

Renewable and Non-Renewable Energy Consumption, CO₂ Emissions and Economic Growth in a Developing Country: Empirical Evidence from Kazakhstan

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The engagement of developing countries is an increasingly important part of addressing Greenhouse Gas (GHG) emission-driven climate change. As such, understanding the patterns of energy use, GHG emissions and economic growth in developing countries is vital. The major Central Asian country of Kazakhstan is important in this respect due to its size, rapid growth and extensive energy reserves. It has experienced rapid growth in its economy, energy consumption and greenhouse gas emissions in recent years. This study examines the relationships between non-renewable and renewable energy consumption, CO₂ emissions, and economic growth in Kazakhstan, using 1990–2014 data from the World Development Indicators (WDI). It performs tests to verifying the existence of the long run relationships among the variables, and examines short and long run causal relationships. It finds that increased fossil fuel use is the main cause of increased CO₂ emissions.

Keywords: Carbon emissions, Economic growth, Environment, Renewable energy, Kazakhstan

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INTRODUCTION

Climate change relating to greenhouse gas (GHG) emissions is a major global problem. Total GHG emissions have doubled since the early 1970s, mainly driven by economic growth and the increasing use of fossil fuels. Developing countries account for an increasing share of this economic growth and fossil fuel-use. Moreover, the still pressing need for sustainable economic development and better living standards in developing countries makes the trade-offs involved especially important.

The Kyoto Protocol (1997) represented a landmark agreement to control greenhouse gas emissions. With the first commitment of the Kyoto Protocol ending in 2012, the world is looking for more effective ways to reduce carbon, which necessarily includes the active participation of developing countries. As such, understanding the patterns of energy use, GHG emissions and economic growth in developing countries is vital.

To examine these patterns, time-series econometrics techniques based on the Auto Regressive Distributed Lag (ARDL) models developed by Pesaran et al., (2001) to tests for the existence of long-run linkages and Granger causality tests. Although a number of empirical investigations have been carried out into the nexus between economic growth and energy consumption, relatively few attempts have been made to examine the relationship between emissions, renewable, and non-renewable energy consumptions, and economic growth. For example,

Apergis and Payne (2009) use panel data for six Central American countries for the period 1971 to 2004 to find that there exists bidirectional causality between energy consumption and emissions. Apergis and Payne (2010b) focused on Eurasian countries to study the link between renewable energy and output between 1990 and 2007. The results suggest feedback linking between the two variables by building panel data models with additional variables. Apergis et al., (2010) studied 19 developed and developing countries over the period of 1984 to 2004. They reported a positive and significant relationship between renewable energy consumption and CO₂ emissions. Riti et al., (2017) studied the association between CO₂ emissions, energy consumption, and economic growth in China. They employed a panel unit root test for stationarity, a panel co-integration test for a long-run relationship, and lastly a panel causality test to examine the relationship among CO₂ emissions, energy use, and economic growth. They used annual data from 1970 to 2015. Their results reveal no causality between Gross Domestic Product (GDP) and energy consumption, or between energy consumption and CO₂ emissions in the short-run.

Only a few panel studies have included Kazakhstan in Central Asia in their CO₂ analysis. To the best of our knowledge, there has not been a time series study investigating the causal relationship between non-renewable and renewable energy consumption, CO₂ emissions, and economic growth in Kazakhstan. This is in congruous because Kazakhstan represents an important case in this regard. As a resource-rich country, Kazakhstan has been characterized by a considerable achievement in economic growth and it has been passed through different development stages (Karatayev and Clarke, 2014; Nurgaliyeva, 2016; Amirov, 2018; Karatairi et al., 2018; Wang et al., 2019; Li et al., 2020). It has an important geo-economic role and significant energy reserves. The country has 33.6 billion tons of coal reserves, accounting for 3.6% of the world's total coal and the largest coal reserve in Central Asia. In 2018, the country produced 50.6 million tons of coal. Kazakhstan also has 30 billion barrels of oil reserves and 172 oil fields. It holds 3% of the world's oil reserves and is one of the top 15 countries in terms of oil reserves. With 9–11 billion barrels, Kashagan is the largest oil field outside of the Middle East. Kazakhstan also has proven reserves of 85 trillion cubic meters of natural gas. Most of the natural gas reserves are located in the western part of Kazakhstan. These fossil fuels are the main source of GHG emissions, but this energy it is also necessary for economic production, and therefore, economic growth and the development of society.

The purpose of this article, then, is to study investigating the causal relationship between non-renewable and renewable energy consumption, CO₂ emissions, and economic growth in Kazakhstan. The article is divided into five sections. Following this introduction in Section 1, there is a review of related literature in Section 2. Section 3 discusses the methodology. Section 4 examines the data analysis with a discussion of the findings, while Section 5 concludes with some recommendations and suggestions for future research.

LITERATURE REVIEW

Many studies have been conducted on the relationship between energy consumption, CO₂ emissions, and economic growth for different individual countries. The empirical literature abounds with studies that investigate the environmental effects of energy use and economic growth for both developed and developing countries using different datasets, model specifications, methodologies, and functional forms.

Several of these studies inform this article's approach. Mikayilov et al., (2018) empirically investigate the relationship between economic growth and CO₂ emissions in Azerbaijan. Cointegration analysis is conducted over the period 1992 to 2013. For more robust results, Johansen, ARDL, DOLS, FMOLS, and CCR methods are employed to explore cointegration and estimate long-run coefficients. The results from the different cointegration methods are consistent with each other and show that economic growth has a positive and statistically significant impact on emissions in the long run, implying that the environmental Kuznets curve (EKC) hypothesis does not hold for Azerbaijan. For China, Riti et al., (2017) explore the interrelationship among CO₂ emissions, economic growth, disaggregated energy (fossil fuel and renewable) consumption, and population. The results from auto regression distributed lag suggests that fossil fuel energy consumption increases CO₂ emissions, both

in the short and the long run, but renewable energy consumption reduces CO₂ emissions in the long run. Abokyi et al., (2019) showed the ARDL procedure with structural breaks and the Bayer–Hanck joint cointegration approach to examine the validity of the EKC hypothesis in the dynamic linkage between industrial growth and emissions of carbon dioxide in Ghana, capturing the role of fossil fuel consumption and financial development. For Kuwait, Wasti and Zaidi (2020) adopted Augmented Dicky-Fuller (ADP) and Phillips-Perron (PP) methods to review stationarity among the data sets. Their results explained a mixed trend, some variables followed the $I(1)$ process, and few are $I(0)$. Based on the findings, a well-defined ARDL model was applied to the data sets and the outcome was in support of the long and short-run relationship between variables. Cherni and Jouini (2017) examined the relationship between CO₂ emissions, renewable energy consumption (REC), and economic growth in Tunisia via an ARDL model. However, the Granger causality tests indicate a bidirectional relationship between GDP and CO₂ emissions as well as between REC and GDP but no relationship between CO₂ emissions and REC. Riti et al., (2016) explores the linkages between renewable energy and energy efficiency in ensuring an eco-friendly environment in Nigeria. Four independent variables were examined using time series data from 1981 to 2013 with pollution (CO₂) emission as an indicator of environmental degradation. The study also emanates with the view of proffering policies on how the use of renewable energy resulting in energy efficiency instead of traditional fossil fuel can be used to sustain the environment. For Thailand, Boontome et al., (2017) used the Error Correction Model (ECM) Granger Causality technique to demonstrate that consumption of non-renewable energy increased carbon emission but had a negligible impact on economic growth.

