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Original Research Article

Investigation of the Causal Relationships between Economic Development and Combustible Renewables and Waste Consumption in Central Asian Countries

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Abstract

This study examines the relationships between Foreign direct investment (FDI), Gross domestic product (GDP), Trade, Inflation, Labor force, Population density, Combustible renewables and waste consumption for the case of Central Asia, spanning the period 1990 to 2020. The combustible renewables and wastes consumption in Central Asia are based on the long run and short run relationship between economic development with the Error Correction Model (ECM) based Panel Cointegration tests and Panel Vector Error Correction Model (VECM) Granger causality test tried to explain using the causality test, spanning the period 1990 to 2020. An empirical analysis uses the Im, Pesaran, and Shin (CIPS) Panel Unit Root test and Westerlund ECM to test the basics of the data unit based on this information. The Panel Vector Autoregression (PVAR) specification was based on the results of the Lag-order selection criteria, and the stability of the PVAR model was checked through the observation of the Hausman test and Eigenvalue stability condition. It performs tests to verify the existence of the long run relationships among the variables and examines short and long run causal relationships. It finds that increased combustible renewables and waste consumption use is the main cause of increased economic growth.

Keywords: Combustible renewables; Waste; Central Asia; Economic development; Environmental Economics.

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1. INTRODUCTION

One of the main purposes of any country is to maintain continuous economic growth. For this reason, lots of studies are conducted for examining the factors affecting economic growth. Those studies generally support policymakers develop the appropriate strategy of economic growth. As the global economy grows, energy consumption grows simultaneously. Central Asian countries have rich resources of energy. Tajikistan and Kyrgyzstan have a big resource of hydropower; and Kazakhstan, Turkmenistan, and Uzbekistan have a huge resource of coal, natural gas, and oil. Consequently, any country in this region still has not generated any energy from solar and wind power. Renewable energy reduces the investment cost of new industrial plants and accelerates development. Renewable energy is derived from natural processes (such as sunlight and wind etc.,) and is replenished at a higher speed than it is consumed. Solar energy, wind energy, geothermal power, hydropower, and biomass are considered the most common renewable energy sources. Combustible renewable and waste comprise solid biomass, liquid biomass, and biogas. Animal products, municipal and industrial wastes are combusted in specific plants and transferred into energy. Biomass is a plant that is used as a fuel to produce heat or energy. Humans started struggling to build an environment-oriented future, in consequence, faced challenges of waste management. Although combustive renewables and waste production increase CO_2 emission, it is much smaller than fossil fuel energy consumption.

An overview of the Central Asian countries (multi-country) literature on the Granger causality (Granger, 1969) and VAR methodology (Sims, 1972) that plethora of surveys around (Ashurov *et al.*, 2020; Batsaikhan and Marek, 2017; Bird *et al.*, 2020; Nurseiit, 2020; *Rosenbaum et al.*, 2012). For example, Ashurov *et al.*, (2020) investigated and identified the determinants of foreign direct investment (FDI) in the Central Asian countries, specifically Tajikistan, Kazakhstan, Kyrgyzstan, Turkmenistan, and Uzbekistan, between 2000 to 2017. The methodology employed in the first part included a comparative analysis of the foreign investment trends and GDP, as well as an endogenous growth model. The result showed that five variables are robustly significant of FDI determinants: FDI, GDP, labor force, trade openness, and tax. Moreover, it is essential to highlight the strong dynamic causal links between renewable energy consumption and economic growth which have been examined in several empirical studies either for the case of cross-sectional time series or the case of the panel. Above mentioned studies examined short-term and long-term relationships using variable methods. The study on the relationship between renewable energy consumption and economic growth of Central Asia is very rare, and even more, there is not any study conducted using combustible renewables and waste data. The relationship between renewable energy and economic growth varies in different studies. These differences depend on many factors such as selection of the countries, empirical methodology, technique, and duration of the research.

In this study, the combustible renewables and wastes consumption in Central Asia are based on the long run and short run relationship between economic development with the Error Correction Model (ECM) based Panel Cointegration tests and Panel Vector Error Correction Model (VECM) Granger causality test tried to explain using the causality test, spanning the period 1990 to 2020. An empirical analysis uses the Im, Pesaran, and Shin (CIPS) Panel Unit Root test and Westerlund ECM to test the basics of the data unit based on this information. Following the best econometric practices, the descriptive statistics, Correlation matrix, and Cross-sectional dependence unit roots test were computed to understand the characteristics of the variables and countries under analysis and to ensure that the necessary conditions for the estimation were fulfilled. The Panel Vector Autoregression (PVAR) specification was based on the results of the Lag-order selection criteria, and the stability of the PVAR model was checked through the observation of the Hausman test and Eigenvalue stability condition. Long run and short run causal relationships between the variables were performed in the ECT augmented Panel Granger causality experiment, which revealed long run causality only during regression of Combustible renewables and wastes consumption. The main idea of this study is aimed at generating energy products from waste. The main problem of the study is “How do Combustible renewables waste consumption and economic development affect each other? The purpose of this study is to determine generating energy from waste not only reduces the waste but also benefits the environment and plays an important role in economic development. This research uses namely variables Foreign direct investment (FDI), Gross domestic product (FDI), Trade, Inflation, Labor force, Population density, and Combustible renewables and waste to examine the relationship which will answer the above-asked question. The result of this empirical research will examine the relationship between the economic development of Central Asian countries and the energy sector. In particular, it will support policymakers of those countries to develop a strategy to promote economic growth. The article is divided into six sections. Following this introduction in Section 1, there is a review of related literature in Section 2. Section 3 discusses the methodology and data. Section 4 examines the data analysis. Section 5 is the discussion of the findings, while Section 6 concludes with some recommendations and suggestions for future research.

2. LITERATURE REVIEW

The existing empirical literature is presented to have an idea of past empirical findings on the investigation of the causal relationships between economic development and combustible renewables and waste for different individual countries. The empirical literature abounds with studies that investigate the environmental effects of energy use and economic development for both developed and developing countries using different datasets, model specifications, methodologies, and functional forms. The existing literature related to this research is reviewed under the following four categories: (I) the studies on the economic development, using the different variables (II), the studies on combustible renewables and waste for different countries, (III) the studies on causal effect using the Panel Cointegration test, and Panel Granger causality test, and (IV) the studies on economic development in Central Asian countries. A more detailed analysis is presented in the following categories.

The first category of existing literature on the effect of economic development and urban haze pollution in Chinese (Gan *et al*., 2021; Wei *et al*., 2021; Sun and Wang, 2021) and comparative regional studies combined a set of similar income countries, such as panel data economic development studies (Wang *et al*., 2021; Alcay *et al*., 2021; Riti *et al*., 2017; *Guzmán-Martínez et al*., 2020; Nádudvari *et al*., 2021; Pactwa *et al*., 2020; Zine *et al*., 2020), and others, see (Hosseinalizadeh *et al*., 2021; Xiong and Xu, 2021). For example, Alcay *et al*., (2021) showed the relationship between waste generation and economic development for a sample of European countries. They apply methods for testing the presence of structural breaks located at unknown periods. Once these breaks are considered, they observe that waste generation shows considerable dependence on the evolution of the economy for those countries with the lowest per capita income levels. Wang *et al*., (2021) use the Tapio elastic decoupling analysis method and an empirical model of the environmental Kuznets curve (EKC) to analyze the decoupling between municipal solid waste generation and economic development in 285 of China's cities from 2002 to 2017. The decoupling analysis results show that the decoupling states in China's cities generally improved first and then deteriorated from 2002 to 2017. The proportion of cities experiencing deterioration of decoupling states had increased to 60% by 2014 to 2017, and cities with a higher economic development level generally had more serious deterioration. Gan *et al.*, (2021) use the generalized three-stage least squares (GS3SLS) method to establish a spatial simultaneous equation model to explore the interaction mechanism between haze and economic development. Regarding the entire country, the relationship between $PM_{2.5}$ and per capita GDP presents an inverted U-shaped curve, which verifies the existence of the EKC. The relationship curves for the eastern and western regions also show this feature, but the relationship in the central region increases monotonically. To further observe whether the interaction mechanism between haze and economy has changed before and after the 2008 financial crisis, this paper takes 2008 to examine the time heterogeneity.

