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RESEARCH ARTICLE

Analysis on the nexus amid CO_2 emissions, energy intensity, economic growth, and foreign direct investment in Belt and Road economies: does the level of income matter?

Olivier Joseph Abban[1] · Jiying Wu[1] · Isaac Adjei Mensah[2]

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Abstract

This study determines the relationship between economic growth, foreign direct investment, energy intensity, and carbon dioxide emissions along the Belt and Road initiative considering their income classification. The study employs data from 1995 to 2015, the panel unit root test, Westerlund cointegration test, augmented mean group estimation, and the Dumitrescu-Hurlin Granger causality test. The empirical results indicate that (1) the data from all income group had cross-sectional association; (2) the variables are integrated of order 1 after first difference; (3) The variables under discussion were cointegrated; (4) at 1% increase in energy consumption, carbon dioxide emissions increased by 0.8606%, 0.9082%, 0.91815%, and 0.8043% in high-, upper-middle-, lower-middle-, and low-income countries, respectively; (5) a bidirectional causal relationship was found between foreign direct investment and carbon dioxide across all income groups. Energy intensity has a bidirectional association with carbon dioxide in low-, upper-middle-, and high-income countries but one-way association in lower-middle-income countries. These recent methodologies take cross-sectional dependence into account in their estimation and findings show that the causal affiliations together with long-run estimated effects amid employed variables are influenced by the different income levels of Belt and Road countries in a tender to reduce carbon dioxide emissions. The empirical results point to some important policy implications.

Keywords Carbon emissions · Energy intensity · Economic growth · Foreign direct investment · Belt and Road initiative · Income classification

Introduction

The Belt and Road initiative (BRI) is an ambitious move by China to promote economic cooperation. The "Belt" (Silk Road economic belt) links China with central Asia, South Asia, and Europe. The "Road" (new maritime Silk Road) connects China with Southeast Asian countries, gulf countries, North Africa, and Europe. As an economic cooperation, it provides interaction for organizations, enterprises, and governments along the BRI route. The interaction among these countries basically is to increase their economic growth. As stated by Mishkin (2009) in order to attain economic growth, countries must be open to the world through economic cooperation. Through economic cooperation, the host countries have several benefits not limited to wealth creation, increased in capita income, innovation products, and investments (Shahbaz et al. 2016).

In ripple effects, economic cooperation affects human lives in several ways, being it through overexploitation of natural resources, changes in consumption of energy, economic growth, foreign direct investment (FDI), jobs creation, and environmental changes (Benería et al. 2015). Among the various changes, CO_2 emissions resulting from economic growth and the concomitant changes in the environmental are of much concern. In order to achieve the sustainable developmental goals, especially goal number 13, reduction of CO_2 emissions which is known to be the main contributor to global

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✉ Olivier Joseph Abban
olivierjosephs@yahoo.com

Jiying Wu
wjy@jus.edu.cn

[1] Department of Statistics, School of Finance and Economic, Jiangsu University, Zhenjiang 212013, People's Republic of China

[2] Institute of Applied Systems and Analysis (IASA), Faculty of Science, Jiangsu University, Zhenjiang 212013, People's Republic of China

warming cannot be underscored (Shahbaz et al. 2019). To this light Bulkeley and Newell (2015) stated that Climate change has become a key issue which has been debated worldwide and a global phenomenon which has become a threat to sustainable development.

The effects of economic cooperation on environmental pollution have had diverging opinions such that the endorsement of economic cooperation without paying attention to environmental pollution has been opined albeit the existence of opposing views. The principle that environmental pollutions are the trade-offs for economic benefits is arguable (Wang et al. 2016). Moreover, the economic cooperation benefits are felt only in developed economies as a result of social and political stability (Lipset 2018). Also, Ghosh (2010) stated that the effects of economic cooperation with regards to the environment pollutions are highly susceptible in developing countries owing to weak environmental standards and institutional quality.

The linkage between economic cooperation and pollution has been a subject of global discussion. Mishkin (2009) stated that economic cooperation leads to rise in gross domestic product (GDP), but some studies have hinted that the rise in GDP spikes CO_2 emissions since it lowers the economic credit limits. The quest to establish the long-term link between the environment quality and GDP was set off by early works of Grossman and Krueger (1995). The existing literature widely used Kuznets Curve Environment (EKC) concept to depict the association among economic growth and carbon emissions. The inverted U-shape of EKC suggests the direct relationship between economic growth and the deterioration of the quality of environment. However, as the economic growth reaches its turning limit, the further increase in economic growth leads to environmental improvements (Charfeddine and Mrabet 2017). Recently, the EKC hypothesis has utilized in several studies (Hanif et al. 2019; Kaika and Zervas 2013; Sarkodie and Strezov 2018). Considering an increase in gross domestic product in the BRI countries from US $23.3199 trillion to US$ 25.466 trillion (constant in 2010) between 2014 and 2016 with a growth rate averaged at 1.2% (author computation), the BRI could be marked for emissions of CO_2. Intriguingly, the findings by Sun et al. (2019) earlier envisaged the economic growth along the BRI upon using the PSM-DID to evaluate BRI. Therefore, this study included GDP into the discussion of carbon dioxide emissions in BRI countries.

The quality of the environment can as well be examined using foreign direct investment inflows (FDI). The relationship between FDI and environmental pollution has been controversial one. The pollution haven hypothesis has been the most famous hypothesis supporting the relationship between FDI and environmental pollution (López et al. 2018; Yang et al. 2018). The hypothesis stated that multi-state companies, mostly in developed countries, shift pollution-intensive industries to countries with lower environmental regulations to avoid costly compliance rules in their homeland. Hence, environmental pollution is heavily felt by developing countries making these developing countries a pollution haven. FDI can generate more pollution issues in the host country (Li et al. 2018; Zaidi et al. 2019). Hence, it was appropriate to include FDI in this study.

Energy intensity (EI) has been identified as another determinant of environmental quality. Energy intensity is the amount of energy required to produce a unit of an output (Greening et al. 2000). Since energy is equivalent to the value of converting energy into economic development, it functions as an indicator of energy usage and is debated as a necessary condition for economic cooperation (Overland 2016). Several studies have described a long-term link among EI and environmental pollution (Ben Jebli and Hadhri 2018; Solarin and Al-Mulali 2018). Therefore, this study included EI into the discussion of carbon dioxide emission in "One Belt And One Road" countries.

The relationship between CO_2 emissions, GDP, EI, and FDI has been investigated for both developing countries (Liu and Hao 2018; Salahuddin et al. 2018; Saud et al. 2019b) as well as developed countries (Cai et al. 2018; Sarkodie and Strezov 2019) for which the long-term cointegration between those variables was established. It is worth noting that the validity of the EKC was established for some studies (Abdouli et al. 2018; Phuong 2018). The summary of literature in relation to this study is presented in Table 1.

Although the relationship between CO_2 emissions, GDP, EI, and FDI has been well studied and reported in literature, the various income classification among the countries under studied remains vague. In response to this deficiency, we propose the significance of analyzing the different income samples from different countries. It is noteworthy that BRI can be a platform for countries to make greater contributions to achieving CO_2 emission reduction targets (Liu and Hao 2018). By exploring links between these variables, researchers may be able to help determine whether FDI or EI is the main driver of increased CO_2 emissions in various income groups. If FDI or EI helps mitigate emissions in income groups, then pursuing more FDI and the usage of EI will have beneficial effects on mitigating CO_2 emissions. On the other hand, if FDI or EI increases CO_2 emissions in income groups, then policies in reduction CO_2 emission should be considered.

Therefore, the present study seeks to establish the dynamic link between CO_2 emission and GDP, EI, and FDI of countries on the "One Belt And One Road" taking into consideration the income classifications. Also, the newly developed panel data augmented mean group (AMG) estimator employed in the study. More obviously, the advantage of the AMG is it robustness when dealing with cross-sectional dependency and the parameter of universal dynamic effect.