In most of the panel analyses that examined the environment-growth-energy, their results indicate that energy consumption, particularly non-renewable energy consumption, contributes to CO₂ emissions (Apergis and Payne, 2010a; Martínez-Zarzoso and Maruotti, 2011; Menegaki, 2011; Salim and Rafiq, 2012; Shafiei and Salim, 2014; Adewuyi and Awodumi, 2017; Amri, 2017; Riti et al., 2017; Riti et al., 2018; Hanif et al., 2019; Muhammad, 2019; Awodumi and Adewuyi, 2020). For example, Awodumi and Adewuyi (2020) employed panel data non-linear ARDL techniques to the relationship of non-renewable energy with economic growth and carbon emissions among the top oil-producing economies in African countries throughout 1980–2010. The results suggest that a complete significant interactive relationship exists among GDP, biomass consumption, and carbon emission in five West African countries. Using panel data for 11 countries of the Commonwealth of Independent States for 1992 to 2004, Apergis and Payne (2010a) state that energy consumption is positively associated with economic growth. The authors also find the existence of bidirectional causality between energy consumption and emissions. Nepal and Paija (2019) examine the interactions between energy security captured through the channel of electricity availability based on electricity consumption and economic output in a multivariate framework incorporating the effects of capital formation and population. They found that there is no long-run relationship between electricity consumption and economic output for Nepal, distinguishing it at the regional level for South Asia. Hanif et al., (2019) examined in detail, the effects of energy consumption, economic growth, population pressure, natural resource scarcity, and carbon emissions on Asian developing countries.

DATA AND METHODOLOGY

The present article follows from this literature on energy consumption. It seeks to extend knowledge on this topic and underline the roles of renewable and non-renewable energy consumption on carbon emissions, using a broad range of the latest data. The key contribution of the present research to the existing literature will be to shed light on and quantify the impact of energy consumption, economic growth, and natural resources on carbon emissions in Kazakhstan.

Source of Data and Model

To study the impacts of non-renewable and renewable energy consumption, economic growth, and natural resource depletion in CO₂ emissions, time-series data for Kazakhstan was used, covering a period of 25 years from

1990 to 2014. The data were retrieved from the World Development Indicators (WDI).

The study uses CO₂ emissions as a dependent variable, measured by annual per capita carbon dioxide emissions in metric tons.

For fossil fuels energy consumption (FEC), annual per capita fossil fuels energy consumption in kilograms of oil equivalent per capita was used. The author hypothesizes that fossil fuel consumption contributes to carbon emissions.

Renewable energy consumption (REC) measured by annual per capita renewable energy consumption in kilograms of oil equivalent. The author hypothesizes that renewable energy consumption reduces carbon emissions.

Forest area (FOA) shows the covered forest area in square kilometers (% of land area). As a result, the hypothesis is that a rise in deforestation increases carbon emissions.

Gross domestic product (GDP) per capita in constant 2010 US dollars is applied for economic growth. According to the hypothesis, economic growth contributes to carbon emissions in Kazakhstan. For the estimates the coefficient of the variables, the following empirical model is formulated. Stata 14.0 econometrics software was used for the analysis.

The purpose of this section is to examine the relationship between energy consumption (renewable and non-renewable), CO₂ emissions, and economic growth in Kazakhstan between 1990 and 2014. It adopted the Autoregressive Distributive Lag (ARDL) and Vector Error Correction Model (VECM) Granger causality methodologies and reports some findings.

$$CO_{2t} = f(FEC, REC, FOA, GDP, \omega) \quad (1)$$

The model is then converted to a natural logarithm to bring the data to the same units, reduce the variance as well as to interpret the coefficients in terms of elasticities.

$$\ln CO_{2it} = \alpha_0 + \beta_1 \ln FEC_{it} + \beta_2 \ln REC_{it} + \beta_3 \ln FOA_{it} + \beta_4 \ln GDP_{it} + \omega_{it} \quad (2)$$

Where, ω and ω_{it} is the error term for Equation (1) and (2).

$$\Delta y = \alpha_0 + \beta_2 x_{t-1} + \beta_3 y_{t-1} + \beta_4 z_{t-1} + \sum_{i=1}^q \gamma_i \Delta x_{t-i} + \sum_{j=0}^q \delta_j \Delta y_{t-j} + \sum_{k=0}^q \varepsilon_k \Delta z_{t-k} + \omega_i \quad (3)$$

Where t is time period, α_0 is constant, β_i is drift component x, y, z are the independent variables and ω_i represents white noise error processes. The ARDL approach estimates $(q + 1)^k$ the number of regressions necessary in order to obtain optimal lag length for each variable, where q refers to the maximum number of lags used; and k to the number of variables in Equation (4). If co-integration exists among the variable, then the error correction model (ECM) can be represented by the following.

$$\Delta y_t = \sum_{i=1}^q \gamma_i \Delta x_{t-i} + \sum_{j=1}^q \delta_j \Delta y_{t-j} + \sum_{k=1}^q \varepsilon_k \Delta z_{t-k} + \eta ECT_{t-1} + \omega_i \quad (4)$$

Unit Root Tests

This section shows graphically the overall statistics of quantitative data in the survey. The different axes show the different units of measure of the variables, and the graphs for each are converted to natural logarithmic values. The simplest study of data properties begins with a study of relative averages and variances of the data.

The descriptive statistics and correlation matrix in Table 1 shows the logarithmic variable data. Table 2 presents the overall mean values and units of measure for the 25 years of the survey between 1990 and 2014. The author performed unit tests using the variables included in the regression section using Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Augmented Dickey-Fuller Generalized Least Squares (ADF - GLS) tests at a significance level of 1%, 5%, and 10% (shown in Table 3). In this study, the Bayesian information criterion (BIC) or Schwarz criterion performed relatively well, so the Author used the Akaike information criterion (AIC) to determine the optimal number of latencies for the conditional ECM. It can be used to choose the best ARDL model after the AIC test. The AIC gives dynamic results compared to the Schwartz-Bayesian information criterion (SBIC). Table 3 also shows the AIC, SBIC, sequential modified LR test, final prediction error (FPE), and Hannan-Quinn information criterion (HQIC) delays at a significance level of 0.05.