The second category of the only one study on combustible renewables and waste consumption and Carbon emissions in the case of Tunisia. Jabri and Belloumi (2017) investigate the dynamic causal links between carbon dioxide (CO_2) emissions, real GDP, combustible renewables and waste consumption, and maritime and rail transport in Tunisia spanning the period 1980 to 2011. The autoregressive distributed lag (ARDL) approach and Granger causality tests are employed to examine the short- and long-run relationships between variables. The empirical results suggest a bidirectional short-run causality between CO_2 emissions and maritime transport, and a unidirectional causality running from real GDP, combustible renewables and waste consumption, rail transport to CO_2 emissions. The long-run estimates reveal that real GDP contributes to the decrease of CO_2 emissions, while combustible renewables and waste consumption and maritime and rail transport have a positive impact on emissions. Also, Liddle (2009) examines whether a systemic, mutually causal, cointegrated relationship exists among mobility demand, gasoline price, income, and vehicle ownership using United States data from 1946 to 2006. They found that those variables co-evolve in a transport system; and thus, they cannot be easily disentangled in the short run. The analysis shows that the fuel standards program was effective in improving the fuel economy of the United State vehicle fleet and in temporarily lessening the impact on fuel use of increased mobility demand.

The third category of the literature investigates the many studies that were conducted using the Panel Cointegration test, and Panel Granger causality test (Jabri and Belloumi, 2017; Wang *et al*., 2018; Santiago *et al*., 2020; Riti *et al*., 2017; Boubellouta and Sigrid, 2021). For example, Santiago *et al*., (2020) analyzed the relationship between public capital stock, private capital stock, and economic growth for a group of 30 Latin American and Caribbean countries from 1970 to 2014. To achieve our goals, the panel vector autoregression methodology, panel dynamic ordinary least squares, and panel fully modified ordinary least square estimators were used. The results from our estimations point to both public and private capital having a positive effect on the long-run economic growth of the countries in this study sample. However, the results also point to public capital seeming to crowd private capital in the short run, which could consequently be one of the explanations for the adverse effect that public capital stock seems to have on growth. Riti *et al*., (2017) examine the impacts of energy use and financial development indicators by source in the environment-growth-energy model for 90 countries categorized based on income possession over the period 1980 to 2014. The study applies the panel analysis that accounts for cross-sectional dependence and heterogeneity of series used in the estimation. Results from panel Dynamic Ordinary Least Squares (DOLS) show that in all the categories of countries, fossil fuel energy use and GDP per capita are found to be the major drivers of CO_2 emissions through fossil fuel energy use possesses the bigger elasticities.

The fourth category of the literature explores economic development in Central Asian countries (Bajra *et al*., 2020; Sentürk and Sataf, 2015; Bird *et al*., 2020; Huang, 2021; Doytch, 2021). For example, Bajra *et al*., (2020) examine whether the ease of doing business (EDB) frontier improves economic growth by considering a sample of 47 European and Central Asian countries, clustered into lower-middle, upper-middle, and high-income economies. The results show these economies have never reached the EDB frontier. The high-income economies prove to be more advanced in their EDB frontier, especially in terms of legal reforms and satisfying infrastructure needs, access to finance, and the quality of policy-making institutions. Doytch (2021) construct a model that controls for established determinants of FDI, including income, human capital, quality of institutions, and natural resource endowments, and apply a dynamic panel Generalized Method of Moments (GMM) estimator to data for 19 Eastern European and Central Asian economies.

3. METHODOLOGY AND DATA

3.1. Source of Data and Model

The present study follows from this literature on economic development. It seeks to extend knowledge on this topic and underline the roles of economic growth and combustible renewables and waste, using a broad range of the latest data. To study examine the relationship between economic development and combustible renewables and waste, panel data for Central Asian Countries was used, covering 31 years. This study collected data from official sources, including the World Development

Indicators (WDI), Food and Agriculture Organization (FOA), International Monetary Fund (IMF) database, International Energy Agency (IEA) database, and Central Asian National Statistics database, electronic files and web site. The author used the average combustible renewables and waste (*lnCRW*) levels at the Central Asian countries, as reported in the official database, to measure the dependent variables of this study. The author calculated the annual average dependent variable for each country from 1990 to 2020 and sorted the results by country. The study uses the Gross domestic product (*lnGDP*), Foreign direct investment, net inflows (*lnFDI*), Trade (*lnTRA*), Inflation (*lnINF*), the Labor force (*lnLAB*), and Population density (*lnPOD*) as independent variables. The purpose of this study is to evaluate the role of economic development when combustible renewables and waste is considered as an energy source in Central Asian countries between 1990 to 2017. It adopted the Panel non-stationarity test, Panel Vector Auto Regression (PVAR), Vector Error Correction Model (VECM), and Panel Granger (1969) causality methodologies, and reports some findings. This paper is focused on economic activities. The key contribution of the present research to the existing literature will be to shed light on and quantify the impact of combustible renewables and waste, and economic development in Central Asia.

$$CRW = f(GDP, FDI, TRA, INF, LAB, POD, \omega) \quad (1)$$

where, ω is the error term for Equation (1). The model is then converted to a natural logarithm to bring the data to the same units, reduce the variance as well as interpret the coefficients in terms of elasticities.

$$lnCRW_{it} = \alpha_0 + \beta_1 lnGDP_{it} + \beta_2 lnFDI_{it} + \beta_3 lnTRA_{it} + \beta_4 lnINF_{it} + \beta_5 lnLAB_{it} + \beta_6 lnPOD_{it} + \omega_{it} \quad (2)$$

In the Equation (2), where, t is time period. α_0 is constant, β_t is drift component *lnGDP*, *lnFDI*, *lnTRA*, *lnINF*, *lnLAB*, and *lnPOD* are the independent variables and ω_i represents white noise error processes.

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

where, t is time period, α_0 is constant, β_t is drift component x, y, z are the independent variables and ω_i represents white noise error processes. The parameters γ, δ and ε are short run dynamic coefficients. 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 cointegration exists among the variable, then the ECM can be represented by the following.

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

In the Equation (4) the remaining variables are the same as in Equation (2) and (3).

3.2. 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 show the logarithmic variable data. Table 2 presents the overall mean values and units of measure for the 31 years of the survey between 1990 and 2020. The author performed unit tests using the variables included in the regression section using average correlation coefficients & Pesaran (2004) coefficient of determination (CD) test tests at a significance level of 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. Table 4 also shows the Akaike information criterion (MAIC), Bayesian information criterion (MBIC), sequential modified CD test, coefficient of determination (CD) test (each test at 5% level), J - Hansen's J statistic, J p-value - Hansen's J statistics p-value (Hansen, 1982), and the Quinn information criterion (MQIC) introduced by Andrews and Lu (2001) the test was conducted for first- to third-order panel VAR using the first four lags of the regressors as instruments.

3.3. Panel non-stationarity test

The stationarity test of Levin, Lin, and Chu (LLC), (2002) and Im, Pesaran, and Shin (CIPS), (2003) become inappropriate in the absence of independence of cross-sections across countries in the panels. However, Im, Pesaran and Shin introduced other techniques that account for the dependency in the cross-sections across countries and provide robust consistent outcomes. The Cross-Sectional CIPS tests, as proposed by Pesaran (2007) LM panel unit root test, are used for checking the stationary properties of the variables. So, the information regarding the stationary properties given by these tests is robust. The following equation can be written in reflecting the standard CIPS framework.

$$\Delta\chi_{it} = \alpha_i + \beta_i\chi_{i,t-1} + \rho_i T + \sum_{k=1}^{q} \vartheta_{ij}\chi_{i,k-1} + \omega_{it} \qquad (5)$$

In the Equation (5), where, Δ indicates the first differenced operator. χ_{it} is the objective variable; α_i and T are the constant and time trend. ω_{it} is the error term. The null hypothesis is that individuals in the panel dataset are not stationary. An alternative for both tests is that at least one individual within the dataset is stationary. Since the variable's stationary properties may change in the presence of structural breaks, the author checks the stationary properties in the presence of structural breaks to ensure the previous stationary test results' robustness. The test depends on a transformation procedure, which makes it invariant to the nuisance parameters. Therefore, it is more statistically robust than the conventional panel unit root tests when dealing with breaks in cross-sections.