Table 1 Summary of some recent empirical studies on the relationship among GDP, EI, FDI, and CO_2 emissions

References	Countries	Period	Variables	Methodology	Results
Salahuddin et al. (2018)	Kuwait	1980–2013	GDP, EC, FDI	VECM Granger causality	FDI $\Rightarrow$ CO_2 (long and short run) GDP $\Leftrightarrow$ CO_2 (short and long run)
Destek and Sarkodie (2019)	11 newly industrialized countries	1977–2013	GDP, EC, FDI	AMG, D-H granger causality	Inverted U-shaped EKC confirmed
Zaidi et al. (2019)	APEC countries	1990–2016	FD, GDP, EI	CUP-FM, CUP-BC, D-H granger causality	Existence of EKC. GDP$\Leftrightarrow$ CO2. EI $\Leftrightarrow$$CO_2$
Nasir et al. (2019)	ASEAN-5 economies	1982–2014	CO_2, FDI, GDP, %GDP	DOLS, FMOLS	FDI $\Rightarrow$ CO_2, GDP $\Rightarrow$ CO_2, existence of EKC
Sarkodie and Strezov (2019)	5 top emitters of CO_2	1982–2016	FDI, GDP, CO_2, EC	Quantile regression	Strong relationship between CO_2 and FDI Strong relationship between CO_2 and EC Strong relationship between CO_2 and GDP
Liu and Hao (2018)	BRI	1970–2013	CO_2, EC, GDP	VECM, FMOLS, DOLS	$CO_2$$\Leftrightarrow$EI, CO_2 $\Rightarrow$ GDP
Saud et al. (2019b)	BRI	1980–2016	GDP, CO_2, FD, EC	DSUR, D-H	GDP$\Leftrightarrow$FDI, GDP $\Leftrightarrow$ CO_2, EC$\Leftrightarrow$ CO_2 and EC $\Leftrightarrow$ CO_2.
Phuong (2018)	Vietnam	1986–2015	FDI, GDP, CO_2	ARDL	Existence of inverse U-shape
Abdouli et al. (2018)	BRICTS	1990–2014	GDP, CO_2, FDI	GMM	$CO_2$$\Leftrightarrow$GDP, existence of inverse U-shape
Wang et al. (2018)	170 countries	1980–2011	CO_2, GDP, EC, UR	VECM	$CO_2$$\Leftrightarrow$EI (all panel except HIC) GDP$\Leftrightarrow$$CO_2$ (all panel except LMIC)
Cai et al. (2018)	G7 countries	1970–2015	CO_2, EI, GDP	Bootstrap ARDL	EI $\Rightarrow$ CO_2, GDP $\Rightarrow$ CO_2
Hanif et al. (2019)	Asian counties	1990–2013	FOS, FDI, GDP	ARDL	Existence of EKC
Shahbaz et al. (2019)	MENA	1990–2015	CO_2, FDI, BM	GMM	FDI $\Leftrightarrow$ CO_2, GDP $\Leftrightarrow$$CO_2$
Jugurnath and Emrith (2018)	SIDS	2004–2014	CO_2, FDI, ED	FE, SUR	FDI $\not\Leftrightarrow$ CO_2
Ben Jebli and Hadhri (2018)	10 tourism destinations	1995–2013	EI, TO, CO_2, GDP	VECM	CO_2 $\Rightarrow$ GDP, EI$\Leftrightarrow$$CO_2$
Solarin and Al-Mulali (2018)	20 countries	1960–2015	FDI, CO_2, EI	AMD, CCEMG	EI and GDP increase CO_2
Cetin et al. (2018)	Turkey	1960–2013	GDP, EI, TD, CO_2	ARDL	Presence of EKC, GDP $\Rightarrow$ CO_2, EI $\Rightarrow$ CO_2
Liu and Kim (2018)	BRI	1990–2016	FDI, GDP, CO_2	PVAR	FDI$\Leftrightarrow$CO2
Magazzino (2016)	GCC	1960–2013	CO_2,EI, GDP	TIME SERIES	Existence of growth hypothesis
Hafeez et al. (2018)	BRI	1980–2016	FIN, END, POP, GDP	FMOLS, DOLS	Validation of EKC, FIN$\Leftrightarrow$END
Dong et al. (2019)	Developed economies	1970–2013	GDP, CO_2	AR	GDP has a double threshold effect on CO_2 emissions
Saud et al. (2019a)	BRI	1990–2014	CO_2, EF, EC, GDP, FD, TR	PMG, Granger causality	EF affects END CF$\Leftrightarrow$ CO_2, TR $\Leftrightarrow$ EF, GDP $\Leftrightarrow$CF
Sun et al. (2019)	BRI	2011–2016	FDI, EDU, GDP, IE	PSM-DID	GDP has increased along the BRI
Saud et al. (2019c)	BRI	1980–2016.	FD, GDP, CO_2, EC, UR, TRD	DSUR, FMOLS, D-H	GPD$\Leftrightarrow$$CO_2$, FD$\Leftrightarrow$ EC EKC PRESENT

CO_2 CO_2 emissions, *GDP* economic growth, *EI/EC/EU* energy intensity/consumption/use, *FDI* foreign direct investment, *UR* urbanization, *FOS* fossil fuels, *FD* financial development, *TD* trade, *Fin* finance, *END* environmental degradation, *POP* population, *EF* ecological footprint, *VECM* vector error-correction model, *VAR* vector autoregressive, *ECM* error-correction model, *ARDL* autoregressive distributed lag, *DSUR* dynamic seemingly unrelated regression, *GMM* generalized method of moments, *FMOLS* fully modified OLS, *DOLS* dynamic OLS, *CCEMG* common correlated effect mean group, *PVAR* panel vector auto regression, *AMG* augmented mean group, *PSM-DID* propensity score matching difference in difference, *MENA* Middle East and North Africa, *SIDS* six small islands developing countries, *GCC* gulf cooperation council, $\Rightarrow$ denotes unidirectional, $\Leftrightarrow$ denotes bidirectional, $\not\Leftrightarrow$ denotes non-causality

The remainder of this paper is organized as follows: section "Methodology" presents the methodology followed by empirical analysis; section "Long-run estimation and coefficient analysis" presents long run estimation and coefficient analysis, lastly with conclusion and policy recommendation.

Methodology

Theoretical model specification

Examining the causal relationship among GDP, EI, FDI, and CO_2 emissions, this study adopts Balsalobre-Lorente et al. (2018) and others' model; hence, we write our carbon emission estimate function as:

$$CO_2 = \left(GDP, GDP^2, EI, FDI\right) \tag{1}$$

Where CO_2 is carbon emission, GDP represents gross domestic product, GDP^2 represents gdp squared, to measure EKC, EI stands for energy intensity, and foreign direct investment is represented by FDI. To address the problem of heteroskedasticity, the variables converted into natural log. Therefore, our multivariate carbon emission function for our natural log model is given by

$$LnCO_{2it} = \beta_0 + \beta_1 LnGDP_{it} + \beta_2 LnGDP^2{}_{it} + \beta_3 LnEI_{it} + \beta_4 LnFDI_{it} + \varepsilon_{it} \tag{2}$$

where β_0 represents the slope coefficient, i denotes the countries selected in this study (1, 2… N), t indicates the time frame for the analysis, and ε_{it} designates the error term. β_1, β_2, β_3, and β_4 are the coefficients of GDP, GDP^2, EI, and FDI. The association between economic growth and CO_2 emissions is known as the environmental Kuznets curve hypothesis (EKC). According to the EKC hypothesis, economic growth is initially accompanied by high carbon dioxide emissions and then declines as the economy reaches a mature level and reaches the threshold of real income per capita (Stern 2004). We therefore expect $\beta_1 > 0$, $\beta_2 < 0$ if linkage between economic growth and CO_2 emissions is inverted U-shaped, i.e., EKC hypothesis otherwise $\beta_1 < 0$, $\beta_2 > 0$ if the relationship is U-shaped between economic growth and CO_2 emissions.

Econometric approach

This study employs newly developed panel data analysis to obtain the empirical results. Panel data analysis is generally superior to pure cross section analysis. The advantage of panel data is its ability to provide least collinearity between larger data sets, greater variability among variables, which is not a criterion in cross-sectional data analysis. Therefore, a more reliable estimate can be obtained in the empirical analysis. In addition, the advantage of using panel data is the power to check individual heterogeneity between groups. The framework of the methods is as follows:

Cross-sectional dependence

Cross-sectional dependence is usually found in panel data, since countries are related at regional, income, and global level. CSD in different groups may occur due to mutual shock, spillovers, or common factors that cannot be observed. If studies ignore the existence of CSD, then the efficiency of the estimated results is arguable (Urbain and Westerlund 2006). Hence, before the empirical analysis, the Pesaran (2004) CD test was used to access the cross-sectional dependency. The panel data model can be described as

$$y_{it} = \alpha_i + \beta_{it} x_{it} + \mu_{it} \tag{3}$$

where i = 1, 2, ……N, t = 1, 2……T, β_{it} is the K × 1 parameter vector to be estimated, x_{it} is the K × 1 explanatory variable, α_i is the individual redundant parameter, and μ_{it} is the time invariant assuming independent and identical distributions. The Pesaran (2004) statistic test is given by

$$CD = \sqrt{\frac{2T}{N(n-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \tag{4}$$

where N is the sample size, T represents the period, and ρ_{ij} is the product correlation errors of country i and j.