Autoregressive Distribution Lag Model

The review of the relationships between CO₂ emissions, FEC, REC, and the effects of short run and long run on forest growth and forest carbon dioxide ARDL models (Perasan et al., 2001) were carried out as follows. To

Table 1. Descriptive statistics and correlation matrix

Variable	<i>lnCO2</i>	<i>lnFEC</i>	<i>lnREC</i>	<i>lnFOA</i>	<i>lnGDP</i>
Mean	2.4719	4.5862	0.4907	0.2177	8.7176
Std. Dev.	0.2453	0.0084	0.2566	0.0115	0.3610
Minimum	2.0546	4.5704	0.1431	0.2035	8.2264
Maximum	2.7688	4.5971	1.0202	0.2371	9.2729
Variance	0.0602	0.0001	0.0658	0.0001	0.1303
Skewness	-0.4267	-0.1874	0.4586	0.2159	0.1073
Kurtosis	1.6415	1.5438	2.1049	0.2159	1.5424
Jarque-Bera	1.470	2.048	4.738	1.676	0.004
<i>lnCO2</i>	1.0000				
<i>lnFEC</i>	0.4627	1.0000			
<i>lnREC</i>	-0.7016	-0.2255	1.0000		
<i>lnFOA</i>	-0.2617	-0.8861	0.0438	1.0000	
<i>lnGDP</i>	0.6768	0.8821	-0.3186	-0.8423	1.0000

Notes: All variables are expressed in their logarithms, Std. Dev. = standard deviation. Source: Compiled by the author based on World Bank data (1990-2014).

Table 2. ADF, PP and DF-GLS unit root tests

VAR	Deterministic	ADF		PP		DF-GLS	
		<i>I(0)</i>	<i>I(1)</i>	<i>I(0)</i>	<i>I(1)</i>	<i>I(0)</i>	<i>I(1)</i>
<i>lnCO2</i>	Trend & cons	-1.497	-0.115*	-1.334	-1.531*	-3.599	-3.046*
<i>lnFEC</i>	Trend & cons	-3.079	-1.033	-1.220	-3.111	-2.083	-0.620
<i>lnREC</i>	Trend & cons	-1.625*	-0.786*	-1.604*	-1.579*	-1.166*	-1.112**
<i>lnFOA</i>	Trend & cons	1.488	-8.953	-2.150	-2.075	-1.919	-1.404
<i>lnGDP</i>	Trend & cons	-4.274*	-1.755*	-0.037**	-3.448*	-3.486**	-2.793*

I(0) and *I(1)* stands for order of integration at level and on first difference. ADF is an Augmented Dickey-Fuller. PP is Philips and Pearson test for stationarity. * and ** represent 1% and 5% levels of significance. Source: Compiled by the author based on World Bank data (1990-2014).

Table 3. Lag length selection order criteria

Lag	L	LR	df	p	FPE	AIC	HQIC	SBIC
0	217.389				1.10E-15	-20.2275	-20.1736	-19.9788
1	339.295	243.81	25	0.0000	1.20E-19	-29.4566	-29.1328	-27.9644
2	378.11	77.631	25	0.0000	5.30E-20	-30.7724	-30.1787	-28.0367
3	451.223	146.23	25	0.0000	3.3e-21*	-35.3546	-34.491	-31.3755
4	3225.36	5548.3*	25	0.0000		-297.177*	-296.043*	-291.954*

Endogenous: InCO₂, InFEC, InREC, InFOA, and InGDP. Exogenous: constant, *Lag selection by the criteria. LR = sequential modified LR test (each test at 5% level); FPE = Final prediction error; AIC = Akaike information criterion; HQIC = Hannan-Quinn information criterion and SBIC- Schwarz's. Bayesian information criterion. Source: Compiled by the author based on World Bank data (1990-2014).

test the strength of co-integration results, the study used the co-integration method of the ARDL test in the presence of structural gaps to find long run relationships between variables. This method was chosen from traditional co-integration methods because it yields small and stable sample data. The ARDL method is capable of solving interconnected variables with a mixture of $I(0)$ and $I(1)$. The long run representation of ARDL model for the paper is specified as follows:

$$\begin{aligned} \Delta CO_{2t} = & \alpha_1 + \beta_{1a}CO_{2t-1} + \beta_{2a}FEC_{t-1} + \beta_{3a}REC_{t-1} + \beta_{4a}FOA_{t-1} + \beta_{5a}GDP_{t-1} \\ & + \sum_{k=1}^q \gamma_{1k} \Delta CO_{2t-k} + \sum_{k=0}^q \delta_{1k} \Delta FEC_{t-k} + \sum_{k=0}^q \varepsilon_{1k} \Delta REC_{t-k} \\ & + \sum_{k=0}^q \varphi_{1k} \Delta FOA_{t-k} + \sum_{k=0}^q \mu_{1k} \Delta GDP_{t-k} + \omega_1 \end{aligned} \quad (5)$$

$$\begin{aligned} \Delta FEC_t = & \alpha_2 + \beta_{1b}CO_{2t-1} + \beta_{2b}FEC_{t-1} + \beta_{3b}REC_{t-1} + \beta_{4b}FOA_{t-1} + \beta_{5b}GDP_{t-1} \\ & + \sum_{k=0}^q \gamma_{2k} \Delta CO_{2t-k} + \sum_{k=1}^q \delta_{2k} \Delta FEC_{t-k} + \sum_{k=0}^q \varepsilon_{2k} \Delta REC_{t-k} \\ & + \sum_{k=0}^q \varphi_{2k} \Delta FOA_{t-k} + \sum_{k=0}^q \mu_{2k} \Delta GDP_{t-k} + \omega_2 \end{aligned} \quad (6)$$

$$\begin{aligned} \Delta REC_t = & \alpha_3 + \beta_{1c}CO_{2t-1} + \beta_{2c}FEC_{t-1} + \beta_{3c}REC_{t-1} + \beta_{4c}FOA_{t-1} + \beta_{5c}GDP_{t-1} \\ & + \sum_{k=0}^q \gamma_{3k} \Delta CO_{2t-k} + \sum_{k=0}^q \delta_{3k} \Delta FEC_{t-k} + \sum_{k=1}^q \varepsilon_{3k} \Delta REC_{t-k} \\ & + \sum_{k=0}^q \varphi_{3k} \Delta FOA_{t-k} + \sum_{k=0}^q \mu_{3k} \Delta GDP_{t-k} + \omega_3 \end{aligned} \quad (7)$$