3.4. Error Correction based Panel Cointegration tests

In this section, the author applies the panel cointegration tests developed by Westerlund (2007). The rationale here is to test for the absence of cointegration by determining whether Error Correction exists for individual panel members or the panel as a whole. Given the fact that the individual variables are integrated of the first order, the divergent panel cointegration analysis set forth possibly takes into account the profile mutual dependence with separate individual effects Westerlund (2007). Consider the Error Correction Models described by equations (6) to (12), in which all variables in levels are assumed to be $I(1)$:

$$\begin{aligned}\Delta lnCRW_t = {} & \alpha_1 + \lambda_1(lnCRW_{t-1} - \beta_{1a}lnGDP_{t-1} - \beta_{2a}lnFDI_{t-1} - \beta_{3a}lnTRA_{t-1} - \beta_{4a}lnINF_{t-1} - \beta_{5a}lnLAB_{t-1} \\ & - \beta_{6a}lnPOD_{t-1}) + \sum_{k=1}^{q} \gamma_{1k}\,\Delta lnCRW_{t-k} + \sum_{k=1}^{q} \delta_{1k}\,\Delta lnGDP_{t-k} + \sum_{k=1}^{q} \varepsilon_{1k}\,\Delta lnFDI_{t-k} \\ & + \sum_{k=1}^{q} \varphi_{1k}\,\Delta lnTRA_{t-k} + \sum_{k=1}^{q} \mu_{1k}\,\Delta lnINF_{t-k} + \sum_{k=1}^{q} \eta_{1k}\,\Delta lnLAB_{t-k} + \sum_{k=1}^{q} \psi_{1k}\,\Delta lnPOD_{t-k} + \omega_1 \qquad (6)\end{aligned}$$

$$\begin{aligned}\Delta lnGDP_t = {} & \alpha_2 + \lambda_2(lnGDP_{t-1} - \beta_{1b}lnCRW_{t-1} - \beta_{2b}lnFDI_{t-1} - \beta_{3b}lnTRA_{t-1} - \beta_{4b}lnINF_{t-1} - \beta_{5b}lnLAB_{t-1} \\ & - \beta_{6b}lnPOD_{t-1}) + \sum_{k=1}^{q} \delta_{2k}\,\Delta lnGDP_{t-k} + \sum_{k=1}^{q} \gamma_{2k}\,\Delta lnCRW_{t-k} + \sum_{k=1}^{q} \varepsilon_{2k}\,\Delta lnFDI_{t-k} \\ & + \sum_{k=1}^{q} \varphi_{2k}\,\Delta lnTRA_{t-k} + \sum_{k=1}^{q} \mu_{2k}\,\Delta lnINF_{t-k} + \sum_{k=1}^{q} \eta_{2k}\,\Delta lnLAB_{t-k} + \sum_{k=1}^{q} \psi_{2k}\,\Delta lnPOD_{t-k} + \omega_2 \qquad (7)\end{aligned}$$

$$\begin{aligned}\Delta lnFDI_t = {} & \alpha_3 + \lambda_3(lnFDI_{t-1} - \beta_{1c}lnCRW_{t-1} - \beta_{2c}lnGDP_{t-1} - \beta_{3c}lnTRA_{t-1} - \beta_{4c}lnINF_{t-1} - \beta_{5c}lnLAB_{t-1} \\ & - \beta_{6c}lnPOD_{t-1}) + \sum_{k=1}^{q} \varepsilon_{3k}\,\Delta lnFDI_{t-k} + \sum_{k=1}^{q} \gamma_{3k}\,\Delta lnCRW_{t-k} + \sum_{k=1}^{q} \delta_{3k}\,\Delta lnGDP_{t-k} \\ & + \sum_{k=1}^{q} \varphi_{3k}\,\Delta lnTRA_{t-k} + \sum_{k=1}^{q} \mu_{3k}\,\Delta lnINF_{t-k} + \sum_{k=1}^{q} \eta_{3k}\,\Delta lnLAB_{t-k} + \sum_{k=1}^{q} \psi_{3k}\,\Delta lnPOD_{t-k} + \omega_3 \qquad (8)\end{aligned}$$

$$\begin{aligned}\Delta lnTRA_t = {} & \alpha_4 + \lambda_4(lnTRA_{t-1} - \beta_{1d}lnCRW_{t-1} - \beta_{2d}lnGDP_{t-1} - \beta_{3d}lnFDI_{t-1} - \beta_{4d}lnINF_{t-1} - \beta_{5d}lnLAB_{t-1} \\ & - \beta_{6d}lnPOD_{t-1}) + \sum_{k=1}^{q} \varphi_{4k}\,\Delta lnTRA_{t-k} + \sum_{k=1}^{q} \gamma_{4k}\,\Delta lnCRW_{t-k} + \sum_{k=1}^{q} \delta_{4k}\,\Delta lnGDP_{t-k} \\ & + \sum_{k=1}^{q} \varepsilon_{4k}\,\Delta lnFDI_{t-k} + \sum_{k=1}^{q} \mu_{4k}\,\Delta lnINF_{t-k} + \sum_{k=1}^{q} \eta_{4k}\,\Delta lnLAB_{t-k} + \sum_{k=1}^{q} \psi_{4k}\,\Delta lnPOD_{t-k} + \omega_4 \qquad (9)\end{aligned}$$

$$\begin{aligned}\Delta lnINF_t = {} & \alpha_5 + \lambda_5(lnINF_{t-1} - \beta_{1e}lnCRW_{t-1} - \beta_{2e}lnGDP_{t-1} - \beta_{3e}lnFDI_{t-1} - \beta_{4e}lnTRA_{t-1} - \beta_{5e}lnLAB_{t-1} \\ & - \beta_{6e}lnPOD_{t-1}) + \sum_{k=1}^{q} \mu_{5k}\,\Delta lnINF_{t-k} + \sum_{k=1}^{q} \gamma_{5k}\,\Delta lnCRW_{t-k} + \sum_{k=1}^{q} \delta_{5k}\,\Delta lnGDP_{t-k} \\ & + \sum_{k=1}^{q} \varepsilon_{5k}\,\Delta lnFDI_{t-k} + \sum_{k=1}^{q} \varphi_{5k}\,\Delta lnTRA_{t-k} + \sum_{k=1}^{q} \eta_{5k}\,\Delta lnLAB_{t-k} + \sum_{k=1}^{q} \psi_{5k}\,\Delta lnPOD_{t-k} + \omega_5 \qquad (10)\end{aligned}$$

$$\Delta lnLAB_t = \alpha_6 + \lambda_6\big(lnLAB_{t-1} - \beta_{1f} lnCRW_{t-1} - \beta_{2f} lnGDP_{t-1} - \beta_{3f} lnFDI_{t-1} - \beta_{4f} lnTRA_{t-1} - \beta_{5f} lnINF_{t-1} - \beta_{6f} lnPOD_{t-1}\big) + \sum_{k=1}^{q} \eta_{6k}\, \Delta lnLAB_{t-k} + \sum_{k=1}^{q} \gamma_{6k}\, \Delta lnCRW_{t-k} + \sum_{k=1}^{q} \delta_{6k}\, \Delta lnGDP_{t-k} + \sum_{k=1}^{q} \varepsilon_{6k}\, \Delta lnFDI_{t-k} + \sum_{k=1}^{q} \varphi_{6k}\, \Delta lnTRA_{t-k} + \sum_{k=1}^{q} \mu_{6k}\, \Delta lnINF_{t-k} + \sum_{k=1}^{q} \psi_{6k}\, \Delta lnPOD_{t-k} + \omega_6 \quad (11)$$

$$\Delta lnPOD_t = \alpha_7 + \lambda_7\big(lnPOD_{t-1} - \beta_{1g} lnCRW_{t-1} - \beta_{2g} lnGDP_{t-1} - \beta_{3g} lnFDI_{t-1} - \beta_{4g} lnTRA_{t-1} - \beta_{5g} lnINF_{t-1} - \beta_{6g} lnLAB_{t-1}\big) + \sum_{k=1}^{q} \psi_{1k}\, \Delta lnPOD_{t-k} + \sum_{k=1}^{q} \gamma_{1k}\, \Delta lnCRW_{t-k} + \sum_{k=1}^{q} \delta_{1k}\, \Delta lnGDP_{t-k} + \sum_{k=1}^{q} \varepsilon_{1k}\, \Delta lnFDI_{t-k} + \sum_{k=1}^{q} \varphi_{1k}\, \Delta lnTRA_{t-k} + \sum_{k=1}^{q} \mu_{1k}\, \Delta lnINF_{t-k} + \sum_{k=1}^{q} \eta_{1k}\, \Delta lnLAB_{t-k} + \omega_7 \quad (12)$$