Panel unit root test

Pesaran (2007) CD cross-sectionally dependent augmented dickey fuller (CADF) test was adopted since it considers CSD. The regression for this test is given as

$$\Delta y_{it} = \alpha_i + \beta_i y_{it-1} + \theta_i \bar{y}_{t-1} + \sum_{j=1}^{\rho} \gamma_{ij} \Delta y_{it-1} + \sum_{j=0}^{\rho} \delta_{ij} \Delta \bar{y}_{t-j} + d_{it} + \varepsilon_{it} \tag{5}$$

where $\bar{y}_t = \frac{1}{N} \sum_{i=1}^{N} y_{it}$ and its inclusion in the equation can be used to replace the effect of the unseen common factor. α_i is the time invariant individual intercept parameters, β_i, θ_i, γ_{ij} and δ_{ij} represent individual specific effect, individual specific linear trend, and common time effect, respectively. ε_{it} is the error term. According to Pesaran (2007), stationarity test can be performed on the t-value of β_i, either seperately or jointly. Since the test is like to the IPS statistic of Im et al. (2003), it is given as;

$$CIPS(N, T) = \frac{1}{N} \sum_{i=1}^{N} t_i(N, T) \tag{6}$$

where $t_i(N, T)$ is the measure of β_i in the equation above.

Panel cointegration

In observing the long run association amidst the variables in the model, the Westerlund-Edgerton bootstrap panel cointegration was adopted. They proposed four panel cointegration tests for the null hypothesis of no cointegration, taking into account structural dynamics. This test does not enforce any common constraints. This test not only provides good results, but also applies to all situations where CSD exists or does not exist. Westerlund and Edgerton (2007) suggested four residual test methods to evaluate the null hypothesis of no cointegration. Two of the tests are panel statistics (Gt and Ga), and the other two are group statistics (Pt and Pa), which are normally distributed. In effect, this test measures the existence of cointegration by judging whether there is an error correction in a single panel group and the whole panel. The model was built on

$$y_{it} = \delta_{0i} + \delta_{1it} + n_i D_{it} + x_{it}^{'}\beta_i + (D_{it}x_{it})^{'}\gamma_i + z_{it} \tag{7}$$

where i = 1……N, t = 1……T, $x_{\mathrm{it}} = x_{\mathrm{i,\ t-1}} + v_{\mathrm{it}}$ is the k-dimensional vector being I(1). D_{it} represents the break dummy variables. $D_{\mathrm{it}} = 1$ if $t > T_{\mathrm{i}}^{\mathrm{b}}$ and zero otherwise. $T_{\mathrm{i}}^{\mathrm{b}}$ represents the break for individual i.

Long run parameter estimation

AMG estimator formulated by Bond and Eberhardt (2013) was used in estimating the variables in this study. Ma (2015) stated that AMG method is robust in handling cross-sectional dependence. In addition, the AMG algorithm is not restricted by non-stationarities of variables during estimation (Balcilar et al. 2019). The main panel model Eq. (2) can be calculated as follows:

$$\Delta LnCO_{2it} = \beta_0 + \beta_1 \Delta LnGDP_{it} + \beta_2 \Delta LnGDP^2{}_{it} + \beta_3 \Delta LnEI_{it} + \beta_4 \Delta LnFDI_{it} + \sum_{t=2}^{T} q_t(\Delta D_t) + \mu_{it} \tag{8}$$

Equation 8 represents a standard ordinary least square (OLS) regression in the first difference (FD-OLS) with T-1 period dummies in the first difference(ΔD_t), where q_t is the parameter of the periodic dummy. Equation 9 contains ω_t in the model. The inclusion of ω_t is to compensate any excluded idiosyncratic process which evolve over time. ω_t is subtracted from the dependent variable (equation 10), which means a common procedure is imposed on each set of unit coefficient. The AMG estimates are then derived as averages of the individual country estimates. The regression model for the group specific was first adjusted with β_t; then, the average group-specific parameters were computed.

$$\Delta LnCO_{2it} = \beta_0 + \beta_1 \Delta LnGDP_{it} + \beta_2 \Delta LnGDP^2{}_{it} + \beta_3 \Delta LnEI_{it} + \beta_4 \Delta LnFDI_{it} + d_1(\omega_t) + \mu_{it} \tag{9}$$

$$\Delta LnCO_{2it} - \omega_t = \beta_0 + \beta_1 \Delta LnGDP_{it} + \beta_2 \Delta LnGDP^2{}_{it} + \beta_3 \Delta LnEI_{it} + \beta_4 \Delta LnFDI_{it} + \mu_{it} \tag{10}$$

Causality estimation method

AMG algorithm estimation only gives the long-run estimation for the variables and cannot give the direction of causality unlike pooled mean group (PMG). Hence, the panel causality test proposed by Dumitrescu and Hurlin (2012) was employed. The D-H causality test adapts heterogeneousness and cross-sectional dependence in panel data, which cannot in the case vector error correction model (VECM) granger causality. The data model can be specified as

$$y_{i.t} = \alpha_i + \sum_{i=1}^{p} \gamma_i^{(\rho)} y_{i.t-n} + \sum_{i=1}^{p} \beta_i^{(\rho)} x_{i.t-n} + \mu_{i.t} \tag{11}$$

where n refers to lag length, x and y are the basic variables for n cross section in t perios. $\gamma_{\mathrm{i}}^{(\rho)}$ and $\beta_{\mathrm{i}}^{(\rho)}$ are the autoregressive parameters and regression coefficient for each panel or country, respectively.

Empirical results

Data source and description

About 70 countries make up the BRI; however, due to the availability of data and since this study used balanced data sets, only 44 countries were selected for this study with respect to the variables involved, with period 1995–2015. According to the 2014 world bank atlas method of gross national income per capita (GNI), the 44 countries were divided into four categories: high income (more than \$12,736), upper-middle income (\$4126–\$12,736), lower-middle income (\$1046–\$4125), and low income (less than \$1045). The HIC in this study consists of data from 15 countries, UMIC, LMIC, and LIC consist of data from 13, 10, 6 countries, respectively (Table 10). The data is converted into natural logarithms for the coefficient estimates to be explained as the elasticity of the dependent variable (carbon emissions). The countries involved were selected from the belt and road initiative book published in May 2016. Variables selected as a result of data are exemplified in Table 2 with their definition, symbol, and unit of measurement.

Table 2 Variable description and data source

Variable	Symbol	Unit of measurement	Source
CO_2 Emission	$LnCO_2$	Kilo Tons	World bank development indicators (WDI)
GDP per Capita	Lngdp	Constant 2010 US $	World bank development indicators (WDI)
GDP squared	$Lngdp^2$	Constant 2010 US $	World bank development indicators (WDI)
EI	Lnei	Kilograms of oil equivalent	World bank development indicators (WDI)
FDI inflows	lnfdi	BoP Constant US $	World bank development indicators (WDI)

Descriptive statistics for the selected variables with respect to the sampled countries and the various income groups are presented in Table 3. It reveals that for the selected sampled countries, GDP is on average of 8.491 with a standard deviation of 0.918 compared to CO_2 (M = 10.727, SD = 1.765). EI and FDI have M = 8.056 , SD = 1.411 and M = 15.662, SD = 1.701 , respectively. Comparing the descriptive for the various income groups, Table 3 again depicts that for GDP, HIC have M = 8.703 , SD = 0.720, UMIC have M = 8.881, SD = 0.304, LMIC have M = 8.407 , SD = 0.505, and LIC have M = 7.256, SD = 1.519, indicating that GDP is relatively high in UMIC followed by HIC then with LMIC and LIC having the lowest GDP among the income classification. In regard to CO_2 emissions, HIC (M = 10.851, SD = 1.429), UMIC (M = 11.118, SD = 1.811), LMIC (M = 10.911, SD = 1.998), and LIC (M = 9.261, SD = 1.208), depicting CO_2 emissions is averagely higher in UMIC and low in LIC among the groups. Considering energy intensity among the groups, HIC (M = 9.350 , SD = 0.767), UMIC (M = 7.990, SD = 0.914), LMIC (M = 7.026, SD = 0.746), and LIC (M = 6.680, SD = 1.598), indicating that energy consumption is averagely high in HIC and low in LIC among the classification. In regards to FDI, HIC (M = 14.756, SD = 1.304), UMIC (M = 15.761, SD = 1.731), LMIC (M = 16.615, SD = 1.841), and LIC (M = 16.122, SD = 1.037), revealing that FDI inflows is relatively

