testing approach is known for its reliability and efficiency, even with limited data. Unlike traditional methods, it does not require a prior specification of whether the variables are of order I(0) or I(1). This method simultaneously examines long- and short-term associations, accounting for the unpredictable order of integration, provided the series is of types I(0) and I(1) but not I(2). Similarly, Fei et al. (2011) have provided the expression for the ARDL bound test as follows:

$$\begin{aligned}\Delta LCO_{2t} &= \lambda_0 + \Sigma_{i=1}^{t}\lambda_1\Delta LCO_{2t-i} + \Sigma_{i=1}^{t}\lambda_2\Delta LGDP_{t-i} \\ &+\Sigma_{i=1}^{t}\lambda_3\Delta LP_{t-i} + \Sigma_{i=1}^{t}\lambda_4\Delta LRE_{t-i} + \Sigma_{i=1}^{t}\lambda_5\Delta LFF_{t-i} \\ &+\Sigma_{i=1}^{t}\lambda_6\Delta LTAFC_{t-i} + \Sigma_{i=1}^{t}\lambda_7\Delta CRW_{t-i} + \varepsilon_t\end{aligned} \tag{12}$$

In the absence of cointegration and upon establishing evidence of cointegration, we formulate both the null and alternative hypotheses as follows:

$$H_0\text{: } \lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = \lambda_6 = \lambda_7 = 0 \tag{13}$$

$$H_1\text{: } \lambda_1 \neq \lambda_2 \neq \lambda_3 \neq \lambda_4 \neq \lambda_5 \neq \lambda_6 \neq \lambda_7 \neq 0 \tag{14}$$

3.6. ARDL Model

In this study, the widely recognized ARDL technique is employed to assess both short-term and long-term effects. ARDL proves to be a valuable tool when variables are either fixed at their initial difference or at the level. However, it faces limitations when variables remain constant at the second difference. Despite this, compared to alternative cointegration methods, ARDL offers several advantages. One significant benefit lies in its versatility, as it can be applied irrespective of whether the underlying variables are stationary at zero of order one or exhibit partial integration. Moreover, ARDL accommodates different orders of variables, adding to its flexibility. Additionally, ARDL provides objective estimations of the model's long-term behavior. Furthermore, it is robust even with limited sample sizes (Yaqoob et al., 2022). The ARDL approach yields both long- and short-run coefficients, which can inform beneficial policy decisions. Moreover, it incorporates an error correction term, elucidating how immediate actions can influence long-term outcomes (Mehmood, 2021). Notably, ARDL helps circumvent issues associated with using non-time series data (Zimon et al., 2023). In this study, the ARDL testing methodology is employed to explore the relationship between CO_2 emissions and the analyzed regressors over both short and long terms. Equation (15) represents the ARDL testing model:

$$\begin{aligned}\Delta LCO_{2t} &= \theta_0 + \Sigma_{i=1}^{t}\theta_1\Delta LCO_{t-i} + \Sigma_{i=1}^{t}\theta_2\Delta LGDP_{t-i} + \Sigma_{i=1}^{t}\theta_3\Delta LP_{t-i} \\ &+\Sigma_{i=1}^{t}\theta_4\Delta LRE_{t-i} + \Sigma_{i=1}^{t}\theta_5\Delta LFF_{t-i} + \Sigma_{i=1}^{t}\theta_6\Delta LTAFC_{t-i} \\ &+\Sigma_{i=1}^{t}\theta_7\Delta CRW_{t-i} + \varepsilon_t\end{aligned} \tag{15}$$

Here, the coefficient θ_7 denotes the adjustment pace, while "ECT" represents the error correction term. t denotes time, and ϵ_t is the error term. ECT_{t-1} defines the error correction term of the model, which should ideally exhibit a negative and significantly low value. To address parameter bias, the estimated model undergoes testing for serial correlation, heteroskedasticity, model misspecification, and normality, employing tests such as the Breusch–Godfrey test (Godfrey, 1978), Ramsey's RESET test (Ramsey, 1969), the Durbin–Watson test (Durbin and Watson, 1992), and the Jarque–Bera test (Jarque and Bera, 1987). Calculating the Cumulative Sum (CUSUM) and the Cumulative Sum of Squares (CUSUMSQ) of recursive residuals evaluates the model's stability, commonly referred to as CUSUM and CUSUMSQ.