Here, from Equations (6) – (12), Δ is the first difference operator, in 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_7 function as the long run multipliers of the underlying error correction model. The residuals ω_1 and ω_7 assumed to be normally distributed, are white noise. Two different classes of tests can be used to evaluate the null hypothesis of no cointegration and the alternative hypothesis: group-mean tests and panel tests. Westerlund (2007) developed four panel cointegration test statistics (Ga, Gt, Pa and Pt) based on the ECM.

3.5. Panel 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:

$$\Delta lnCRW_t = \alpha_1 + \sum_{k=1}^{q} \gamma_{1k}\, \Delta lnCRW_{t-k} + \sum_{k=1}^{q} \delta_{1k}\, \Delta lnGDP_{t-k} + \sum_{k=1}^{q} \varepsilon_{1k}\, \Delta lnFDI_{t-k} + \sum_{k=1}^{q} \varphi_{1k}\, \Delta lnTRA_{t-k} + \sum_{k=1}^{q} \mu_{1k}\, \Delta lnINF_{t-k} + \sum_{k=1}^{q} \eta_{1k}\, \Delta lnLAB_{t-k} + \sum_{k=1}^{q} \psi_{1k}\, \Delta lnPOD_{t-k} + \rho_3 ECT_{t-1} + \omega_1 \quad (13)$$

$$\Delta lnGDP_t = \alpha_2 + \sum_{k=1}^{q} \delta_{2k}\, \Delta lnGDP_{t-k} + \sum_{k=1}^{q} \gamma_{2k}\, \Delta lnCRW_{t-k} + \sum_{k=1}^{q} \varepsilon_{2k}\, \Delta lnFDI_{t-k} + \sum_{k=1}^{q} \varphi_{2k}\, \Delta lnTRA_{t-k} + \sum_{k=1}^{q} \mu_{2k}\, \Delta lnINF_{t-k} + \sum_{k=1}^{q} \eta_{2k}\, \Delta lnLAB_{t-k} + \sum_{k=1}^{q} \psi_{2k}\, \Delta lnPOD_{t-k} + \rho_3 ECT_{t-1} + \omega_2 \quad (14)$$

$$\Delta lnFDI_t = \alpha_3 + \sum_{k=1}^{q} \varepsilon_{3k}\, \Delta lnFDI_{t-k} + \sum_{k=1}^{q} \gamma_{3k}\, \Delta lnCRW_{t-k} + \sum_{k=1}^{q} \delta_{3k}\, \Delta lnGDP_{t-k} + \sum_{k=1}^{q} \varphi_{3k}\, \Delta lnTRA_{t-k} + \sum_{k=1}^{q} \mu_{3k}\, \Delta lnINF_{t-k} + \sum_{k=1}^{q} \eta_{3k}\, \Delta lnLAB_{t-k} + \sum_{k=1}^{q} \psi_{3k}\, \Delta lnPOD_{t-k} + \rho_3 ECT_{t-1} + \omega_3 \quad (15)$$

$$\Delta lnTRA_t = \alpha_4 + \sum_{k=1}^{q} \varphi_{4k}\, \Delta lnTRA_{t-k} + \sum_{k=1}^{q} \gamma_{4k}\, \Delta lnCRW_{t-k} + \sum_{k=1}^{q} \delta_{4k}\, \Delta lnGDP_{t-k} + \sum_{k=1}^{q} \varepsilon_{4k}\, \Delta lnFDI_{t-k} + \sum_{k=1}^{q} \mu_{4k}\, \Delta lnINF_{t-k} + \sum_{k=1}^{q} \eta_{4k}\, \Delta lnLAB_{t-k} + \sum_{k=1}^{q} \psi_{4k}\, \Delta lnPOD_{t-k} + \rho_3 ECT_{t-1} + \omega_4 \quad (16)$$

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$$\Delta lnINF_t = \alpha_5 + \sum_{k=1}^{q} \mu_{5k}\, \Delta lnINF_{t-k} + \sum_{k=1}^{q} \gamma_{5k}\, \Delta lnCRW_{t-k} + \sum_{k=1}^{q} \delta_{5k}\, \Delta lnGDP_{t-k} + \sum_{k=1}^{q} \varepsilon_{5k}\, \Delta lnFDI_{t-k} + \sum_{k=1}^{q} \varphi_{5k}\, \Delta lnTRA_{t-k} + \sum_{k=1}^{q} \eta_{5k}\, \Delta lnLAB_{t-k} + \sum_{k=1}^{q} \psi_{5k}\, \Delta lnPOD_{t-k} + \rho_3 ECT_{t-1} + \omega_5 \quad (17)$$

$$\Delta lnLAB_t = \alpha_6 + \sum_{k=1}^{q} \eta_{6k}\, \Delta lnLAB_{t-k} + \sum_{k=1}^{q} \gamma_{6k}\, \Delta lnCRW_{t-k} + \sum_{k=1}^{q} \delta_{6k}\, \Delta lnGDP_{t-k} + \sum_{k=1}^{q} \varepsilon_{6k}\, \Delta lnFDI_{t-k} + \sum_{k=1}^{q} \varphi_{6k}\, \Delta lnTRA_{t-k} + \sum_{k=1}^{q} \mu_{6k}\, \Delta lnINF_{t-k} + \sum_{k=1}^{q} \psi_{6k}\, \Delta lnPOD_{t-k} + \rho_3 ECT_{t-1} + \omega_6 \quad (18)$$

$$\Delta lnPOD_t = \alpha_7 + \sum_{k=1}^{q} \psi_{1k}\, \Delta lnPOD_{t-k} + \sum_{k=1}^{q} \gamma_{1k}\, \Delta lnCRW_{t-k} + \sum_{k=1}^{q} \delta_{1k}\, \Delta lnGDP_{t-k} + \sum_{k=1}^{q} \varepsilon_{1k}\, \Delta lnFDI_{t-k} + \sum_{k=1}^{q} \varphi_{1k}\, \Delta lnTRA_{t-k} + \sum_{k=1}^{q} \mu_{1k}\, \Delta lnINF_{t-k} + \sum_{k=1}^{q} \eta_{1k}\, \Delta lnLAB_{t-k} + \rho_3 ECT_{t-1} + \omega_7 \quad (19)$$

From Equations (13) to (19), 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.