Table 3 Summary of descriptive statistics

Panel	Variable	Mean	Std.Dev	Skewness	Kurtosis	JB test
Sampled BRI	$LnCO_2$	10.727	1.765	0.474	2.947	34.839[a]
	Lngdp	8.491	0.918	− 2.323	8.792	2122.972[a]
	$Lngdp^2$	20.810	2.115	− 0.506	4.236	98.4168[a]
	Lnei	8.056	1.411	0.660	8.118	1075.84[a]
	Lnfdi	15.662	1.701	0.797	3.199	99.431[a]
High-income countries	$LnCO_2$	10.851	1.429	0.933	3.101	45.854[a]
	Lngdp	8.703	0.720	− 2.302	8.452	668.622[a]
	$Lngdp^2$	21.059	2.037	− 0.855	6.044	160.133[a]
	Lnei	9.350	0.767	− 0.384	2.703	8.917[b]
	Lnfdi	14.756	1.304	1.061	3.771	66.872[a]
Upper-middle-income countries	$LnCO_2$	11.118	1.811	0.634	3.734	24.475[a]
	Lngdp	8.881	0.304	− 1.557	6.315	235.402[a]
	$Lngdp^2$	21.433	2.037	− 0.269	3.449	5.590[c]
	Lnei	7.990	0.914	− 0.308	2.308	9.766[a]
	Lnfdi	15.761	1.731	1.317	4.494	104.342[a]
Lower-middle-income countries	$LnCO_2$	10.911	1.998	− 0.054	1.613	16.918[a]
	Lngdp	8.407	0.505	− 0.511	2.923	9.222[a]
	$Lngdp^2$	20.778	1.715	− 0.099	2.743	10.920[a]
	Lnei	7.026	0.746	0.309	2.421	6.276c
	Lnfdi	16.615	1.841	0.036	1.962	9.461[a]
Low-income countries	$LnCO_2$	9.261	1.208	0.251	1.737	9.699[a]
	Lngdp	7.256	1.519	− 0.458	1.906	10.678[a]
	$Lngdp^2$	18.890	1.986	− 0.820	3.335	14.742[a]
	Lnei	6.680	1.598	1.276	44.629	683.025[a]
	Lnfdi	16.122	1.037	0.107	1.927	6.277[b]

Note: The Jarque-Bera test was used to determine whether the variables followed the normal distribution or not. The JB test the null hypothesis that a series is normally distributed. "a, b, and c" indicate the probability of rejection at 1%, 5%, and 10%

high in LMIC while HIC has the lowest inflows among the income classification.

For normality test, skewness and kurtosis were to specify the normality assumption. For normal distribution, skewness and kurtosis must be 0, and 3 respectively. The results considering the sampled BRI countries, Table 3 reveals skewness for GDP and the squared of GDP are to the left which means that these variables are more to the left than normal distribution. CO_2 emissions, FDI, and EI are skewed right, that is flattering to the right. This indicates that three out of five of the observations are heavily right tailed. With the peakness (kurtosis) of the distribution, CO_2 emissions and FDI were approximately 3, indicating a mesokurtic distribution. For the value of GDP, squared of GDP and EI were above 3 which also symbolizes that their distribution is leptokurtic. Therefore, kurtosis and skewness conditions for normality were not satisfied by any variables; hence, we affirm that none of the variables were normally distrusted. Table 3 again reveals the violation of the normality assumption among the income groups for all the variables. In HIC and UMIC, GDP, GDP^2, and EI are flattering to the left while CO_2 and FDI are skewed to the right. In LMIC, GDP, GDP^2, and CO_2 are skewed to the left while EI and FDI are flattering to the right. This results from the three groups that indicate that three of variables are heavily left tailed. However, in LIC, CO_2, EI, and FDI are skewed to the right while GDP and GDP^2 are skewed to the left indicating more variables tailed to the right. The rejection of the normality assumption was strongly supported by the Jarque-Bera test for normality with the null hypothesis that all the variables follow a normal distribution at a rejection of a probability less than 0.05.

Multicollinearity among the independent variables (GDP, the square of GDP, EI, and FDI) was done using correlation and variance inflating factor. Table 4 gives the results of the interconnection test. The VIF value must not be greater than 5 and the tolerance value should be greater than 0.2 (Craney and Surles 2002). Hence, it can be concluded that each independent variable is uniquely impacting the dependent variable. The results from the correlation test support that there is no strong correlation among the independent variable (threshold 0.7). Hence, each variable is independent of the other and a unique and significant impact on CO_2 emission.

Table 4 Multicolinearity test results

Variable	Lnei	$Lngdp^2$	Lngdp	Lnfdi	VIF	Tolerance
Lnfdi	− 0.3268	0.4489	− 0.0720	1	0.505	1.982
Lngdp	0.375	0.3599	1		0.785	1.274
$Lngdp^2$	0.371	1			0.457	2.190
Lnei	1				0.545	1.834

Note: Dependent variable is carbon emission (kt), tolerance value should be more than 0.2, and the VIF value should be less than 5, indicating no multicolinearity

Cross-sectional dependence test

Cross-sectional dependency (CSD) has been the key focus in current energy-economic literature (Dogan and Inglesi-Lotz 2017; Ozcan and Ari 2017). Table 5 gives the value of the CSD test and their corresponding probability values. CSD test values of each series in each panel (sampled BRI, HIC, UMIC, LMIC, and LIC) are significant at 1% level. Hence, the countries involved are connected in some way. Having confirmed CSD among groups of countries, the study relies on the second-generation panel unit root test to check stationarities of the variables. Therefore, CIPS and CADF were used in this study.

Panel unit root test

Table 6 indicates that variables in this study have unit roots at the level; however, in their first difference, they have no unit roots. Convinced that all variables are non-stationary at I(0), but become stationary at I(1), it is appropriate to study the existence of long-term association among variables.

Panel cointegration test

Westerlund-Edgerton bootstrap panel cointegration test was utilized to analyze whether there was a long-run association among variables. Techniques such as Kao and Johansen's panel cointegration ignore CSD when testing for the long-term association. Findings from the Westerlund-Edgerton bootstrap panel cointegration are displayed in Table 7. Using CO_2 as the dependent variable revealed that all the variables have long-term association in the various panels. Hence, the null hypothesis of no long-term association is declined at various significant level with respect to the statistics G_τ, G_α, P_τ, and P_α. Our argument was based on the robust p values which gives a robust evidence of long-term association within the series.

Long-run estimation and coefficient analysis

Long-run analysis (AMG estimation)

In the estimation analysis of our parameters, the paper employed AMG estimator to check the effects of GDP, GDP^2, EI, and FDI on CO_2 emissions. The results obtained are displayed in Table 8. The relationship between coefficients of GDP^2 and CO_2 emissions reflects the concept of EKC. When GDP increases by 1%, CO_2 discharge also goes up by 0.0189%, while 1% rise in GDP^2, shorten the quality of the environment by 0.2055% which is statistically significant for all countries in BRI. Likewise for HIC when GDP accelerates by 1%, the quality of the environment is shortened by 0.0208% while a percentage mount in GDP^2 diminishes CO_2 discharge by 0.3243% significantly. Also, for UMIC 1% increases in

Table 5 Cross-sectional independence test results

Group	Test	$LnCO_2$	Lngdp	$Lngdp^2$	Lnei	lnfdi
BRI countries	CD test value	30.24[a] (0.000)	8.05[b] (0.094)	76.91[a] (0.000)	121.29[b] (0.000)	34.72[a] (0.000)
HIC	CD test value	7.48[b] (0.019)	14.26[a] (0.000)	24.03[a] (0.000)	43.59[a] (0.000)	8.66[b] (0.000)
UMIC	CD test value	8.62[a] (0.000)	3.03[b] (0.053)	22.27[a] (0.000)	37.98[a] (0.000)	5.56[b] (0.000)
LMIC	CD test value	10.05[a] (0.000)	3.70[a] (0.000)	20.08[a] (0.000)	26.54[a] (0.000)	2.38[c] (0.017)
LIC	CD test value	12.17[a] (0.000)	5.40[a] (0.001)	11.09[a] (0.000)	9.76[a] (0.000)	17.37[a] (0.000)

Note: Values in parenthesis represent *p* values whereas a, b, and c denote statistical significance at 1%, 5%, and 10% level, respectively

GDP vitiate the quality of environment by 0.01660% which is statistically significant, while 1% rise in GDP^2 quashes the quality of the environment by 0.1909% significantly. Similarly in LMIC countries, a 1%, rise in GDP also corrupts the environment by 0.0095%, while a 1% boost in GDP^2 increases CO_2 emissions by 0.3094% but not significant.

Likewise for LIC when GDP increases by 1%, it weakens the environment quality by 0.0572%, and while 1% rise in GDP^2 diminishes the quality of the environment by 0.9552% but not statistically significant. Considering the insignificant GDP^2 in LMIC and LIC suggests that EKC does not exist in this income group. This may be due to the same concept as other developing economies, LMIC and LIC have not yet achieved a full-standard industrial economy. The inverted U-shaped in HIC suggests increased economic growth in HIC at early stage also stimulated carbon dioxide emissions to a certain level in the early stages, but after reaching this limit, carbon dioxide emissions began to decline as economic growth increased further.