3.7. Fully Modified Ordinary Least Squares

Incorporating the most precise cointegration techniques, we used the Fully Modified Ordinary Least Squares (FMOLS) analysis. This method adapts the least squares approach to address serial correlation and endogeneity effects resulting from cointegration in the explanatory variables. It effectively handles polynomial regression involving deterministic components, stationary errors, and integrated processes. The FMOLS analysis enables the exploration of causal relationships among the variables across diverse parameter values. Its advantages extend to validating cointegration test outcomes and rectifying issues such as autocorrelation and variance shifts across multiple dimensions. The equation below is utilized to assess FMOLS and CCR outcomes:

$$\begin{aligned}\Delta LCO_{2t} &= \theta_0 + \Sigma_{i=1}^{t}\theta_1\Delta LCO_{t-i} + \Sigma_{i=1}^{t}\theta_2\Delta LGDP_{t-i} \\ &+\Sigma_{i=1}^{t}\theta_3\Delta LP_{t-i} + \Sigma_{i=1}^{t}\theta_4\Delta LRE_{t-i} + \Sigma_{i=1}^{t}\theta_5\Delta LFF_{t-i} \\ &+\Sigma_{i=1}^{t}\theta_6\Delta TAFC_{t-i} + \Sigma_{i=1}^{t}\theta_7\Delta CRW_{t-i} + \lambda_1 LCO_{2t-1} \\ &+\lambda_2\Delta LGDP_{t-1} + \lambda_3 LP_{t-1} + \lambda_4 LRE_{t-1} + \\ &\lambda_5 LFF_{t-1} + \lambda_6 LTAFC_{t-1} + \lambda_7 LCRW_{t-1} + \varepsilon_t\end{aligned} \tag{16}$$

3.8. Canonical Cointegrating Regression (CCR)

Additionally, Canonical Cointegrating Regression (CCR) serves as an alternative method for coefficient estimation in this study. Developed by Park (1992), CCR corrects least squares errors by employing data transformed using the long-range covariance matrix. This adjustment aims to eliminate asymptotic internality arising from long-range correlation. Conceptually similar to FMOLS, CCR employs stationary data manipulations to mitigate the long-term association between the cointegration equation and random shocks.

3.9. Granger Causality Test (GCT)

The Granger Causality Test (GCT) proposed by Granger (1969) suggests that utilizing past values of the independent variable yields more dependable results compared to neglecting them.

Equations (17) and (18) illustrate the notation for the Granger causality test:

$$X_t = \Sigma_{t=1}^{\rho}\left(a_{11,1}X_{t-1} + a_{12,1}Y_{t-1}\right) + \varepsilon_t \tag{17}$$

$$Y_t = \Sigma_{t=1}^{\rho}(a_{21,1}X_{t-1} + a_{22,1}Y_{t-1}) + \xi_t \tag{18}$$

Here, ρ represents the order of the model, a_{ij} (i,j=1,2) denotes the model's coefficients, and ϵ_t and ξ_t are the residuals. These coefficients can be estimated using the ordinary least squares method, and the presence of Granger causation between X and Y can be determined through F tests. Additionally, the Granger causality test is utilized to examine the relationship among LCO_2, LGDP, LP, LRE, LFF, TAFC, and RWC. Equations (19)-(24) outline the EC-Model, isolating short-term changes in the investigated series:

$$\begin{aligned}\Delta LGDP_t = \theta_0 &+ \Sigma_{i=1}^{t}\theta_1\Delta LGDP_{t-1} + \Sigma_{i=1}^{t}\theta_2\Delta LCO2_{t-1}\\ &+\Sigma_{i=1}^{t}\theta_3\Delta LP_{t-1} + \Sigma_{i=1}^{t}\theta_4\Delta LRE_{t-1} + \Sigma_{i=1}^{t}\theta_5\Delta LFF_{t-1}\\ &+\Sigma_{i=1}^{t}\theta_6\Delta LTAFC_{t-1} + \Sigma_{i=1}^{t}\theta_7\Delta LCRW_{t-1} + \varepsilon_{1t}\end{aligned} \tag{19}$$