$$\begin{aligned} \Delta FOA_t = & \alpha_4 + \beta_{1d}CO_{2t-1} + \beta_{2d}FEC_{t-1} + \beta_{3d}REC_{t-1} + \beta_{4d}FOA_{t-1} + \beta_{5d}GDP_{t-1} \\ & + \sum_{k=0}^q \gamma_{4k} \Delta CO_{2t-k} + \sum_{k=0}^q \delta_{4k} \Delta FEC_{t-k} + \sum_{k=0}^q \varepsilon_{4k} \Delta REC_{t-k} \\ & + \sum_{k=1}^q \varphi_{4k} \Delta FOA_{t-k} + \sum_{k=0}^q \mu_{4k} \Delta GDP_{t-k} + \omega_4 \end{aligned} \quad (8)$$

$$\begin{aligned}
\Delta GDP_t = & \alpha_5 + \beta_{1e} CO_{2t-1} + \beta_{2e} FEC_{t-1} + \beta_{3e} REC_{t-1} + \beta_{4e} FOA_{t-1} + \beta_{5e} GDP_{t-1} \\
& + \sum_{k=0}^q \gamma_{5k} \Delta CO_{2t-k} + \sum_{k=0}^q \delta_{5k} \Delta FEC_{t-k} + \sum_{k=0}^q \varepsilon_{5k} \Delta REC_{t-k} \\
& + \sum_{k=0}^q \varphi_{5k} \Delta FOA_{t-k} + \sum_{k=1}^q \mu_{5k} \Delta GDP_{t-k} + \omega_5
\end{aligned} \tag{9}$$

Here, from Equations (5) – (9), Δ is the first difference operator, $\ln$ denotes the natural logarithm, and q is the lag order selected by AIC. The parameters $\gamma, \delta, \varepsilon, \varphi$ and μ are short run dynamic coefficients while the parameters β_1 to β_5 function as the long run multipliers of the underlying ARDL model. The residuals ω_p , assumed to be normally distributed, are white noise.

Granger Causality Test

Although the ARDL approach is preferable in verifying the existence of the long run among the variables, it does not explain the direction of a cause-effect relationship. Therefore, VECM is used. The vector auto-regression (VAR) model is also available for this purpose. Granger noted that if a set of variables is co-integrated, there must be a short and long run causality that cannot be captured by the standard first difference VAR model (Riti et al., 2017). The VECM shows the reason within the sample, and does not explain the reason outside the sample (Apergis and Payne, 2010a). In this case, the author must implement the Granger causality test with the VECM framework as follows:

$$\begin{aligned}
\Delta CO_{2t} = & \alpha_1 + \sum_{k=1}^q \gamma_{1k} \Delta CO_{2t-k} + \sum_{k=1}^q \delta_{1k} \Delta FEC_{t-k} + \sum_{k=1}^q \varepsilon_{1k} \Delta REC_{t-k} + \sum_{k=1}^q \varphi_{1k} \Delta FOA_{t-k} \\
& + \sum_{k=1}^q \mu_{1k} \Delta GDP_{t-k} + \rho_1 ECT_{t-1} + \omega_{1t}
\end{aligned} \tag{10}$$

$$\begin{aligned}
\Delta FEC_t = & \alpha_2 + \sum_{k=1}^q \gamma_{2k} \Delta CO_{2t-k} + \sum_{k=1}^q \delta_{2k} \Delta FEC_{t-k} + \sum_{k=1}^q \varepsilon_{2k} \Delta REC_{t-k} + \sum_{k=1}^q \varphi_{2k} \Delta FOA_{t-k} \\
& + \sum_{k=1}^q \mu_{2k} \Delta GDP_{t-k} + \rho_2 ECT_{t-1} + \omega_{2t}
\end{aligned} \tag{11}$$

$$\begin{aligned}
\Delta REC_t = & \alpha_3 + \sum_{k=1}^q \gamma_{3k} \Delta CO_{2t-k} + \sum_{k=1}^q \delta_{3k} \Delta FEC_{t-k} + \sum_{k=1}^q \varepsilon_{3k} \Delta REC_{t-k} + \sum_{k=1}^q \varphi_{3k} \Delta FOA_{t-k} \\
& + \sum_{k=1}^q \mu_{3k} \Delta GDP_{t-k} + \rho_3 ECT_{t-1} + \omega_{3t}
\end{aligned} \tag{12}$$

$$\begin{aligned}
\Delta FOA_t = & \alpha_4 + \sum_{k=1}^q \gamma_{4k} \Delta CO_{2t-k} + \sum_{k=1}^q \delta_{4k} \Delta FEC_{t-k} + \sum_{k=1}^q \varepsilon_{4k} \Delta REC_{t-k} + \sum_{k=1}^q \varphi_{4k} \Delta FOA_{t-k} \\
& + \sum_{k=1}^q \mu_{4k} \Delta GDP_{t-k} + \rho_4 ECT_{t-1} + \omega_{4t}
\end{aligned} \tag{13}$$

$$\Delta GDP_t = \alpha_5 + \sum_{k=1}^q \gamma_{5k} \Delta CO_{2t-k} + \sum_{k=1}^q \delta_{5k} \Delta FEC_{t-k} + \sum_{k=1}^q \varepsilon_{5k} \Delta REC_{t-k} + \sum_{k=1}^q \varphi_{5k} \Delta FOA_{t-k} + \sum_{k=1}^q \mu_{5k} \Delta GDP_{t-k} + \rho_5 ECT_{t-1} + \omega_{5t} \quad (14)$$

From Equations (10)-(14), where Δ is the first difference operator and $\ln$ is the natural logarithm, $\rho_1, \rho_2, \rho_3, \rho_4$ and ρ_5 are the coefficients of error correction terms in the equations. The dynamic error correction term is represented by ECT_{t-1} which displays the rate of adjustment mechanism from the short run distortions to long run stability. It shows model convergence to long run equilibrium path in case of disturbance in the short run.