At the initial stages of economic growth, these countries focused mainly on economic expansion, ignoring the environment and aiming at boosting trade and infrastructure with other countries through cooperation and financial development. Economic growth has increased personal income, thus increasing energy demand and worsening environmental conditions. Finally, rising income levels bring social and environmental awareness, which helps abridge environmental pollution (Zaidi et al. 2018). The evolution of EKC effect is due to the improvement of mass production technology and citizens' demands on environmental quality. These results are consistent to those of Rafindadi and Ozturk, 2017for African economies, Haseeb et al. (2018) for BRICS countries, Bekhet and Othman, 2017 on Malaysia, and Sinha and Shahbaz (2018) for India. The U-shape in BRI panel and UMIC is an indication of no strong evidence for the existence of EKC for CO_2 emissions. Therefore, these results are consistent with Liu and Hao, 2018 research in investigating EKC hypothesis in the BRI, Balaguer and Cantavella (2016) for Spain, Pata (2018) for Turkey.

Table 6 Results from CADF and CIPS panel unit root test

Groups	$LnCO_2$ level	Δ	Lngdp level	Δ	Lngdp2 level	Δ	Lnei level	Δ	Lnfdi level	Δ
Sampled BRI										
CIPS	− 2.96	− 4.78[a]	2.29	− 4.20 [a]	− 2.97	− 5.06 [a]	− 2.21	− 3.88[a]	− 2.35	− 3.57[a]
CADF	− 2.48	3.28[a]	− 2.09	− 3.16[a]	− 2.27	− 3.66[a]	− 2.28	− 3.02[a]	− 2.47	− 2.96[a]
High-income countries										
CIPS	− 2.86	− 4.78[b]	− 2.11	− 4.06[a]	− 3.41	− 5.57[b]	− 3.13	− 4.57[b]	− 2.22	− 3.83[b]
CADF	− 2.83	− 3.70[b]	− 2.50	− 3.64[a]	− 2.53	− 3.97[b]	− 2.49	− 3.39[b]	− 3.16	− 3.09[b]
Upper-middle-income countries										
CIPS	− 2.15	− 4.18[b]	− 2.17	− 3.88[a]	− 2.97	− 4.80[b]	− 2.50	− 3.90[b]	− 1.86	− 3.52[a]
CADF	− 2.26	− 3.00[b]	− 2.06	− 2.84[a]	− 2.56	− 3.74[a]	− 2.75	− 3.59[b]	− 2.10	− 3.84[a]
Lower-middle-income countries										
CIPS	− 2.49	− 4.54[a]	− 2.69	− 4.81[a]	− 2.73	− 4.99[b]	− 3.94	− 4.89[a]	− 1.88	− 3.92[a]
CADF	− 2.14	− 2.92[a]	− 1.91	− 3.33[a]	− 1.99	− 3.65[a]	− 2.33	− 3.42[a]	− 2.05	− 4.32[a]
Low-income countries										
CIPS	− 2.50	− 4.68[a]	− 2.10	− 5.05[a]	− 2.66	− 5.64[b]	− 1.67	− 2.92[a]	− 1.27	− 3.82[a]
CADF	2.17	− 3.01[a]	− 1.45	− 3.28[a]	− 3.07	− 4.20[b]	− 1.12	− 2.87[a]	− 2.11	− 3.96[a]

Note: CIPS: H0 is "series have unit root for each panel". CADF: H0 is "series have unit root for each panel". Δ represents the first difference. a, b, c indicate statistical significance at 1%, 5%, 10% level, respectively

Table 7 Panel cointegration test (Westerlund and Edgerton (2007)

Groups	G_τ		G_α		P_τ		P_α	
	value	p-robust	value	p-robust	value	p-robust	value	p-robust
BRI	− 3.320[a]	(0.010)	− 6.708[b]	(0.020	− 8.100[b]	(0.021)	− 6.421[a]	(0.010)
HIC	− 2.808[a]	(0.010)	− 4.031[a]	(0.010)	− 7.764[c]	(0.070)	− 4.430[a]	(0.034)
UMIC	− 2.197[b]	(0.040)	− 7.590[a]	(0.010)	− 6.176[a]	(0.190)	− 7.524[b]	(0.020)
LMIC	− 3.263[a]	(0.000)	− 9.054[a]	(0.000)	− 8.788[b]	(0.040)	− 7.735[c]	(0.060)
LIC	− 3.040[c]	(0.062)	− 5.283[c]	(0.070)	− 6.848[b]	(0.020)	− 4.625[c]	(0.052)

Note: P values are calculated on the basis of normal distribution for a one-sided test. a, b, and c show statistical significance at the 1%, 5%, and 10% levels, respectively. () indicate the probability of acceptance

The results also display that EI has a significant positive relation with CO_2 emissions, as a 1% rise in EI corresponds to a 0.9441% rise in CO_2 emissions in BRI panel. In their income group levels, 1% increase in EI increases 0.8606%, 0.9082%, 0.91815%, 0.8043% rise in CO_2 emissions in HIC, UMIC, LMIC, and LIC, respectively, which are statistically significant. This result depicts that the establishment of more local and foreign companies in these countries enable local residents have more jobs and energy needs rises. The increment of firms enhances energy usage which then increases CO_2 emissions. However, at later stages, when the local and foreign firms have matured, they invest in energy-efficient infrastructure to lessen CO_2 emissions. Our results show that energy use is the main cause of carbon dioxide emissions. Therefore, BRI construction must shift energy consumption to renewable energy and achieve zero-emission growth. In addition as stated by Qasemi-Kordkheili and Nabavi-Pelesaraei (2014), energy efficiency demands innovative models to estimate the optimization of energy need and the potential decrease of greenhouse gases. We support their view that traditional energy can promote economic growth, but it is very harmful to the environment since it increases carbon dioxide emissions.

For the link between FDI with CO_2 emissions, a percentage increment in FDI pollutes the environmental quality by 0.6945% for all countries involved in the whole panel. For high-income countries, a 1% increase in FDI mitigates the quality of environment by 0.0581%. In low-income countries, a rise of 1% in FDI also corrupts the environment by 1.8287%. It can be concluded that FDI stimulates carbon emission in the long term in this panel group.

The RMSE value is a good measure of how accurately the model predict the response variable. Small value of RMSE indicates a better model fit; hence, it can be deduced that the values of RMSE for BRI countries, HIC, UMIC, LMIC, and LIC are

Table 8 Results of AMG panel data estimation method

BRI countries				Main AMG				
	Lngdp	Lngdp^2	Lnei	Lnfdi	*cdp*	Trend	Constant	EKC
	0.0189[a]	0.2055[c]	0.9441[a]	0.6945[b]	− 0.0245[a]	− 0.0245[c]	− 17.916[c]	×
	(0.004)	(0.067)	(0.000)	(0.036)	(0.004)	(0.067)	(0.076)	
RMSE	*0.0553*							
Income group			Individual group AMG					
HIC	0.0208[b]	−0.3243[a]	0.8606[a]	− 0.0581[a]	0.6547b	− 0.0156	3.791	√
	(0.026)	(0.009)	(0.000)	(0.008)	(0.067)	(0.192)	(0.642)	
RMSE	*0.0353*							
UMIC	0.0166[b]	0.1909[a]	0.9082[a]	0.11361	0.6977[c]	0.0037	− 6.839	×
	(0.017)	(0.010)	(0.000)	(0.785)	(0.096)	(0.374)	(0.244)	
RMSE	*0.0383*							
LMIC	0.0095	−0.3094	0.9181[a]	1.2760	1.0706[b]	− 0.0218	− 31.591[b]	×
	(0.456)	(0.808)	(0.000)	(0.135)	(0.028)	(0.152)	(0.034)	
RMSE	*0.02558*							
LIC	0.0572[c]	−0.9552	0.8043[a]	1.8287[b]	0.9369[a]	− 0.0772[c]	− 101.22[b]	×
	(0.081)	(0.930)	(0.008)	(0.019)	(0.004)	(0.077)	(0.016)	
RMSE	*0.0432*							

Note: Value in parenthesis is probability value; √ shows for the presence of EKC and × indicated no EKC. Common dynamic process (cdp) included as an additional regressors. [a, b, c] Significance level at 1%, 5%, and 10%. () indicate the probability

0.0553, 0.0353, 0.0383, 0.02558, and 0.0432, respectively. Therefore, each panel model is fit in predicting the CO_2 emissions.

Panel causality test

Dumitrescu and Hurlin (2012) causality test (D-H) was used due to the occurrence of CSD among the variables since AMG estimate does not propose a causal path. In the D-H test, the significance of causal relationship is tested by two kinds of statistics: w-bar statistics (average statistics are used for the test) and z-bar information (standard normal distribution is used for the test). The results of D-H causality test are reproduced in Table 9 for all countries in the Belt and Road initiative.