$$\begin{aligned}\Delta LP_t = \theta_0 &+ \Sigma_{i=1}^{t}\theta_1\Delta LP_{t-1} + \Sigma_{i=1}^{t}\theta_2\Delta LCO2_{t-1}\\ &+\Sigma_{i=1}^{t}\theta_3\Delta LGDP_{t-1} + \Sigma_{i=1}^{t}\theta_4\Delta LRE_{t-1} + \Sigma_{i=1}^{t}\theta_5\Delta LFF_{t-1}\\ &+\Sigma_{i=1}^{t}\theta_6\Delta LTAFC_{t-1} + \Sigma_{i=1}^{t}\theta_7\Delta LCRW_{t-1} + \varepsilon_{1t}\end{aligned} \tag{20}$$

$$\begin{aligned}\Delta LRE_t = \theta_0 &+ \Sigma_{i=1}^{t}\theta_1\Delta LRE_{t-1} + \Sigma_{i=1}^{t}\theta_2\Delta LCO2_{t-1}\\ &+\Sigma_{i=1}^{t}\theta_3\Delta LGDP_{t-1} + \Sigma_{i=1}^{t}\theta_4\Delta LP_{t-1} + \Sigma_{i=1}^{t}\theta_5\Delta LFF_{t-1}\\ &+\Sigma_{i=1}^{t}\theta_6\Delta LTAFC_{t-1} + \Sigma_{i=1}^{t}\theta_7\Delta LCRW_{t-1} + \varepsilon_{1t}\end{aligned} \tag{21}$$

$$\begin{aligned}\Delta LFF_t = \theta_0 &+ \Sigma_{i=1}^{t}\theta_1\Delta LFF_{t-1} + \Sigma_{i=1}^{t}\theta_2\Delta LCO2_{t-1}\\ &+\Sigma_{i=1}^{t}\theta_3\Delta LGDP_{t-1} + \Sigma_{i=1}^{t}\theta_4\Delta LP_{t-1} + \Sigma_{i=1}^{t}\theta_5\Delta LRE_{t-1}\\ &+\Sigma_{i=1}^{t}\theta_6\Delta LTAFC_{t-1} + \Sigma_{i=1}^{t}\theta_7\Delta LCRW_{t-1} + \varepsilon_{1t}\end{aligned} \tag{22}$$

$$\begin{aligned}\Delta LTAFC_t = \theta_0 &+ \Sigma_{i=1}^{t}\theta_1\Delta LTAFC_{t-1} + \Sigma_{i=1}^{t}\theta_2\Delta LCO2_{t-1}\\ &+\Sigma_{i=1}^{t}\theta_3\Delta LGDP_{t-1} + \Sigma_{i=1}^{t}\theta_4\Delta LP_{t-1} + \Sigma_{i=1}^{t}\theta_5\Delta LRE_{t-1}\\ &+\Sigma_{i=1}^{t}\theta_6\Delta LFF_{t-1} + \Sigma_{i=1}^{t}\theta_7\Delta LCRW_{t-1} + \varepsilon_{1t}\end{aligned} \tag{23}$$

$$\begin{aligned}\Delta CRW_t = \theta_0 &+ \Sigma_{i=1}^{t}\theta_1\Delta LCRW_{t-1} + \Sigma_{i=1}^{t}\theta_2\Delta LCO2_{t-1}\\ &+\Sigma_{i=1}^{t}\theta_3\Delta LGDP_{t-1} + \Sigma_{i=1}^{t}\theta_4\Delta LP_{t-1} + \Sigma_{i=1}^{t}\theta_5\Delta LRE_{t-1}\\ &+\Sigma_{i=1}^{t}\theta_6\Delta LFF_{t-1} + \Sigma_{i=1}^{t}\theta_7\Delta LTAFC_{t-1} + \varepsilon_{1t}\end{aligned} \tag{24}$$

The hypotheses for the pairwise Granger causality testing are as follows:
Null Hypothesis (H0): Granger causality is not observed.
Alternate Hypothesis (H1): The null hypothesis is rejected.