3.6. 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:

$$(1-p)\begin{bmatrix} lnCRW \\ lnGDP \\ lnFDI \\ lnTRA \\ lnINF \\ lnLAB \\ lnPOD \end{bmatrix} = \begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \\ \theta_4 \\ \theta_5 \\ \theta_6 \\ \theta_7 \end{bmatrix} + \begin{bmatrix} lnCRW \\ lnGDP \\ lnFDI \\ lnTRA \\ lnINF \\ lnLAB \\ lnPOD \end{bmatrix} + \sum_{k=1}^{q}(1-p)\begin{bmatrix} Y_{11i} & Y_{12i} & Y_{13i} & Y_{14i} & Y_{15i} & Y_{16i} & Y_{17i} \\ Y_{21i} & Y_{22i} & Y_{23i} & Y_{24i} & Y_{25i} & Y_{26i} & Y_{27i} \\ Y_{31i} & Y_{32i} & Y_{33i} & Y_{34i} & Y_{35i} & Y_{36i} & Y_{37i} \\ Y_{41i} & Y_{42i} & Y_{43i} & Y_{44i} & Y_{45i} & Y_{46i} & Y_{47i} \\ Y_{51i} & Y_{52i} & Y_{53i} & Y_{54i} & Y_{55i} & Y_{56i} & Y_{57i} \\ Y_{61i} & Y_{62i} & Y_{63i} & Y_{64i} & Y_{65i} & Y_{66i} & Y_{67i} \\ Y_{71i} & Y_{72i} & Y_{73i} & Y_{74i} & Y_{75i} & Y_{76i} & Y_{77i} \end{bmatrix}\begin{bmatrix} lnCRW_{t-k} \\ lnGDP_{t-k} \\ lnFDI_{t-k} \\ lnTRA_{t-k} \\ lnINF_{t-k} \\ lnLAB_{t-k} \\ lnPOD_{t-k} \end{bmatrix} + \begin{bmatrix} \varphi_1 \\ \varphi_2 \\ \varphi_3 \\ \varphi_4 \\ \varphi_5 \\ \varphi_6 \\ \varphi_7 \end{bmatrix}[ECT_{t-1}] + \begin{bmatrix} \omega_{1t} \\ \omega_{2t} \\ \omega_{3t} \\ \omega_{4t} \\ \omega_{5t} \\ \omega_{6t} \\ \omega_{7t} \end{bmatrix} \quad (20)$$

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 whiles $\omega_{1t}, \omega_{2t}, \omega_{3t}, \omega_{4t}$ 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 cointegration among the variables in the ARDL model presents an interesting platform to conduct the Granger causality test.

3.7. Diagnostic Analysis

In this section presents the residual diagnostic for the Hausman test and Eigenvalue stability condition. First, the Hausman's (1978) specification test, which compares an estimator $\widehat{\theta_1}$ that is known to be consistent with an estimator $\widehat{\theta_2}$ that is efficient under the assumption being tested. The null hypothesis is that the estimator θ_2 is indeed an efficient estimator of the true parameters. The Hausman statistic is distributed as χ^2 and is computed as:

$$H = (\beta_c - \beta_e)'(V_c - V_e)^{-1}(\beta_c - \beta_e) \qquad (21)$$

In the Equation (21), where, β_c is the coefficient vector from the consistent estimator, β_e is the coefficient vector from the efficient estimator, V_c is the covariance matrix of the consistent estimator, and V_e is the covariance matrix of the efficient estimator. The number of degrees of freedom for the statistic is the rank of the difference in the variance matrices. When the difference is positive definite, this is the number of common coefficients in the models being compared. Second, to check the stability of the first-order PVAR model, the author computed the eigenvalue condition after estimating the parameters.

4. RESULT

4.1. Unit root tests

The descriptive statistics of the variables are provided in Table 1, respectively. A look at the descriptive analysis shows that the investigated variables display some insignificant variances in the statistics. For dependent variables, the average and standard deviation values of *lnCRW* are -3.2517 and 1.1289 respectively. The average and standard deviation values of *lnGDP* stand at 23.5447 and 1.3257 respectively. *lnFDI*, *lnTRA*, and *lnINF* use have mean values of 0.9387, 4.4379, and 3.8217 respectively, while the respective standard deviations are 1.2356, 0.3729, and 3.1484 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.

Table 1: Descriptive statistics of variables

	Mean	Std. Dev.	Min	Max	Variance	Skewness	Kurtosis	Jarque-Bera
lnCRW	-3.2517	1.1289	-5.0824	-1.5827	1.2744	-0.2565	1.6479	0.0083
lnGDP	23.5447	1.3257	21.4874	26.0845	1.7574	0.2594	1.8575	0.0062
lnFDI	0.9387	1.2356	-3.0681	3.1145	1.5269	-1.0002	3.8048	3.0e-07
lnTRA	4.4379	0.3729	3.1012	5.2966	0.1391	-0.2039	3.1896	0.5201
lnINF	3.8217	3.1484	-6.9077	7.4140	9.9125	-1.8137	5.6577	4.4e-29
lnLAB	15.1246	0.8059	14.0532	16.5075	0.6496	0.3901	1.4288	4.8e-05
lnPOD	3.0896	0.9130	1.7054	4.3528	0.8337	-0.2356	1.4989	3.4e-04

Notes: All variables are expressed in their logarithms. Std. Dev.=standard deviation, Min=minimum, and Max=maximum. Data source: Compiled by the author based on WDI, IMF, FOA, and IEA database (1990-2020).

The correlation coefficient between *lnCRW* and *lnGDP* is -0.3341, implying that the relationship between *lnCRW* and *lnGDP* is 33.41% in a positive direction. The relationship between *lnCRW* and *lnFDI* is approximately 47.1%. The relationship between *lnGDP* and *lnLAB* is approximately strongly by 75.3%, while the relationship between *lnTRA* and *lnLAB* and *lnPOD* is 64.6% and 33.6% in a positive direction. The relationship between *lnFDI* and *lnTRA* and *lnINF* is approximately 51.1% and 49.5%. The relationship between *lnLAB* and *lnPOD* is approximately 21.6%. The relationship between *lnCRW* and lnLAB and *lnPOD* are approximately strongly by 56.7% and 62.7% in a positive direction. The correlation matrix of all variables is shown in Table 2.

Table 2: Correlation matrix of variables

	lnCRW	*lnGDP*	*lnFDI*	*lnTRA*	*lnINF*	*lnLAB*	*lnPOD*
lnCRW	1.0000						
lnGDP	-0.3341	1.0000					
lnFDI	0.4706	0.0148	1.0000				
lnTRA	0.5005	-0.4045	0.5107	1.0000			
lnINF	0.0322	0.2118	0.4945	0.1808	1.0000		
lnLAB	-0.5672	0.7528	-0.3600	-0.6462	-0.0721	1.0000	
lnPOD	-0.6262	-0.3539	-0.5463	-0.3363	-0.2160	0.2161	1.0000

Notes: All variables are expressed in their logarithms. Data source: Compiled by the author based on WDI, IMF, FOA, and IEA database (1990-2020).

After analyzing the descriptive statistics and correlation matrix, a look at the cross-sectional dependence (CD) of the unit-specific variables can give an idea of the extent of its importance in the estimation and testing. Although the presence of some cross-sectionally invariant common variables (both in natural logarithms and in first differences) should itself work as a common factor and reduce CD, the presence cannot be ruled out a priori. In fact, as Table 3 shows, the author concludes that cross-sectional dependence is present in all variables which means that a correlation exists between studies series across countries, according to the Pesaran (2004) test. This provides a good reason to perform testing and estimation by taking CD into account. One reason for this fact can be linked with the common shocks that studies cross share.

Table 3: Average correlation coefficients & Pesaran (2004) CD test

Variable	CD test	p-value	Corr.	Abs. (corr.)
lnCRW	0.64***	0.523	0.081	0.415
lnGDP	11.38***	0.000	0.953	0.953
lnFDI	2.36***	0.018	0.202	0.232
lnTRA	-0.39***	0.699	-0.048	0.295
lnINF	11.81***	0.000	0.988	0.988
lnLAB	10.41***	0.000	0.877	0.877
lnPOD	9.52***	0.000	0.808	0.808
Δ*lnCRW*	1.39***	0.165	0.135	0.196
Δ*lnGDP*	5.80***	0.000	0.474	0.487
Δ*lnFDI*	-1.09***	0.277	-0.089	0.133
Δ*lnTRA*	-0.03***	0.976	0.010	0.191
Δ*lnINF*	7.98***	0.000	0.672	0.672
Δ*lnLAB*	4.10***	0.000	0.337	0.441
Δ*lnPOD*	2.71***	0.007	0.257	0.333

Notes: Under the null hypothesis of cross-section independence CD ~ $N(0,1)$. All variables are expressed in their logarithm and first difference of logarithm. Data source: Compiled by the author based on WDI, IMF, FOA, and IEA database (1990-2020).