Vector Error Correction Model

Researchers have suggested that the existence of a coherent relationship between variables is at least one of the possible reasons for this (Engle and Granger, 1987). To determine the causal direction between the variables, the study used the modified Granger causality analysis. Granger's causal analysis should be used carefully with the first difference through VAR due to the likelihood of bias among variables. Engle and Granger (1987) argue that if all variables are $I(1)$ and with an integrative vector, it is advisable to specify the VECM. Therefore, with evidence for joining the Series $I(1)$ used in this study, we examine in detail the correlation direction between variables using the Granger-Causality Test, an ECT. The following is the Granger causality specification augmented by an error correction term formulated (Equation 15) as a bi-variate path order VECM:

$$(1-p) \begin{bmatrix} \ln CO_2 \\ \ln FEC \\ \ln REC \\ \ln FOA \\ \ln GDP \end{bmatrix} = \begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \\ \theta_4 \\ \theta_5 \end{bmatrix} + \begin{bmatrix} \ln CO_2 \\ \ln FEC \\ \ln REC \\ \ln FOA \\ \ln GDP \end{bmatrix} + \sum_{k=1}^q (1-p) \begin{bmatrix} Y_{11i} & Y_{12i} & Y_{13i} & Y_{14i} & Y_{15i} \\ Y_{21i} & Y_{22i} & Y_{23i} & Y_{24i} & Y_{25i} \\ Y_{31i} & Y_{32i} & Y_{33i} & Y_{34i} & Y_{35i} \\ Y_{41i} & Y_{42i} & Y_{43i} & Y_{44i} & Y_{45i} \\ Y_{51i} & Y_{52i} & Y_{53i} & Y_{54i} & Y_{55i} \end{bmatrix} \begin{bmatrix} \ln CO_{2t-k} \\ \ln FEC_{t-k} \\ \ln REC_{t-k} \\ \ln FOA_{t-k} \\ \ln GDP_{t-k} \end{bmatrix} + \begin{bmatrix} \varphi_1 \\ \varphi_2 \\ \varphi_3 \\ \varphi_4 \\ \varphi_5 \end{bmatrix} [ECT_{t-1}] + \begin{bmatrix} \omega_{1t} \\ \omega_{2t} \\ \omega_{3t} \\ \omega_{4t} \\ \omega_{5t} \end{bmatrix} \quad (15)$$

where $(1-p)$ in the above VECM is the lag operator, the lagged error correction term is ECT_{t-1} derived from the long run relationship while $\omega_{1t}, \omega_{2t}, \omega_{3t}, \omega_{4t}$ and ω_{5t} are the error terms which are expected to be serially uncorrelated with zero mean. The appropriate lag length p was selected based on SIC. The VECM definition helps to establish causality between long run and short run variables. The t-statistical significance of the term ECT_{t-1} over long run causality. The importance of F-statistics on the regression stunted difference shows short Granger causality. Granger causality test directions are provided by VECM and are divided into short and long. Chi-squared statistics or partial F- statistics show the cause of short run current, while the VECM, which includes t -statistics, gives the Granger's long run direction. The determination of the existence of co-integration among the variables in the ARDL model presents an interesting platform to conduct the Granger causality test.

Diagnostic Analysis

Diagnostic, stability, and Wald tests are conducted to assess serial correlation, functional form, normality, and heteroscedasticity associated with the model. Tables 7 presents the residual diagnostic for the ARDL model. Ignoring the correlation between the variables may have serious consequences on the estimated parameters. To test the long run relationship between the underlying variables, we apply the Wald test. Rejecting the null hypothesis means the presence of a long run relationship, while its acceptance denotes the absence of a long run relationship. The cumulative sum of the recursive residuals (CUSUM) test recursively calculates the regression coefficients and residuals at particular thresholds. Figure 2 exhibits the CUSUM and cumulative sum of squares of recursive residuals (CUSUMSQ) graph obtained from ARDL stability tests. The purpose of including these graphs is to investigate the structural stability in the given model.

RESULT AND DISCUSSION

Unit Root Tests

The chart below (Figure 1) describes the evolution of the levels and growth rates of the variables as logarithmic values. From 1993 to 1999, CO₂ emissions were reduced. From 2010 to 2011, CO₂ emissions increased annually. From 2012 to the present, there has been a similar increase. The FEC has grown dramatically from 1994 to 2004 and has been moving up and down since 2005. In 2000, RECs in Kazakhstan climbed to an all-time high, and in 2007 the trend looked likely to stabilize. The volume of forests in the territory of Kazakhstan has been steadily declining from 1991 to 2009. As of 2010, it still accounts for 1.22% of the total area, and much has to be done to reduce the decline. Since 1994, GDP has been growing rapidly, and is likely to continue to grow. Variable trends include CO₂ emissions, fossil fuel consumption as a percentage of total energy consumption, GDP growth, population growth, and REC as a proportion of total energy consumption. From these, we can see that the FEC and GDP of Kazakhstan are expected to continue to grow.

Table 1 provides the descriptive analysis of the variables. A look at the descriptive analysis shows that the in-