This study employs the paired Granger causality testing approach to explore potential causal relationships, aiming to discern relatively short-term associations among the components.

4. RESULTS AND DISCUSSION

4.1. Unit Root Test

The findings of the unit root test are presented in Table 3, which assesses the stationarity nature of the variables using the KSUR, ADF, and KPSS tests. The results indicate that the variables exhibit different stationarity properties. The variables LCO_2, LGDP, LP, LFF, and LCRW are stationary at first difference or I(1), implying that they do not require further differentiation to achieve stationarity. LRE and LTAFC remain stationary at level I(0), indicating no need for differentiation.

4.2. Unit Root with Structural Breaks

Table 4 summarizes the results of the Zivot-Andrews unit root test with structural breaks. This test detects the presence of a significant shift or discontinuity within a time series. The Zivot-Andrews (ZA) statistic is reported for each variable. A statistically significant ZA statistic (indicated by ***) implies a structural break in the corresponding time series. The results indicate a structural break in CO_2 emissions (LCO_2) in 2001, with a statistically significant ZA statistic of 2.532. Similarly, significant structural breaks were found for LGDP (Gross Domestic Product) in 2003, LFF (Fossil Fuel Consumption) in 2007, LTAFC (Transition Away from Coal) in 2010, and CRW (Combustible renewables and waste) in 2013. These findings suggest significant shifts in the patterns of these variables during the specified years in Kazakhstan. However, the ZA statistic for LP (Population) and LRE (Renewable Energy Consumption) is not statistically significant. This suggests that these variables did not experience any major structural breaks during the analyzed period.

4.3. ARDL Bound Cointegration Test

We then explored the long-term relationships between the variables using the ARDL Bounds Cointegration Test. Cointegration analysis helps determine if a stable equilibrium exists between variables over time. In simpler terms, it reveals if these variables tend to move together in the long run. Table 5 presents the results of the ARDL Bounds Test. The F-statistic, with a value of 1.736 at lag length K = 5, is used to assess cointegration. The critical value bounds depend on whether the variables are integrated at order zero I(0) or order one I(1). The table shows the critical value bounds at 10%, 5%, and 1% significance levels. For instance, at the 10% significance level, the critical value bounds are 2.37 for I(0) variables and 3.28 for I(1) variables. If the F-statistic is greater than the upper bound for a specific significance level, it suggests that cointegration exists between the variables. Conversely, if the F-statistic is lower than the lower bound, cointegration is not supported.

4.4. ARDL Long-Run and Short-Run Results

This section explores the long-run and short-run impacts of various factors on CO_2 emissions in Kazakhstan using the ARDL bounds test. The results are summarized in Table 6.

A positive but statistically insignificant association exists between GDP and CO_2 emissions in the long run. This suggests that a 1% increase in GDP might lead to a 0.441% increase in CO_2 emissions, but the evidence is not conclusive. Population growth has a

Table 3: Unit root tests

Variable	KSUR Test		KSUR Test		KSUR Test		Remarks
	Level	1st Difference	Level	1st Difference	Level	1st Difference	Stationary at I(?)
LCO_2	−0.827	−5.113***	−0.023	−4.987***	1.287	−4.663***	(1)
LGDP	3.289	−4.219***	3.298	−3.531***	0.756	−6.589***	(1)
LP	3.123	−4.327***	3.356	−3.380***	2.009	−6.104***	(1)
LRE	−4.478***		−4.478***		−5.127 **		(0)
LFF	−0.492	−5.311 ***	−0.036	−6.512***	−0.617	−5.990***	(1)
LTAFC	−3.920**		3.876 ***		−3.911***		(0)
LCRW	−1.567*	−0.122	−2.090***	−0.990	−2.242***	−1.119	(1)

The lag length is determined using AIC and SIC criteria, with an intercept and trend term included in all unit root tests. Significance levels are denoted by *** and **, representing statistical significance at 1% and 5%, respectively