Regarding PVAR estimation, the last preliminary test is related to the optimal lag-order selection. It is one of the challenging tasks to utilize the PVAR to find out a selection of the optimal lag length. The result of the test of lag-order selection criteria can be seen in Table 4. It requires precision, as the addition of lags to time series models has a direct impact on the estimation process, and the test was conducted for first- to third-order PVAR using the first four lags of the regressors as instruments. The likelihood ratio, sequential modified CD test, the J test (Hansen, 1982), which is a statistical test used for testing over-identifying restrictions following the J p-value, the MBIC- Bayesian information criterion, the Akaike information criterion (MAIC), and the Quinn information criterion (MQIC) selected lag 4 as shown at the 0.05 significance level. This is sufficiently long for a panel data study to capture the dynamic relationship so that the MAIC statistic could then be used to choose the estimation of a first-order PVAR.

Table 4: Lag length selection order criteria

Lag	CD	J	J p-value	MBIC	MAIC	MQIC
1	0.999917	18.00065	0.115670	-35.99707	-5.99935	-18.0961
2	0.999956	6.95564	0.541426	-29.04284	-9.04436	-17.1089
3	0.999963	1.700234	0.790675	-16.299	-6.299766	-10.3320
4	0.999263	0.483636	0.785199	-8.515983	-3.516364	-5.53250

Notes: This procedure gives us the CD test (each test at 5% level). All variables are expressed in their first difference of logarithm. Data source: Compiled by the author based on WDI, IMF, FOA, and IEA database (1990-2020).

4.2. Panel non-stationarity test

This study uses the new conventional panel non-stationary tests of Im, Pesaran, and Shin CIPS (2003). It is important to note that the CIPS analyses generate consistent outcomes in the absence of independence of cross-sections and heterogeneity across countries in the panel. As the presence of CD was detected for all the variables in natural logarithms and first differences, the first-generation unit root tests ceased to be efficient to investigate the stationarity of the variables. To overcome this issue, in this study, the author applied the second-generation unit root test of Im, Pesaran, and Shin (CIPS). The test in Table 5 shows that *lnCRW*, *lnGDP*, *lnFDI*, *lnTRA*, *lnINF*, *lnLAB*, and *lnPOD* are all order one integration level. In first differences, all variables are stationary, with and without trend a necessary condition for the PVAR estimation.

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Table 5: Cross-sectional Im, Pesaran, and Shin (CIPS) Panel Unit Root test result

		Level					First difference			
		without trend		with trend			without trend		with trend	
Lags	Variable	Zt-bar	p-value	Zt-bar	p-value	Variable	Zt-bar	p-value	Zt-bar	p-value
0	*lnCRW*	-0.831	0.2030	0.004	0.5020	Δ*lnCRW*	-6.122***	0.0000	-5.671***	0.0000
1		-0.716	0.2370	-0.097	0.4610		-5.417***	0.0000	-4.943***	0.0000
2		0.625	0.7340	0.284	0.6120		-3.464***	0.0000	-3.475***	0.0000
3		0.707	0.7600	1.562	0.9410		-2.397***	0.0080	-2.797***	0.0030
0	*lnGDP*	5.024	1.0000	2.372	0.9910	Δ*lnGDP*	-4.110***	0.0000	-3.532***	0.0000
1		1.986	0.9760	-0.013	0.4950		-2.078***	0.0190	-1.555***	0.0600
2		1.167	0.8780	-0.449	0.3270		-0.896***	0.1850	-0.673***	0.2510
3		0.409	0.6590	-0.176	0.4300		-0.159***	0.4370	0.102***	0.5410
0	*lnFDI*	-3.361	0.0000	-2.529	0.0060	Δ*lnFDI*	-8.387***	0.0000	-7.831***	0.0000
1		-2.139	0.0160	-1.580	0.0570		-5.743***	0.0000	-6.044***	0.0000
2		-1.800	0.0360	-1.244	0.1070		-4.044***	0.0000	-3.154***	0.0010
3		0.864	0.8060	1.580	0.9430		-1.638***	0.0510	-1.401***	0.0810
0	*lnTRA*	-0.853	0.1970	-1.028	0.1520	Δ*lnTRA*	-6.215***	0.0000	-5.307***	0.0000
1		-0.755	0.2250	-0.573	0.2830		-3.874***	0.0000	-3.075***	0.0010
2		-1.370	0.0850	0.063	0.5250		-2.357***	0.0090	-1.563***	0.0590
3		-0.580	0.2810	1.693	0.9550		-0.939***	0.1740	0.157***	0.5620
0	*lnINF*	-5.514	0.0000	-5.080	0.0000	Δ*lnINF*	-7.017***	0.0000	-6.533***	0.0000
1		-1.585	0.0560	-1.000	0.1590		-2.121***	0.0170	-0.759***	0.2240
2		-2.651	0.0040	-1.722	0.0420		-2.083***	0.0190	-0.197***	0.4220
3		-2.354	0.0090	-3.414	0.0000		-3.316***	0.0000	-1.241***	0.1070
0	*lnLAB*	1.103	0.8650	5.945	1.0000	Δ*lnLAB*	-0.684***	0.2470	-0.723***	0.2350
1		1.354	0.9120	3.754	1.0000		-0.256***	0.3990	-0.401***	0.3440
2		2.168	0.9850	4.890	1.0000		0.232***	0.5920	0.356***	0.6390
3		2.615	0.9960	4.356	1.0000		-0.677***	0.2490	-0.940***	0.1740
0	*lnPOD*	6.477	1.0000	3.869	1.0000	Δ*lnPOD*	-1.018***	0.1540	0.524***	0.7000
1		2.922	0.9980	-2.990	0.0010		-1.515***	0.0650	-2.204***	0.0140
2		5.675	1.0000	1.622	0.9480		0.945***	0.8280	1.740***	0.9590
3		3.995	1.0000	-1.996	0.0230		-1.335***	0.0910	0.608***	0.7290

Note: CIPS test assumes cross-section dependence is in form of a single unobserved common factor. *** indicate significant of the variables at 10% significance level. Pesaran (2007) panel unit root test (CIPS) assumes that cross-sectional dependence is in the form of a single unobserved common factor and H_0: series is $I(1)$. All variables are expressed in their logarithm and first difference of logarithm. Data source: Compiled by the author based on WDI, IMF, FOA, and IEA database (1990-2020).

4.3. Panel cointegration test

Table 6 displays the results of the Westerlund (2007) ECM panel cointegration test. The results of all of these tests pointed that the variables are cointegrated and reject the null hypothesis of no cointegration. The Gt and Pt are computed with the conventional standard error of the parameters of the error correction model, whereas Ga and Pa are adjusted for heteroscedasticity and autocorrelations based on two standard errors. As given in Table 6, for only Gt, the p values reject the null hypothesis of no cointegration at the statistical 1% significance level, meaning that a cointegrating relationship exists between the variables, both for each country and the panel as a whole. When the author analysis the Robust p-values, which account for cross-sectional dependence, that result shows the null hypothesis is still rejected at the 1% significance level for Ga, Pt, and Pa, and a 5% significance level for the case of Gt, Ga, Pt, and Pa. Overall, these results provide strong evidence on the existence of a cointegrating relationship between *lnCRW*, *lnGDP*, *lnFDI*, *lnTRA*, *lnINF*, *lnLAB*, and *lnPOD* in the Central Asian countries.

Table 6: Westerlund ECM panel cointegration test

Statistic	Value	z-value	p-value	Robust p-value
Gt	-7.545	-10.034	0.000	0.034
Ga	-1.452	2.974	0.999	0.868
Pt	-2.933	1.104	0.865	0.435
Pa	-0.844	2.093	0.982	0.855

Note: Bootstrapping regression with 800 reps. H_0: No cointegration; H_1: Gt and Ga test the cointegration for each country individually, and Pt and Pa test the cointegration of the panel as a whole. All variables are expressed in their logarithm. Data source: Compiled by the author based on WDI, IMF, FOA, and IEA database (1990-2020).