For all county panel, the results proposed a bidirectional causality amidst CO_2 emissions and all the independent variables (GDP, EI, and FDI). A bidirectional causal effect was found between GDP and EI, GDP and FDI, and EI and FDI. This outcome implies that EI in countries on the BRI and their economic growth is correlated, such that increase in EI will spark economic growth of these countries. This outcome is in consonant with the study done (Li et al. 2015; Saud et al. 2019c). For HIC, there was an evidence of a unidirectional causality between GDP and CO_2 emissions. Notwithstanding, a bidirectional causality between CO_2 and EI, CO_2 and FDI, and EI and FDI was depicted. Last but not the least, there is a one-way causal effect from EI to GDP. In the case of LIC, there is a unidirectional causality from CO_2 emissions to GDP. Likewise, a bidirectional causal effect between CO_2 and FDI, EI and GDP, and EI and FDI was revealed. Finally, there is a one-way causal relationship from FDI and GDP.

For LMIC, there is a two-way causal relationship that was depicted between CO_2 and GDP, CO_2 and FDI, and GDP and EI. The results also suggest a unidirectional causality from EI to CO_2 emission, likewise from FDI to EI. Lastly for the UMIC, a bidirectional causal effect amidst CO_2 emissions and the each of the other variables (GDP, EI, and FDI), likewise a bidirectional association between GDP and EI and a unidirectional causality from EI to FDI was depicted. Interestingly, the relationship between EI and CO_2 emissions in all panel groups is in consonant with the findings of Liu and Hao (2018) in their study on BRI countries, Asafu-Adjaye et al. (2016) for of 53 countries globally. Not forgetting the causal relationship amid CO_2 emissions and GDP, the findings are consistent with that of Shahbaz et al. (2015) in studying some African countries, and Ali and Malik (2018) for the study on Pakistan. The results from the D-H granger causality links are summarized in Fig. 1.

Conclusion and policy recommendation

This empirical study seeks to establish the dynamic nexus among CO_2 emissions, GDP, EI, and FDI along the BRI countries using data from 1995 to 2015. The main panel was divided into sub-panel group using the four income classification: HIC, UMIC, LMIC, and LIC. Analysis was done on the sampled panel and the sub-panels. In summary, Pesaran CD's test was done to determine CSD among the variables. In addition, the CADF and CIPS panel stationarity tests were performed due to the presence of CSD. From the result, we infer that the variables are unstable at their level, but stable at their first difference. Westerlund-Edgerton panel bootstrap cointegration test was used to determine if the variables are cointegrated. From the results, the variables were cointegrated and we deduced that there is a structural long-run relationship. Hence, we employed AMG estimator which is more robust to CSD in estimation of the variables. Since AMG cannot indicate the direction of the long-run relationship, Dumitrescu and Hurlin (2012) panel causality test employed. The result from the causality test indicated that the results depicted that LIC, UMIC, and HIC followed the feedback hypothesis, which is indicated by a bidirectional causal effect between CO_2 and energy consumption. That income groups (HIC, UMIC, and LIC) exhibited a bidirectional association among EI and CO_2 emissions with exception of LMIC which has a one-way causal effect from CO_2 to EI. However, the main sampled BRI countries, a bidirectional causal effect amidst CO_2 and EI. In addition, all panel exhibits a bidirectional causal effect between CO_2 and FDI, indicating that environmental pollution is enhanced by FDI inflows. Again, UMIC and LMIC displayed a bidirectional causal relationship among GDP and CO_2 emissions. While a unidirectional causal effect was depicted from GDP to CO_2 emissions in HIC and LIC, EKC was found in HIC (inverted U-shape) while in UMIC, LMIC, and LIC, no presence of EKC (U-shape).

Table 9 Summary results from D-H granger causality test

BRI	HIC	LIC	LMIC	UMIC
$LnCO_2 \Leftrightarrow$ Lngdp	$LnCO_2 \Rightarrow$ Lngdp	$LnCO_2 \Rightarrow$ Lngdp	$LnCO_2 \Leftrightarrow$ Lngdp	$LnCO_2 \Leftrightarrow$ Lngdp
$LnCO_2 \Leftrightarrow$ Lnei	$LnCO_2 \Leftrightarrow$ Lnei	$LnCO_2 \Leftrightarrow$ Lnei	Lnei $\Rightarrow LnCO_2$	$LnCO_2 \Leftrightarrow$ Lnei
$LnCO_2 \Leftrightarrow$ Lnfdi	$LnCO_2 \Leftrightarrow$ Lnfdi	$LnCO_2 \Leftrightarrow$ Lnfdi	$LnCO_2 \Leftrightarrow$ Lnfdi	$LnCO_2 \Leftrightarrow$ Lnfdi
Lngdp $\Leftrightarrow$ Lnei	Lnei $\Rightarrow$ Lngdp	Lngdp $\Leftrightarrow$ Lnei	Lngdp $\Leftrightarrow$ Lnei	Lngdp $\Leftrightarrow$ Lnei
Lngdp $\Leftrightarrow$ Lnfdi	Lngdp $\Rightarrow$ Lnfdi	Lnfdi $\Rightarrow$ Lngdp	Lnfdi $\Rightarrow$ Lndgp	Lngdp $\Rightarrow$ Lnfdi
Lnei $\Leftrightarrow$ Lnfdi	Lnei $\Leftrightarrow$ Lnfdi	Lnei $\Leftrightarrow$ Lnfdi	Lnfdi $\Rightarrow$ Lnei	Lnei $\Rightarrow$ Lnfdi

Note: $LnCO_2$, Lngdp, Lnei, Lnfdi represent carbon emissions, gross domestic product, squared of gross domestic product, energy intensity, and foreign direct investment. $\Leftrightarrow$, $\Rightarrow$ represent two-way and one-way causality

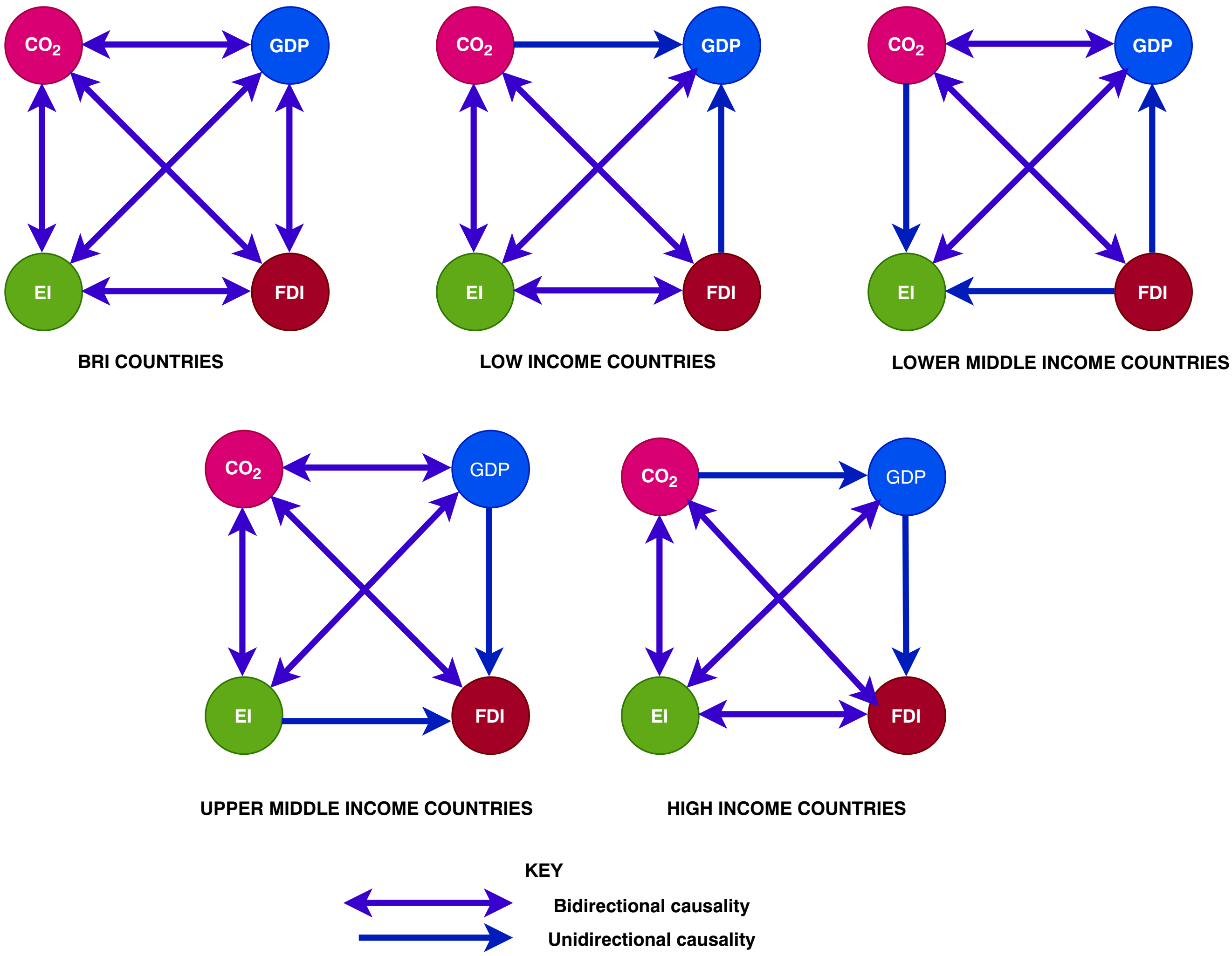

Fig. 1 Graphical representation of two-sided and one-sided causal affiliations among variables in different country group