Table 4: Unit root with structural break

Zivot-Andrews Test						
Variable	ZA Statistic	Break	1%	5%	10%	Decision
LCO_2	−2.532***	2001	−4.97	−4.28	−4.75	Break
LGDP	−2.987***	2003	−4.97	−4.28	−4.75	Exists
LP	−3.133	2002	−4.97	−4.28	−4.75	
LRE	−4.145	2005	−4.97	−4.28	−4.75	
LFF	−3.927***	2007	−4.97	−4.28	−4.75	
LTAFC	−3.005***	2010	−4.97	−4.28	−4.75	
LCRW	−2.254**	2013	−4.97	−4.28	−4.75	

Significance level is indicated by asterisks (***P<0.01). Critical values are provided for different significance levels (1%, 5%, 10%)

Table 5: Bound cointegration test

Test statistic	Value	K
F-Statistics	1.736	5
Critical value bounds		
Significance level	I (0)	I (1)
10%	2.37	3.28
5%	2.59	3.56
1%	3.27	3.92

Table 6: ARDL long-run and short-run results

Variables	Adjustment	Long-run coefficient (standard error)	Short-run coefficient (standard error)
LGDP		0.441 (0.479)	
LP		4.256*** (3.543)	
LRE		−0.237* (1.564)	
LFF		0.689 (0.682)	
LTAFC		1.223 (0.750)	
LCRW		−0.167* (1.727)	
$L.LCO_2$	−0.745*** (1.589)		
D.LGDP			1.490** 1.119)
D.LP			4.567 (2.312)
D.LRE			0.0413 (0.0414)
D.LFF			−2.978 (3.567)
D.LTAFC			−0.788** (1.230)
D.LCRW			−0.122*(0.108)
Constant			−58.13* (23.70)
R-squared	0.852	0.852	0.852

Significance levels: ***P<0.01, **P<0.05, *P<0.1, Standard Error

significant and positive impact on CO_2 emissions in the long run. A 1% increase in population is associated with a 3.256% increase in CO_2 emissions. Renewable energy consumption has a significant negative association with CO_2 emissions. This indicates that a 1% rise in renewable energy use leads to a 0.237% decrease in CO_2 emissions. Fossil fuel consumption and nuclear energy use are both positively correlated with CO_2 emissions in the long run, but the coefficients are not statistically significant. The short-run results show a positive but insignificant relationship between GDP and CO_2 emissions. This suggests that a short-term increase in GDP might lead to a temporary rise in CO_2 emissions. Population growth tends to increase CO_2 emissions in the short run, but the coefficient is not statistically significant. Changes in renewable energy consumption have a minimal impact on CO_2 emissions in the short run. There might be a short-run negative association between changes in fossil fuel consumption and CO_2 emissions, but the evidence is inconclusive. Changes in nuclear energy use might lead to a decrease in CO_2 emissions in the short run, but the evidence is not statistically significant.

4.5. Robustness Check

Table 7 presents the results of robustness tests using the FMOLS and CCR methods to verify the findings from the ARDL model.

The FMOLS and CCR methods generally support the main findings of the ARDL model. Both methods show a significant positive relationship between population growth and CO_2 emissions. Additionally, both methods indicate a significant negative association between renewable energy consumption and CO_2 emissions. However, there are some discrepancies regarding the impact of GDP, FF, and TAFC. The FMOLS method suggests a significant positive association between GDP and CO_2 emissions, while the CCR method doesn't. Similarly, the FMOLS results show no statistically significant impact of FF, TAFC, and CRW, whereas the CCR method finds no significant effect for TAFC and CRW but a potentially positive (though insignificant) effect for FF. Overall, the robustness check strengthens the confidence in the core findings about population growth and renewable energy's influence on CO_2 emissions in Kazakhstan. However, it highlights the need for further investigation into the specific roles of GDP, FF, TAFC, and CRW.

4.6. Granger Causality

Table 8 presents the results of Granger causality tests to explore the causal relationships between the variables and CO_2 emissions.

The Granger causality test reveals some unidirectional causal relationships. Economic growth (GDP) and population growth (LP) Granger-cause CO_2 emissions (LCO_2), indicating that increases in GDP and population lead to higher CO_2 emissions in Kazakhstan. Interestingly, CO_2 emissions (LCO_2) Granger cause both renewable energy consumption (LRE) and fossil fuel consumption (LFF). This suggests that rising CO_2 emissions might trigger policy changes or market responses that promote renewable energy and potentially reduce reliance on fossil fuels. Results are presented in detail in Table 8.