4.4. Panel Granger Causality Test Result

Table 7 shows the significance levels for *lnCRW*, *lnGDP*, *lnFDI*, *lnTRA*, *lnINF*, *lnLAB*, and *lnPOD* for short run and long run analyzes. Coefficient integration of *lnGDP*, *lnFDI*, *lnTRA*, *lnINF*, *lnLAB*, and *lnPOD* expressed in *lnCRW* is based on cointegration among variables. A 1% increase in *lnPOD* contributes 1.419% to *lnCRW* in a positive direction. The long run analysis shows that a 1% increase in *lnGDP* contributes to a 1.095% rise in *lnCRW*. The long run analysis shows that a 1% increase in *lnLAB* contributes to a 0.928% rise in *lnCRW*. This notion shows efficiency and technological change in the process of production and consumption in the long run. Combustible renewables and waste consumption impacts are negative by reducing emissions and ensuring environmental quality. The plausibility of the findings lies with the sign and significance of the coefficient of combustible renewables and waste consumption both in the short run and long runs. The negative and statistical reliability of the combustible renewables and waste consumption factor has shown that it contributes to the reduction of Greenhouse gas (GHG) emissions and, consequently, to climate change. The finding that combustible renewables and waste consumption reduce GHG emissions is in line with the efforts by each countries Ministry of Environment of the Central Asian government to reduce the incidence of climate change impacts in each country. This effort gave rise to the renewable energy program initiated in the country. A 1% increase in *lnFDI* contributes 0.0535% to *lnCRW* in the negative direction. The long run analysis shows that a 1% increase in *lnINF* leads to a 0.0307% rise in *lnCRW*. A has a positive sign and is statistically reliable, but the short circuit current equals 13.15%. Economic growth (*lnGDP*) effects on the environment (*lnCRW*) on the other hand show a diminishing trend from the short run to the long run. In the short run, a 1% increase in *lnGDP* will result in a 0.96% increase in *lnCRW* in the positive directive. However, in the long run, the effect of *lnGDP* increased from 0.96 to 1.095 percent. Overall, the analyses of the short run and long run confirm the dynamic interaction of the variables and agreed with the energy-growth-environment-led thesis where *lnLAB* and *lnPOD* lead to environmental degradation while *lnGDP* ensures environmental quality. Higher combustible renewables and waste consumption tends to reduce from non-renewable sources, while renewable energy and clean energy can increase emissions.

Table 7: Panel Granger Causality test

Dependent variable: *lnCRW*				
Variables	Coefficient	Standard error	z	Probability
Long run elasticities				
lnGDP	-1.095***	0.1066	-10.27	0.000
lnFDI	0.0535	0.0538	0.99	0.320
lnTRA	-0.114	0.2054	-0.56	0.577
lnINF	0.0307	0.0253	1.21	0.226
lnLAB	0.928***	0.1683	5.51	0.000
lnPOD	-1.419***	0.1012	-14.00	0.000
Short run elasticities				
Constant	13.15***	2.0338	6.47	0.000
Δ*lnGDP*	-0.960*	0.4359	-2.20	0.028
Δ*lnFDI*	0.0197	0.0230	0.85	0.393
Δ*lnTRA*	0.0389	0.1256	0.31	0.757
Δ*lnINF*	-0.0400	0.0521	-0.77	0.442
Δ*lnLAB*	2.371	2.0365	1.16	0.244
Δ*lnPOD*	0.126	3.0085	0.04	0.967
$ECT_{(-1)}$	-0.0123	0.0468	-0.26	0.793

Notes: *, ** and *** indicate significant of the variables at 1, 5 and 10% significance level. All variables are expressed in their logarithm and first difference of logarithm. Data source: Compiled by the author based on World Bank data (1990-2020).

4.5. Panel Vector Error Correction Model Result

The results of the ECT cointegration causality test are presented in Table 8. Long run causality indicates a long run relationship between all VECM variables: ECT_{t-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 cointegration. Secondly, the increase *lnGDP*, *lnFDI*, *lnTRA*, *lnINF*, *lnLAB*, and *lnPOD* causes long run *lnCRW*. The F-statistics over a short period show that there are one-way factors to the change in *lnFDI*, *lnINF*, and *lnPOD* to *lnCRW*. In the case of short run distortion, the rate of long run calibration of the *lnCRW* equation is 23.04%. The *lnGDP* equation, on the other hand, is speed setting, fluctuating around 5.008% if the system shakes briefly. The *lnFDI* has a long consolidation rate of 313.2%. *lnTRA* and *lnINF* impact rates are 9.686% and 23.82%. *lnLAB* and *lnPOD* impact rates are relatively low at 0.47% and 1.168%. In the short run Granger presents the results of causation. Even *lnPOD* to *lnCRW* are unidirectional. *lnFDI* and *lnCRW* are bidirectional in the short run. Combustible renewables and waste energy produces short-run economic growth from renewable energy within a short run of time, showing growth forecasts. That means that renewable energy ensures environmental quality in favor of growth while fossil fuel (non-renewable) energy ensures growth at the expense of the environment. In addition, with the increase in *lnGDP*, there is a tendency to increase combustible renewables and waste consumption. Increasing combustible renewables and waste energy consumption, furthering long-run economic growth in Central Asian countries. An increase in economic growth (GDP) and combustible renewables and waste consumption in Central Asia 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.

Table 8: Panel Vector Error Correction Model

VAR	Short run							Long run
	Δ*lnCRW*	Δ*lnGDP*	Δ*lnFDI*	Δ*lnTRA*	Δ*lnINF*	Δ*lnLAB*	Δ*lnPOD*	ECT_{t-1}
Δ*lnCRW*	-	-0.0372 (-1.24)	-0.0171 (-0.06)	-0.124 (-1.63)	-0.216 (-0.76)	0.000722 (0.29)	-0.00256*** (-4.52)	23.04*** (5.27)
Δ*lnGDP*	-0.928* (-2.07)	-	6.054* (2.10)	0.456 (0.72)	-4.899* (-2.51)	-0.0197 (-0.39)	0.00666 (0.53)	-5.008*** (-5.42)
Δ*lnFDI*	0.0296 (1.32)	0.00863 (1.63)	-	0.0632 (1.69)	0.0217 (0.70)	0.00127 (1.09)	-0.000676 (-0.84)	313.2* (2.06)
Δ*lnTRA*	-0.130 (-1.55)	-0.00440 (-0.24)	-0.0444 (-0.16)	-	-0.704* (-2.37)	0.00346 (0.38)	0.000667 (0.25)	9.686** (2.63)
Δ*lnINF*	-0.233 (-1.17)	-0.00547 (-0.25)	-0.254 (-0.42)	-0.584 (-1.20)	-	-0.0114 (-0.90)	-0.00174 (-1.64)	23.82 (1.13)
Δ*lnLAB*	0.287 (0.11)	-0.249 (-0.31)	39.50 (1.20)	-1.666 (-0.30)	6.462 (1.23)	-	0.244 (1.73)	-0.470 (-1.69)
Δ*lnPOD*	-1.339 (-0.46)	3.891* (1.99)	-106.9 (-1.06)	8.313 (1.10)	-7.846 (-0.33)	-0.0669 (-0.34)	-	1.168* (2.54)

Notes: Partial F-statistics reported with respect to short run changes in the independent variables. The sum of the lagged coefficients for the respective short-run changes is denoted in parentheses. Probability values are in brackets and reported underneath the corresponding partial F-statistic and sum of the lagged coefficients, respectively. ECT_{t-1} represents the coefficient of the error correction term and their various *t*-statistics reported in brackets. *, ** and *** indicate significant of the variables at 1, 5 and 10% significance level, respectively. All variables are expressed in their first difference of logarithm. Data source: Compiled by the author based on WDI, IMF, FOA, and IEA database (1990-2020).