Policy implications in regards to this study will be as follows; first, the results indicate that for most countries, CO_2 emissions are energy-driven; the long-term two-way granger causality affirms this conclusion. This result shows that countries along the BRI must strive to establish effective energy policies to reduce CO_2 emissions in order to achieve the sustainable development goal (13). Hence, reducing the use of fossil fuels which is the main cause of CO_2 is a shared responsibility. Secondly in regards to FDI-CO_2 emission relationship, countries along the BRI need to develop policies that encourage public-private partnerships in producing safe energy from different sources. Thirdly from these findings is the role that a country's income level plays, the most common factor in increasing CO_2 emissions among all income groups (HIC, UMIC, LMIC, and LIC) is FDI. However, EI also plays an important role in increasing CO_2 emissions in LIC, UMIC, and HIC while GDP increases CO_2 emissions in UMIC and LMIC. Given these differences, decision makers need to take into account the effects of various variables in their decision-making process and consider them in different ways depending on the income level of a given country. Lastly, for all income groups, GDP tends to mean increase in energy consumption and increased CO_2 emissions; therefore, promoting the transition to a renewable or nuclear energy usage is best way to reduce environmental pollution associated with economic cooperation.

The limitation of this study is that some BRI countries were excluded from the panel set due to missing data. Although this study conducted a preliminary quantitative study on CO_2 emission, GDP, FDI, and EI of countries along the BRI, still has some limitations, which may become the direction of future research. Future research may include all countries using unbalanced data when investigating the income groups in BRI countries. Again, since the relationships discussed in this paper may be quadratic, some appropriate methods, such as panel smooth transition regression models, can be used to establish relationships when the time frame is much longer. Due to non-linear reasons, the longer the sample time and the longer the period, the clearer the result.

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Appendix

Table 10 Income classification of countries

High income	Upper middle income	Lower middle income	Low income
Bahrain	Albania	Armenia	Bangladesh
Croatia	Azerbaijan	Egypt	Belarus
Czech	Bosnia and Herzegovina Bulgaria	Georgia	Cambodia
Estonia	China	India	Kyrgyz republic
Israel	Hungary	Indonesia	Myanmar
Kuwait	Jordan	Moldova	Nepal
Latvia	Kazakhstan	Pakistan	
Lithuania	Malaysia	Sri Lank	
Oman	Mongolia	Ukraine	
Poland	Romania	Vietnam	
Russia	Thailand		
Saudi Arabia	Turkey		
Singapore			
Slovak republic			
Slovenia			

Source: Countries involved were selected from the belt and road initiative book published in May 2016 while their division into income levels was based on 2014 world bank atlas method of gross national income per capita (GNI)

Table 11 D-H causality for BRI countries

Hypothesis	$W_{N,T}^{stat}$	$\overline{Z}_{N,T}^{stat}$	Prob.	Conclusion
$LnCO_2 \rightarrow$ Lngdp	3.457[a]	8.668 [a]	0.0000	Two-way causality relationship between $LnCO_2$ and Lngdp
Lngdp $\rightarrow LnCO_2$	3.069[a]	7.223[a]	0.0000	
$LnCO_2 \rightarrow$ Lngdp2	2.800[a]	6.220[a]	0.0000	Two-way causality relationship between $LnCO_2$ and Lngdp2
Lngdp2 $\rightarrow LnCO_2$	2.192[a]	3.950[a]	0.0000	
$LnCO_2 \rightarrow$ Lnei	2.793[a]	6.192[a]	0.0000	Two-way causality relationship between $LnCO_2$ and Lnei
Lnei $\rightarrow LnCO_2$	5.118[a]	14.86[a]	0.0000	
$LnCO_2 \rightarrow$ Lnfdi	10.538[a]	35.086[a]	0.0000	Two-way causality relationship between $LnCO_2$ and Lnfdi
Lnfdi $\rightarrow LnCO_2$	3.371[a]	8.3511[a]	0.0000	
Lngdp $\rightarrow$ Lngdp2	2.390[a]	4.689[a]	0.0000	Two-way causality relationship between Lngdp and Lngdp2
Lngdp2 $\rightarrow$ Lngdp	2.004[a]	3.249[a]	0.0012	
Lngdp $\rightarrow$ Lnei	2.610[a]	5.511[a]	0.0000	Two-way causality relationship between Lngdp and Lnei
Lnei $\rightarrow$ Lngdp	3.687[a]	9.528[a]	0.0000	
Lngdp $\rightarrow$ Lnfdi	3.395[a]	8.437[a]	0.0000	Two-way causality relationship between Lngdp and Lnfdi
Lnfdi $\rightarrow$ Lngdp	3.208[a]	7.740[a]	0.0000	
Lngdp2 $\rightarrow$ Lnei	3.097[a]	7.325[a]	0.0000	Two-way causality relationship between Lngdp2 and Lnei
Lnei $\rightarrow$ Lngdp2	2.802 [a]	6.228[a]	0.0000	
Lngdp2 $\rightarrow$ Lnfdi	4.718[a]	13.373[a]	0.0000	Two-way causality relationship between Lngdp2 and Lnfdi
Lnfdi $\rightarrow$ Lngdp2	2.132[a]	3.725[a]	0.0000	
Lnei $\rightarrow$ Lnfdi	7.944[a]	25.410[a]	0.0000	Two-way causality relationship between Lnei and Lnfdi
Lnfdi $\rightarrow$ Lnei	7.076[a]	22.172[a]	0.0000	

Table 12 D-H causality for high-income countries

Hypothesis	$W_{N,T}^{stat}$	$\overline{Z}_{N,T}^{stat}$	Prob.	Conclusion
$LnCO_2 \rightarrow$ Lngdp	0.793	− 0.739	0.4596	one-way causality relationship between $LnCO_2$ and Lngdp
Lngdp $\rightarrow LnCO_2$	2.101[a]	2.108[a]	0.0350	
$LnCO_2 \rightarrow$ Lngdp2	1.604	1.025	0.3051	one-way causality relationship between $LnCO_2$ and Lngdp2
Lngdp2 $\rightarrow LnCO_2$	1.734	1.310	0.1901	
$LnCO_2 \rightarrow$ Lnei	2.336 [a]	5.125 [a]	0.0000	Two-way causality relationship between $LnCO_2$ and Lnei
Lnei $\rightarrow LnCO_2$	3.486 [a]	5.125 [a]	0.0088	
$LnCO_2 \rightarrow$ Lnfdi	24.983 [a]	51.948 [a]	0.0000	Two-way causality relationship between $LnCO_2$ and Lnfdi
Lnfdi $\rightarrow LnCO_2$	4.416 [a]	7.150 [a]	0.0000	
Lngdp $\rightarrow$ Lngdp2	1.127	− 0.013	0.9893	No causality relationship between Lngdp and Lngdp2
Lngdp2 $\rightarrow$ Lngdp	1.604	1.025	0.3055	
Lngdp $\rightarrow$ Lnei	1.517	0.836	0.4031	One-way causality relationship between Lngdp and Lnei
Lnei $\rightarrow$ Lngdp	2.702 [a]	3.418 [a]	0.0006	
Lngdp $\rightarrow$ Lnfdi	2.853 [a]	3.745 [a]	0.0002	One-way causality relationship between Lngdp and Lnfdi
Lnfdi $\rightarrow$ Lngdp	1.497	0.794	0.4274	
Lngdp2 $\rightarrow$ Lnei	1.798	1.448	0.1475	One-way causality relationship between Lngdp2 and Lnei
Lnei $\rightarrow$ Lngdp2	2.084 [a]	2.071 [a]	0.0384	
Lngdp2 $\rightarrow$ Lnfdi	4.574 [a]	7.493 [a]	0.0000	Two-way causality relationship between Lngdp2 and Lnfdi
Lnfdi $\rightarrow$ Lngdp2	2.073* [a]	2.047 [a]	0.0406	
Lnei $\rightarrow$ Lnfdi	8.331 [a]	15.677 [a]	0.0000	Two-way causality relationship between Lnei and Lnfdi
Lnfdi $\rightarrow$ Lnei	13.402 [a]	26.723 [a]	0.0000	