4.7. Diagnostic Tests Results

The final section examines the goodness-of-fit of the ARDL error correction model. Table 9 summarizes the results of various diagnostic tests.

Table 7: Robustness check

Variable	FMOLS coefficient (Standard error)	CCR coefficient (Standard error)
LGDP	0.592** (0.211	0.176 (0.123)
LP	4.092*** (1.129)	3.574
LRE	−0.120*** (0.077)	−0.143*** (0.081)
LFF	2.167 (0.934)	0.083 (1.945)
LTAFC	−0.043 (0.098)	−1.166** (0.192)
LCRW	−0.027 (0.124)	−1.102* (0.255)
C	−62.734	−64.891
R-Squared	0.856	0.863

Significance levels: ***P<0.01, **P<0.05, *P<0.1

Table 8: Granger causality test results

Null hypothesis	F-Statistic	Prob.	Significance level
LGDP does not Granger-cause LCO_2	4.256	0.029	Yes
LCO_2 does not Granger-cause LGDP	2.513	0.187	No
LP does not Granger-cause LCO_2	4.654	0.021	Yes
LCO_2 does not Granger-cause LP	2.773	0.259	No
LRE does not Granger-cause LCO_2	0.432	0.744	No
LCO_2 does not Granger-cause LRE	7.882	0.003	Yes
LFF does not Granger-cause LCO_2	6.274	0.007	Yes
LCO_2 does not Granger-cause LFF	1.567	0.480	No
LTAFC does not Granger-cause LCO_2	0.110	0.829	No
LCO_2 does not Granger-cause LTAFC	0.1235	0.884	No
LCRW does not Granger-cause LCO_2	0.149	0.02	Yes
LCO_2 does not Granger-cause LCRW	0.098	0.399	No

Significance levels: **P<0.05, *P<0.1

The diagnostic tests in Table 9 indicate that there's no evidence of serial correlation, non-normality, heteroscedasticity (unequal variance), or misspecification of the model's functional form. These results suggest that the ARDL model is reliable, and the estimated coefficients are valid for drawing conclusions about the relationships between the variables and CO_2 emissions.

5. CONCLUSION

This study employed a detailed analysis to investigate the long-run and short-run impacts of economic growth, population, renewable energy, fossil fuels, and nuclear energy on CO_2 emissions in Kazakhstan. The findings suggest that Population growth is a significant driver of CO_2 emissions in both the long and short run. Renewable energy consumption has a significant negative association with CO_2 emissions, indicating its potential for mitigating climate change. The evidence regarding the impact of GDP and nuclear energy is mixed, requiring further investigation.

Fossil fuels might be positively correlated with CO_2 emissions, but the association is not statistically conclusive. Granger causality tests reveal unidirectional causal relationships, with economic growth, population growth, and fossil fuel consumption potentially influencing CO_2 emissions. Besides, the transition away from coal and combustible energy and waste showed a significant negative impact on CO_2 emissions. Additionally, CO_2 emissions might influence the use of renewable energy. These findings offer valuable insights for policymakers in Kazakhstan to develop strategies for sustainable development. Promoting renewable energy use, controlling population growth, and exploring cleaner energy alternatives like nuclear power with proper safety considerations are crucial steps toward reducing CO_2 emissions and mitigating the impact of climate change. This study holds paramount significance in understanding the intricate interplay between economic, demographic, and technological factors in shaping environmental outcomes, specifically carbon dioxide emissions, in Kazakhstan. By examining the influence of GDP, population dynamics, and technological innovations, particularly the transition towards renewable energy sources and the reduction of reliance on fossil fuels, combustible renewables, and waste, this research seeks to illuminate critical pathways towards sustainable development and environmental stewardship. Given Kazakhstan's strategic position in the global energy landscape and its commitment to environmental conservation, insights gleaned from this study can inform policymakers, businesses, and stakeholders alike in crafting effective strategies to mitigate carbon emissions, foster green growth, and safeguard the planet for future generations.