4.6. Diagnostic test Robustness test

The following estimation step was the execution of the Hausman test (Hausman, 1978). This test allows us to check if fixed or random effects are present in the panel (Table 9). In this framework, the author applied the Hausman test to seven specifications, each one with a different dependent variable (*lnCRW*, *lnGDP*, *lnFDI*, *lnTRA*, *lnINF*, *lnLAB*, and *lnPOD*). The presence of the fixe d effects was detected in three of the seven specifications: with *lnGDP*, *lnLAB*, and *lnPOD* as the dependent variables. Furthermore, the non-stationarity of some variables, such as *lnCRW* *lnFDI*, *lnTRA*, and *lnINF* in the first difference of logarithm is an indication of potential spurious correlation.

Table 9: Hausman test

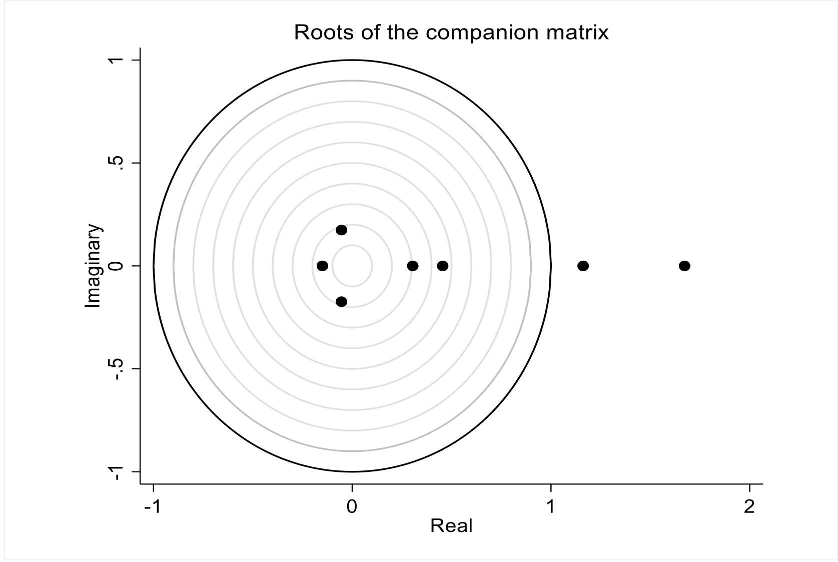
Variable	chi2(6)
Model with Δ*lnCRW* as dependent	0.54(0.9973)
Model with Δ*lnGDP* as dependent	16.78 (0.0101)
Model with Δ*lnFDI* as dependent	0.02(1.0000)
Model with Δ*lnTRA* as dependent	0.53(0.9975)
Model with Δ*lnINF* as dependent	0.74(0.9935)
Model with Δ*lnLAB* as dependent	30.26(0.0000)
Model with Δ*lnPOD* as dependent	10.68(0.0989)

Notes: All variables are expressed in their first difference of logarithm. Data source: Compiled by the author based on WDI, IMF, FOA, and IEA database (1990-2020)

The results and the graph of the eigenvalues are displayed in Table 10. To check the stability of the first difference PVAR model, the author computed the eigenvalue condition after estimating the parameters. At two (*lnINF* and *lnLAB*) eigenvalue lies outside the unit circle, which shows conclusively that the stability condition is not confirmed and, therefore, the PVAR does not satisfy the stability condition.

Table 10: Eigenvalue stability condition

Eigenvalue			**Graph**
Real	Imaginary	Modulus	
1.672173	0	1.672173	
1.1619	0	1.1619	
0.4551901	0	0.4551901	
0.3044777	0	0.3044777	
-0.0538956	0.1741396	0.1822891	
-0.0538956	-0.1741396	0.1822891	
-0.1498499	0	0.1498499	



Note: All variables are expressed in their first difference of logarithm. Data source: Compiled by the author based on WDI, IMF, FOA, and IEA database (1990-2020).

5. DISCUSSION

In recent decades, the main part of renewable energy resources tends to comprise solid biofuel and hydropower. Renewable energy resources have become leverage of the global clean energy sector's development. Thusly, Kyrgyzstan and Kazakhstan built hydropower plants by the river sources in the mountainous area to supply energy demand. Boosting energy efficiency is the cheapest and the simplest way to improve national security and reduce emissions. But, the energy exchange between regional countries is still limited and lower than possible capacity. It is due to lack of management and relationship in the network of Asian countries and absence of adjustment in economical allocation and planning of energy production. These are the factors to enable long-term trading of energy and to develop modern projects in regions capable of energy supply. Central Asian countries are considered highly waste-polluted countries. In highly dense populated cities, waste has become a big challenge. This study aimed to analyze whether generating energy from waste contributed to economic growth or not. The result of this research demonstrated that there is a concrete relationship between economic development in the short term and improvement in environmental quality. It means that any changes derived in combustible renewables and waste consumption will contribute to the economic development of Central Asian countries. The national economies of Central Asia are dominated by agriculture and animal husbandry. Agricultural industries, including cotton, are developed in Kazakhstan, Tajikistan, Uzbekistan, and Turkmenistan, while in Kyrgyzstan the focus is on livestock. It suggests using biofuel for producing energy used in the agricultural sector of Central Asian countries. Biofuel contributes to emission reduction and positively affects economic growth and the environment. Waste recycling for energy production in Central Asian countries is essential for those countries' economies. On other hand, although combustible renewables and waste increases economic growth, some researches show it also increases air pollution and emissions (Jabri and Belloumi, 2017). Therefore, it is demanded to continue the study on greenhouse emissions. In the further, the policy to support the research and development of biofuel production in Central Asian countries and to build a competitive market for increasing production capacity is required. Enlarging the practical scope of waste recycling will increase the efficiency of combustible renewables and waste management, thus recycling the waste for energy production, and the current priority is generating energy from waste recycling and increasing the capacity of production. The research result shows there is an urgent necessity to increase renewables and waste production capacity and it will support economic growth and reduce environmental degradation.

6. CONCLUSION AND RECOMMENDATIONS

This paper investigates the short run and long run dynamic relationships between Foreign direct investment, Gross domestic product, Trade, Inflation, Labor force, Population density, and Combustible renewables and wastes consumption in Central Asia spanning the period 1990 to 2020. The combustible renewables and wastes consumption in Central Asia are based on the long run and short run relationship between Foreign direct investment, Gross domestic product, Trade, Inflation, Labor force, Population density with the Error Correction Model (ECM) based Panel Cointegration tests and Panel Vector Error Correction Model (VECM) Granger causality test tried to explain using the causality test, spanning the period 1990 to 2020. An empirical analysis uses the Im, Pesaran, and Shin (CIPS) Panel Unit Root test and Westerlund ECM to test the basics of the data unit based on this information. Following the best econometric practices, the descriptive statistics, Correlation matrix, and Cross-sectional dependence unit roots test were computed to understand the characteristics of the variables and countries under analysis and to ensure that the necessary conditions for the estimation were fulfilled. Also, The Panel Vector Autoregression (PVAR) specification was based on the results of the Lag-order selection criteria, and the stability of the PVAR model was checked through the observation of the Hausman test and Eigenvalue stability condition. Long run and short run causal relationships between the variables were performed in the ECT augmented Panel Granger causality experiment, which revealed long run causality only during regression of Combustible renewables and wastes consumption. Generally speaking, the result demonstrated that combustible renewables and waste consumption positively affects the economic growth of Central Asian countries, particularly in long-term. According to this, governments have to work implementing effective management schemes for combustible renewables and wastes, collecting and recycling wastes, and intensifying recycling processes. Furthermore, the governmental and non-governmental combination is also required in investment projects for supporting energy production from waste recycling in Central Asian countries. Improvements in investment efficiency, management, and qualifications will affect the economy. So the policymakers of Central Asian countries have to invest in transportation technology by introducing new technologies of renewable energy. Therefore, this strategy may be a good plan for reducing waste, controlling the environmental condition, and supporting economic growth.

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