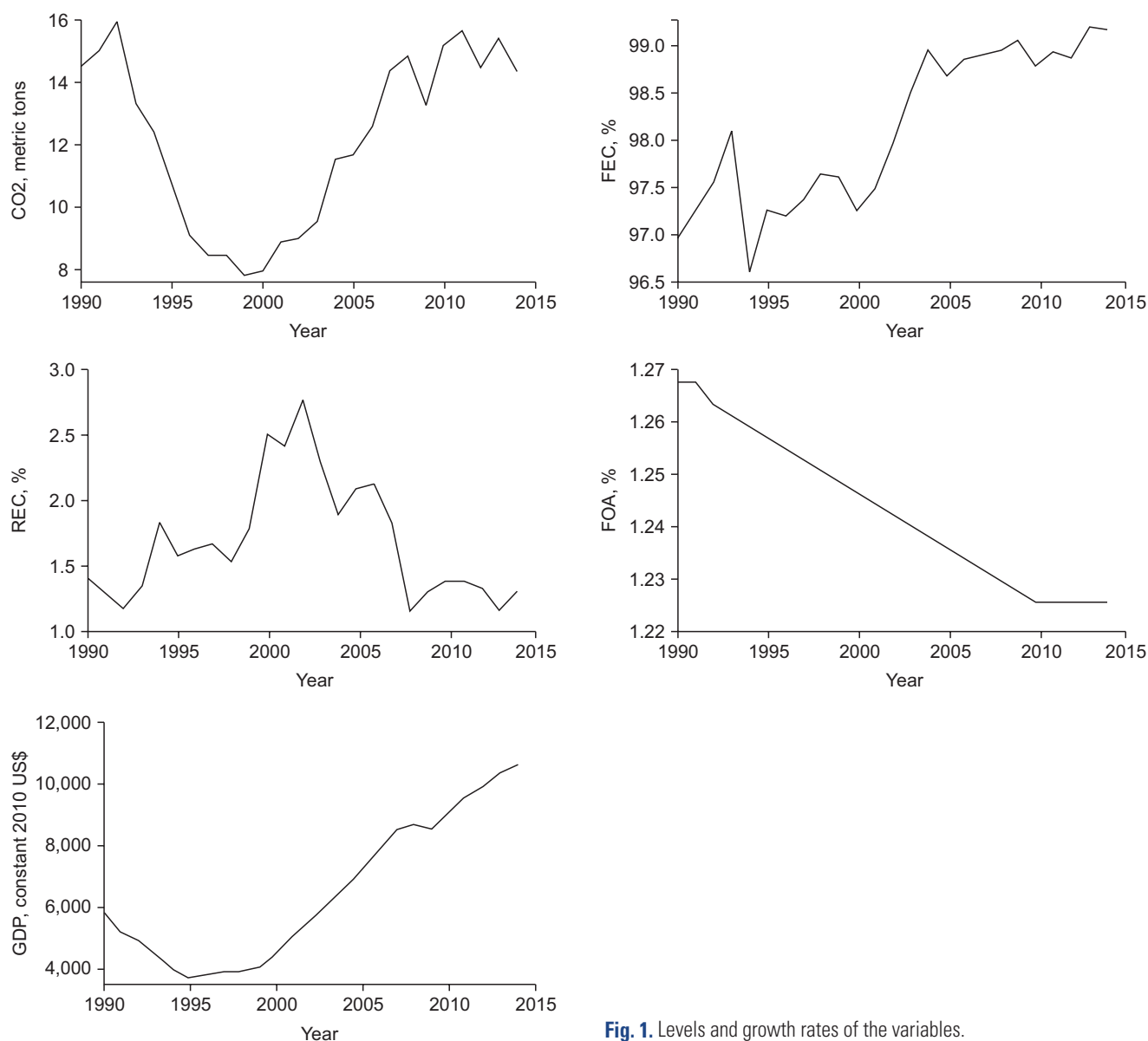


Fig. 1. Levels and growth rates of the variables.

vestigated variables display some insignificant variances in the statistics. The average and standard deviation values of CO₂ emissions are 2.4719 and 0.2453 respectively. The average and standard deviation values of FEC stand at 4.5862 and 0.0084 respectively. REC, FOA and GDP use have mean values of 0.4907, 0.2177 and 8.7176 respectively, while the respective standard deviations are 0.2566, 0.0115, and 0.3610 respectively. The large standard deviations of the variables are indications of large variations of the values around their averages, hence, large disparities. To test the distribution properties of these variables, the study uses Jarque-Bera, Skewness, and Kurtosis as indicators. In a normal distribution Kurtosis is 3, and skewness is 0.

In what follows, more properties of these variables are presented. To examine the intensity of multi-collinearity, the results of the correlation matrix are reported in Table 1. The correlation coefficient between CO₂ emissions and FEC is 0.4627, implying that the relationship between CO₂ emissions and FEC is 46.27%. The relationship between CO₂ emissions and REC is approximately 70.16% in a positive direction, while the relationship between CO₂ emissions and GDP are positively strong by 67.68%. The correlation coefficient of FEC and GDP by 0.8821 (88.21%). The results show that CO₂ emissions are weakly correlated with FEC, REC, FOA, and GDP.

To investigate the unit root properties of the variables, the study employed the ADF, the PP, and the DF-GLS tests which are conventional approaches for unit root testing. Table 2 presents the results of the unit root test through ADF methods. It shows that CO₂ emissions, FEC, and FOA are non-stationary at level ($I(0)$); however, they become stationary at the first difference ($I(1)$). Besides this, REC and GDP are found to be stationary at $I(0)$. For comparison, the study used the PP and DF-GLS method, and its results are consistent with the ADF technique. Once the stationarity was observed, the study moved to check the long run association among variables. In this case, where three variables are two and stationary at the first difference ($I(1)$) are non-stationary at level ($I(0)$), the use of ARDL methods are acceptable. These findings suggest that the ARDL “bounding test” approach is useful for our co-integration analysis and is appropriate to estimate the existence of long run relationships between the variables.

After analyzing the descriptive statistics and correlation matrix, it is one of the challenging tasks to utilize the VAR to find out a selection of the optimal lag length. It requires precision, as the addition of lags to time series

Table 4. ARDL bounds test co-integration analysis

Dependent variable	Optimal lag	F-stat	Significant level (%)
$\ln CO_2 = f(\ln FEC, \ln REC, \ln FOA, \ln GDP)$	1, 0, 1, 2, 2	6.240	
$\ln FEC = f(\ln CO_2, \ln REC, \ln FOA, \ln GDP)$	2, 1, 2, 2, 2	9.032	10
$\ln REC = f(\ln CO_2, \ln FEC, \ln FOA, \ln GDP)$	1, 1, 0, 2, 0	5.242	5
$\ln FOA = f(\ln CO_2, \ln FEC, \ln REC, \ln GDP)$	2, 2, 2, 1, 2	6.603	2.5
$\ln GDP = f(\ln CO_2, \ln FEC, \ln REC, \ln FOA)$	2, 2, 0, 2, 2	4.566	1

Diagnostic test	DW	R ²	Adj-R ²	Lower bound I(0)	Upper bound I(1)
$\ln CO_2$	2.076787	0.8782	0.7766		
$\ln FEC$	1.864371	0.9165	0.7959	2.45	3.52
$\ln REC$	1.591575	0.7659	0.6321	2.86	4.01
$\ln FOA$	2.116848	0.8874	0.7248	3.25	4.49
$\ln GDP$	1.647456	0.9310	0.8482	3.74	5.06

*, ** and *** indicate significant of the variables at 1, 5 and 10% significance level. Critical values are collected from (Perasan et al., 2001), Table, case III (intercept and unrestricted trend). Source: Compiled by the author based on World Bank data (1990-2014).

models have a direct impact on the estimation process, and four lags have suggested by the SBIC method (Table 3). The likelihood ratio, sequential modified LR test, the FPE, the AIC, the HQIC, and the SBIC selected lag 4 as shown by the asterisk at the 0.05 significance level. This is sufficiently long for an annual data study to capture the dynamic relationship so that the AIC statistic could then be used to choose the best ARDL models.