Table 13 D-H causality for Low Income countries

Hypothesis	$W_{N,T}^{stat}$	$\overline{Z}_{N,T}^{stat}$	Prob.	Conclusion
$LnCO_2 \rightarrow$ Lngdp	12.295[a]	15.376 [a]	0.0000	One-way causality relationship between $LnCO_2$ and Lngdp
Lngdp $\rightarrow LnCO_2$	1.424	0.40087	0.6885	
$LnCO_2 \rightarrow$ Lngdp2	2.726 [a]	2.194 [a]	0.0283	One-way causality relationship between $LnCO_2$ and Lngdp2
Lngdp2 $\rightarrow LnCO_2$	1.485	0.484	0.6282	
$LnCO_2 \rightarrow$ Lnei	3.152 [a]	2.781 [a]	0.0054	Two-way causality relationship between $LnCO_2$ and Lnei
Lnei $\rightarrow LnCO_2$	6.974 [a]	8.046 [a]	0.0000	
$LnCO_2 \rightarrow$ Lnfdi	3.385 [a]	3.102***	0.0019	Two-way causality relationship between $LnCO_2$ and Lnfdi
Lnfdi $\rightarrow LnCO_2$	5.022 [a]	5.357 [a]	0.0000	
Lngdp $\rightarrow$ Lngdp2	3.725 [a]	3.569 [a]	0.0004	Two-way causality relationship between Lngdp and Lngdp2
Lngdp2 $\rightarrow$ Lngdp	4.616 [a]	4.798 [a]	0.0000	
Lngdp $\rightarrow$ Lnei	3.152 [a]	2.782 [a]	0.0054	Two-way causality relationship between Lngdp and Lnei
Lnei $\rightarrow$ Lngdp	9.698[a]	11.798 [a]	0.0000	
Lngdp $\rightarrow$ Lnfdi	1.464	0.455	0.6491	One-way causality relationship between Lngdp and Lnfdi
Lnfdi $\rightarrow$ Lngdp	11.474 [a]	14.245 [a]	0.0000	
Lngdp2 $\rightarrow$ Lnei	1.769	0.876	0.3809	One-way causality relationship between Lngdp2 and Lnei
Lnei $\rightarrow$ Lngdp2	5.245 [a]	5.664 [a]	0.0000	
Lngdp2 $\rightarrow$ Lnfdi	3.423 [a]	3.154 [a]	0.0016	One-way causality relationship between Lngdp2 and Lnfdi
Lnfdi $\rightarrow$ Lngdp2	2.313	1.625	0.1042	
Lnei $\rightarrow$ Lnfdi	9.389 [a]	11.373 [a]	0.0000	Two-way causality relationship between Lnei and Lnfdi
Lnfdi $\rightarrow$ Lnei	5.298 [a]	5.737 [a]	0.0000	

Table 14 D-H causality for Lower middle Income countries

Hypothesis	$W_{N,T}^{stat}$	$\overline{Z}_{N,T}^{stat}$	Prob.	Conclusion
$LnCO_2 \rightarrow$ Lngdp	3.894[a]	4.909 [a]	0.0000	Two-way causality relationship between $LnCO_2$ and Lngdp
Lngdp $\rightarrow LnCO_2$	2.702 [a]	2.790 [a]	0.0053	
$LnCO_2 \rightarrow$ Lngdp2	1.918	1.396	0.1627	No-way causality relationship between $LnCO_2$ and Lngdp2
Lngdp2 $\rightarrow LnCO_2$	0.914	− 0.391	0.6961	
$LnCO_2 \rightarrow$ Lnei	1.658	0.934	0.3500	One-way causality relationship between $LnCO_2$ and Lnei
Lnei $\rightarrow LnCO_2$	8.133 [a]	12.448 [a]	0.0000	
$LnCO_2 \rightarrow$ Lnfdi	3.038 [a]	3.388 [a]	0.0007	Two-way causality relationship between $LnCO_2$ and Lnfdi
Lnfdi $\rightarrow LnCO_2$	2.051 [a]	1.63 [a]	0.1026	
Lngdp $\rightarrow$ Lngdp2	2.532 [a]	2.488 [a]	0.0128	One-way causality relationship between Lngdp and Lngdp2
Lngdp2 $\rightarrow$ Lngdp	0.997	− 0.242	0.8088	
Lngdp $\rightarrow$ Lnei	2.374 [a]	2.206 [a]	0.0274	Two-way causality relationship between Lngdp and Lnei
Lnei $\rightarrow$ Lngdp	3.385 [a]	4.006 [a]	0.0000	
Lngdp $\rightarrow$ Lnfdi	1.981	1.508	0.1314	One-way causality relationship between Lngdp and Lnfdi
Lnfdi $\rightarrow$ Lngdp	3.310 [a]	3.872 [a]	0.0001	
Lngdp2 $\rightarrow$ Lnei	6.039 [a]	8.724 [a]	0.0000	Two-way causality relationship between Lngdp2 and Lnei
Lnei $\rightarrow$ Lngdp2	3.076 [a]	3.455 [a]	0.0006	
Lngdp2 $\rightarrow$ Lnfdi	4.175 [a]	5.411 [a]	0.0000	One-way causality relationship between Lngdp2 and Lnfdi
Lnfdi $\rightarrow$ Lngdp2	1.610	0.847	0.3971	
Lnei $\rightarrow$ Lnfdi	2.615 [a]	2.635 [a]	0.0084	Two-way causality relationship between Lnei and Lnfdi
Lnfdi $\rightarrow$ Lnei	5.105 [a]	7.064 [a]	0.0000	

Table 15 D-H causality for upper-middle-income countries

Hypothesis	$\mathrm{W}_{\mathrm{N,T}}^{\mathrm{stat}}$	$\overline{\mathrm{Z}}_{\mathrm{N,T}}^{\mathrm{stat}}$	Prob.	Conclusion
$LnCO_2 \rightarrow$ Lngdp	2.114[a]	1.989 [a]	0.0466	Two-way causality relationship between $LnCO_2$ and Lngdp
Lngdp $\rightarrow LnCO_2$	5.229 [a]	8.305 [a]	0.0000	
$LnCO_2 \rightarrow$ Lngdp2	4.895 [a]	7.627 [a]	0.0000	Two-way causality relationship between $LnCO_2$ and Lngdp2
Lngdp2 $\rightarrow LnCO_2$	4.030 [a]	5.874 [a]	0.0000	
$LnCO_2 \rightarrow$ Lnei	4.028 [a]	5.869 [a]	0.0000	Two-way causality relationship between $LnCO_2$ and Lnei
Lnei $\rightarrow LnCO_2$	3.827 [a]	5.463 [a]	0.0000	
$LnCO_2 \rightarrow$ Lnfdi	2.942 [a]	3.668 [a]	0.0002	Two-way causality relationship between $LnCO_2$ and Lnfdi
Lnfdi $\rightarrow LnCO_2$	2.422 [a]	2.612 [a]	0.0090	
Lngdp $\rightarrow$ Lngdp2	3.123 [a]	4.034 [a]	0.0000	Two-way causality relationship between Lngdp and Lngdp2
Lngdp2 $\rightarrow$ Lngdp	2.035 [a]	1.830 [a]	0.0672	
Lngdp $\rightarrow$ Lnei	3.804 [a]	5.416 [a]	0.0000	Two-way causality relationship between Lngdp and Lnei
Lnei $\rightarrow$ Lngdp	2.282 [a]	2.329 [a]	0.0199	
Lngdp $\rightarrow$ Lnfdi	5.999 [a]	9.867 [a]	0.0000	One-way causality relationship between Lngdp and Lnfdi
Lnfdi $\rightarrow$ Lngdp	1.287	0.313	0.7539	
Lngdp2 $\rightarrow$ Lnei	2.944 [a]	3.673 [a]	0.0002	Two-way causality relationship between Lngdp2 and Lnei
Lnei $\rightarrow$ Lngdp2	2.295 [a]	2.356 [a]	0.0185	
Lngdp2 $\rightarrow$ Lnfdi	5.900 [a]	9.666 [a]	0.0000	Two-way causality relationship between Lngdp2 and Lnfdi
Lnfdi $\rightarrow$ Lngdp2	2.518 [a]	2.809 [a]	0.0050	
Lnei $\rightarrow$ Lnfdi	10.932 [a]	19.870 [a]	0.0000	Two-way causality relationship between Lnei and Lnfdi
Lnfdi $\rightarrow$ Lnei	2.115 [a]	1.991 [a]	0.0465	

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