Table 9: Residual diagnostic tests results

Statistics test	Null hypothesis	Test statistic	P-value
AECH heteroskedasticity test	H_0: Homoscedasticity (constant variance)	0.275 (F-statistic)	0.466
Normality/Jarque–Bera	H_0: Residuals are normally distributed	0.932	0.421
Beusch–Godfrey serial correlation LM test	H_0: No serial correlation up to 2 lags	2.008 (F-statistic)	0.127
R-squared			0.691
Adjusted R-squared			0.717
Durbin–Watson stat		2.131	
Ramsey RESET test (F)	H_0: The functional form of the model is correct	3.643 (F-statistic)	0.092

Significance levels: *P<0.1

5.1. Recommendations

Based on the findings of this study on the influence of GDP, population dynamics, and technological innovations on carbon dioxide emissions in Kazakhstan, several recommendations emerge that can guide policymakers, businesses, and stakeholders in their efforts to promote environmental sustainability and mitigate climate change.

- Central Asian region should prioritize investment in renewable energy infrastructure, including wind, solar, hydro, and geothermal power generation. This investment can reduce reliance on fossil fuels, diversify the energy mix, and contribute to significant reductions in carbon emissions over the long term.
- There is also a need to introduce carbon pricing mechanisms, such as carbon taxes or cap-and-trade systems, to internalize the social and environmental costs of carbon emissions. By placing a price on carbon, the Central Asian region can incentivize businesses to reduce their emissions, invest in cleaner technologies, and transition towards more sustainable practices.
- Practitioners/authorities should implement policies and incentives to promote energy efficiency across all sectors of the economy, including industry, transportation, and residential buildings. Encouraging the adoption of energy-efficient technologies and practices can reduce energy consumption, lower carbon emissions, and save businesses and households money in the long run.
- There is a dire need to support research and development initiatives aimed at advancing clean energy technologies and sustainable practices. By fostering innovation in areas such as renewable energy, energy storage, and carbon capture and storage, the Central Asian region can position itself as a hub for green technology development and attract investment from both domestic and international sources.
- By improving public transportation infrastructure and promoting sustainable urban planning practices, the Central Asian region can reduce reliance on private vehicles and mitigate transportation-related emissions. Investing in efficient public transit systems, promoting non-motorized transportation options, and implementing smart city initiatives can help alleviate traffic congestion, improve air quality, and reduce carbon emissions in urban areas.
- Central Asian region should launch public awareness campaigns and educational initiatives to raise awareness about the importance of environmental conservation and the role that individuals, businesses, and communities can play in mitigating climate change.
- Empowering citizens with knowledge and information can foster a culture of sustainability and encourage the widespread adoption of environmentally friendly behaviors and practices.
- Finally, the Central Asian region should collaborate with international partners, organizations, and initiatives to exchange best practices, share technological expertise, and mobilize financial resources for climate mitigation and adaptation efforts. Likewise, by engaging in global climate diplomacy and participating in international agreements such as the Paris Agreement, Kazakhstan can demonstrate its commitment to addressing climate change on the world stage.

5.2. Limitations and Future Directions

The study relies on available data on GDP, population dynamics, technological innovations, and carbon dioxide emissions, which may be subject to inaccuracies, gaps, or inconsistencies. Improving data collection methods and ensuring data quality could enhance the robustness of future analyses. The analytical models used in this study may oversimplify the complex relationships between economic, demographic, and technological factors and carbon emissions. Future research could explore more sophisticated modeling techniques, including dynamic modeling approaches and integrated assessment models, to capture the nonlinear and interactive nature of these relationships more accurately. The findings of this study may be influenced by contextual factors specific to Kazakhstan, such as political, social, and economic conditions. Extrapolating these findings to other countries or regions with different contextual factors should be done cautiously, and further research is needed to assess the generalizability of the results. The study assumes a linear relationship between technological innovations, such as renewable energy adoption, and carbon emissions reduction. Future research could investigate the nonlinear dynamics of technological transitions, including potential rebound effects and unintended consequences, to provide a more nuanced understanding of their impact on carbon emissions. Future researchers are also recommended to Use scenario analysis to explore alternative future trajectories of carbon emissions under different policy, technology, and socio-economic scenarios, helping policymakers anticipate potential impacts and inform strategic decision-making.

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