Bounds Test Approach to Co-Integration

For the ARDL limitation test method, the F-test was calculated and tested for correlation between variables to test for the joint significance of a series of lagging variables. The ARDL method calculates four F-statistics by normalizing each variable to a dependent variable to determine the total number of aggregated vectors. Before calculating the F-test, AIC was first used to choose the optimum latency to avoid pattern matching. As shown in Table 4 where the result of the bound test is reported, the author found the existence of co-integration only in one case, when carbon dioxide emissions are the dependent variable. Using the other variables as dependent variables produced no evidence of co-integration and thus confirming the existence of only one co-integration relationship between the variables. The experiment showed that the F-statistic value of CO₂ emissions exceeded the upper critical boundary of 6.240, the FEC was 9.032, the REC was 5.242, and the total hollow forestry value was 6.603. The F-statistical value of the economic increase (GDP) is 4.566, which is 1% below the critical threshold and validates the inconclusiveness when the population is a dependent variable. Based on these results, the author can conclude that CO₂ emissions and economic growth in Kazakhstan are cointegrating.

Short Run and Long Run Estimated Coefficient

Table 5 shows the significance levels for FEC, REC, FOA, and GDP for short and long run analyzes. Coefficient integration of FEC, REC, FOA, and GDP expressed in CO₂ emissions is based on co-integration among variables. The sign of the coefficient of FEC is negative in the short run but turns out to be positive in the long run. A 1% increase in FEC contributes 12.2628% to CO₂ emissions in the negative direction. The long run analy-

Table 5. Statistical output for parsimonious model (long run and short run analysis)

Dependent variable: <i>lnCO2</i>				
Variables	Coefficient	Standard error	t-statistic	Probability
Long run elasticities				
<i>lnFEC</i>	-11.7789**	4.4332	-2.66	0.021
<i>lnREC</i>	-0.0424	0.0913	-0.47	0.650
<i>lnFOA</i>	22.3382***	3.9385	5.67	0.000
<i>lnGDP</i>	1.4516*	0.1425	10.18	0.000
Short run elasticities				
Constant	40.5517*	19.8112	2.05	0.063
$\Delta \ln FEC$	-12.2628*	4.6278	-2.65	0.021
$\Delta \ln REC$	-0.1996**	0.0785	-2.54	0.026
$\Delta \ln FOA$	-66.893**	23.7731	-2.81	0.016
$\Delta \ln GDP$	-1.0633**	0.4325	-2.46	0.030
$ECT_{(-1)}$	-1.041***	0.2294	-4.54	0.001
$R^2 = 0.8782$		Adjusted $R^2 = 0.7766$		
F-statistic = 6.24		DW = 2.076787		

*, ** and *** indicate significant of the variables at 1, 5 and 10% significance level. Source: Compiled by the author based on World Bank data (1990-2014).

sis shows that a 1% increase in FEC contributes a 11.7789% rise in CO₂ emissions. Long-run analysis shows that a 1% increase in fossil fuel energy consumption contributes a 0.485% rise in CO₂ emissions. This notion shows efficiency and technological change in the process of production and consumption in the long run. REC impacts are negative by reducing emission and ensuring environmental quality. A 1% increase in renewable energy consumption decreases emissions by 0.1996 and 0.0424% in the short and long run, respectively. The plausibility of the findings lies with the sign and significance of the coefficient of renewable energy consumption both in the short and long runs. The negative and statistical reliability of the renewable energy factor has shown that it contributes to the reduction of greenhouse gas emissions and, consequently, to climate change. The finding that renewable energy reduces greenhouse gas emissions is in line with the efforts by the Ministry of Environment and Water Resources of the Republic of Kazakhstan to reduce the incidence of climate change impacts in the country. This effort gave rise to the renewable energy program initiated in the country. A 1% increase in FOA contributes 66.893% to CO₂ emissions in the negative direction. The long-run analysis shows that a 1% increase in FOA leads to a 22.3382% rise in CO₂ emissions. An $ECT_{(-1)}$ has a negative sign and is statistically reliable, but the short circuit current equals 1.041%. Economic growth (GDP) effects on the environment (CO₂ emissions) on the other hand show a diminishing trend from the short run to the long run. In the short run, a 1% increase in GDP will result in a 1.0633% increase in CO₂ emissions. However, in the long run, the effect of GDP increased from 1.0633 to 1.4516 percent. Overall, the analyses of the short and long run confirm the dynamic interaction of the variables and agreed with the energy-growth-environment led thesis where FEC, FOA, and GDP lead to environmental degradation while REC ensures environmental quality. Higher energy consumption tends to increase emissions from non-renewable sources, while renewable energy and clean energy can reduce emissions.

Direction of Causality within VECM

The results of the ECT co-integration causality test are presented in Table 6. Long run causality indicates a long run relationship between all VECM variables: $ECT_{(-1)}$ coefficient was found to be negative and significant at 5% according to t-statistics. This result has two implications. First, it confirms the long run equilibrium relationship between variables between the ARDL's restriction and the Bayer-Hanck co-integration. Secondly, the increase in FEC, REC, and GDP causes long run CO₂ emissions. The F-statistics over a short period of time show that there are one-way factors to the change in CO₂ emissions, FEC, and CO₂ emissions to REC. In the case of short run distortion, the rate of long run calibration of the CO₂ emissions equation is 20.670%. The FEC equation, on the other hand, is speed setting, fluctuating around 3.8% if the system shakes briefly. REC has a long consolidation rate of 61.47%. FOA and GDP impact rates are relatively low at 0.391% and 0.946%. The short run Granger presents the results of causation. Even FEC to CO₂ emissions are unidirectional. GDP and CO₂ emissions are bi-directional in the short run. Renewable energy produces short run CO₂ emissions from renewable energy within a short run of time, showing growth forecasts. This means that renewable energy ensures environmental quality

Table 6. Statistical output for VECM granger causality

VAR	Short run					Long run
	$\Delta \ln CO_2$	$\Delta \ln FEC$	$\Delta \ln REC$	$\Delta \ln FOA$	$\Delta \ln GDP$	$ECT_{(-1)}$
$\Delta \ln CO_2$	-	0.000111 (0.00730)	-0.389 (0.302)	-0.000763 (0.00139)	-0.169** (0.0621)	-20.67 (16.05)
$\Delta \ln FEC$	2.993 (3.484)	-	14.02* (7.969)	-0.0874** (0.0368)	0.0187 (1.638)	3.800** (0.887)
$\Delta \ln REC$	0.102 (0.0689)	0.00486 (0.00381)	-	-0.00113 (0.000727)	0.0656** (0.0324)	-61.47* (36.72)
$\Delta \ln FOA$	12.47** (3.306)	-0.195 (0.183)	2.980 (7.561)	-	-3.864** (1.554)	0.391** (0.169)
$\Delta \ln GDP$	0.625** (0.137)	0.0132* (0.00759)	-0.261 (0.314)	0.00215 (0.00145)	-	0.946 (7.545)

*, ** and *** indicate significant of the variables at 1, 5 and 10% significance level, respectively. Source: Compiled by the author based on World Bank data (1990-2014).

in favor of growth while fossil fuel energy ensures growth at the expense of the environment. In addition, with the increase in GDP, there is a tendency to increase energy consumption. Increasing energy consumption, furthering long run economic growth in Kazakhstan, is increasing emissions. An increase in CO₂ emissions and energy consumption in Kazakhstan indicates that feedback prediction forecasts are bidirectional. In summary, Granger's causal test has long been the cause of the impact in the entire series.

Diagnostic Analysis Result

Table 7 presents the diagnostic tests for the long run ARDL estimates as well as the short run. A maximum of two lags was initially considered and both lag selection criteria and lag exclusion tests statistics proposed that indeed a lag of order two was optimal. The F-statistics of serial correlation is 18.676 with a p-value being 0.823, indicating that there are no serial correlations. The result of the normality test shows the F-statistic as 1.470 with its p-value being 0.479. The normality test shows that the residuals are normally distributed and are homoscedastic. The Wald test also shows the model is correctly specified. In addition to this, the value of the Jarque-Bera test shows residuals are normally distributed. This step consists of applying the CUSUM test to predict the presence of a stable long run relationship. In order to check the stability of the parameters, the CUSUM and CUSUMSQ are reported in Figure 2, respectively. All the lines range between the critical bounds and no line crosses acritical bound throughout the span. These graphs provide evidence about the stability of the ARDL estimation results presented above.

Table 7. VAR residual diagnostics, stability and Wald test results

Panel A: Serial Correlation LM test		
lags	LM-Statistic	p-value
1	18.676	0.813
2	24.756	0.476
3	19.272	0.782
Panel B: Normality test		
Statistics	χ^2	p-value
Jarque-Bera	1.470	0.479
Panel C: Heteroscedasticity test		
	χ^2	p-value
White statistic	23.00	0.4017
Panel D: Wald test		
	χ^2	Prob.
<i>lnCO2</i>	9.4711	0.1318
<i>lnFEC</i>	5.7917	0.3895
<i>lnREC</i>	1.3999	0.3443
<i>lnFOA</i>	2.6328	0.2155
<i>lnGDP</i>	4.4177	0.2635

Source: Panel A = Serial Correlation LM test's null hypothesis in the is no serial correlation at lag of order h of the residuals; Panel B = The employed Urzua (1997) system normality test's null hypothesis is residuals are multivariate normal; Panel C = The used White Heteroscedasticity Test's null is no cross terms heteroscedasticity in the residuals; Panel D = Author calculation.

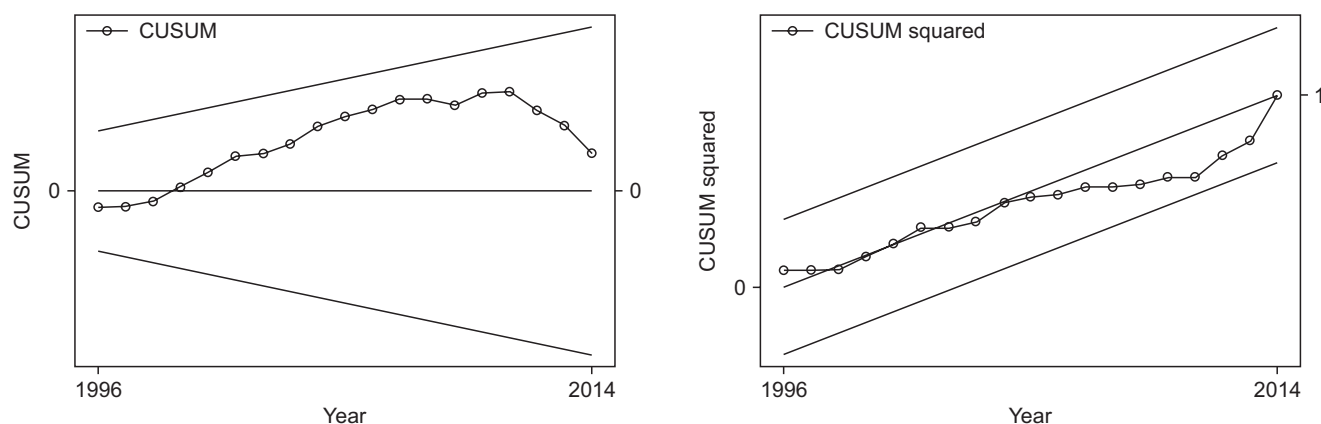


Fig. 2. Plot of CUSUM and CUSUMQ stability test. The straight lines represent critical bounds at 5% level of significance. Source: Compiled by the author based on World Bank data (1996-2014).

CONCLUSION AND RECOMMENDATIONS

This study used annual data from the World Bank's World Development Indicators for the period from 1990 to 2014. The CO₂ emissions in Kazakhstan are based on the long run and short run relationship between fossil fuels energy consumption, renewable energy consumption, forest area and economic growth with the ARDL model and VECM-Granger tried to explain using the causality test. An empirical analysis uses the Augmented Dickey-Fuller and Philip-Perron method to test the basics of the data unit based on this information. The model also maintained stability through the Jarque-Bera, Wald test, and CUSUM tests. The Jarque-Bera and Wald tests show that the residue is distributed normally. According to the CUSUM test results, the model was stable. Long run and short run causal relationships between the variables were performed in the ECT augmented Granger causality experiment, which revealed long run causality only during regression of CO₂ emissions. The increase in fossil fuel use in Kazakhstan is the main cause of CO₂ emissions. Our research hypothesis is therefore confirmed.

Kazakhstan is a relatively large economy in the Central Asian region. Especially during the transition period, its economic growth has increased relatively rapidly and so have greenhouse gas emissions. The results of the analysis show that this use of fossil fuels has been harmful to the environment. In recent years, Kazakhstan's economy has been growing rapidly, and as energy consumption has increased, so have greenhouse gas emissions, especially from fossil fuels. Power plants use much fossil fuel. Kazakhstan is rich in natural resources such as coal, oil, natural gas and, uranium, and has significant renewable energy resources from wind, solar, hydro, and biomass. It is possible to change the total energy mix by replacing renewable energy sources with wind, hydropower, and solar energy.

Today, Kazakhstan has 65 active renewable energy facilities. There are 33 hydropower plants, 19 solar power plants, 12 wind farms, and 1 biomass facility. Solar energy will play an important role in furthering economic growth. Kazakhstan has significant reserves of wind power, small, medium, and large hydropower and solar power plants. Almost half of the population lives in rural areas, and it is possible to create a small centralized renewable energy systems. Further development of renewable energy based on its resource and renewable energy facilities such as wind, solar, water, and biomass is very beneficial to the environment and human health.

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