**RESEARCH ARTICLE** 



# Energy efficiency and green innovation and its asymmetric impact on CO2 emission in China: a new perspective

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#### Abstract

Green innovation undoubtedly plays a significant role in generating employment opportunities, improving green economic activity, and increasing environmental sustainability. This study scrutinizes the effect of energy efficiency and green innovation on CO2 emissions for China using nonlinear autoregressive distributed lag (NARDL) from 1991 to 2019. Findings show that energy efficiency and green innovation contribute to reducing CO2 emissions in China. Energy efficiency and green innovation lowers CO2 emissions, while a fall in energy efficiency and green innovation increases CO2 emissions in China in the long run. Some policy measures are suggested to attain carbon neutrality.

Keywords Energy efficiency · Green innovation · CO2 emission · China

## Introduction

Since the industrial revolution, the increase in global economic activities has raised the living standards of the people significantly. However, the rise in economic activities also causes the CO2 and other greenhouse gas (GHG) emissions to rise at an incredible pace, wreaking havoc on the environment in the form of floods, droughts, rise in global temperatures, and climate change (Danish et al. 2018) Therefore, the issue of global warming and climate change has become the central focus of all international discussions. In this context, Paris Agreement in 2015 proved to be a milestone that demands to restrict the average rise in global

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<sup>1</sup> China University of Geosciences, Wuhan, China

<sup>2</sup> Department of Economics, Government College University Faisalabad, Faisalabad, Pakistan temperature below 2 °C compared to the preindustrial era by curbing CO2 emissions. As a result, the empirics have shifted their focus toward the factors that can contribute to economic development without damaging the environment too much. In the recent literature, renewable energy consumption and technological innovations come to the fore as the most important mitigating factors to CO2 emissions (Usman et al. 2020, 2021; Ullah et al. 2021). However, the role of energy efficiency and green innovations, which could prove as essential factors in mitigating CO2 emissions, are not studied extensively as promoters of sustainable development and a clean environment. The relationship between these factors and CO2 emissions is mainly observed over a long period of time. Therefore, in this study, we aim to observe the relationship between energy efficiency and green innovations on environmental quality in China.

Energy is served as an essential input in production; hence, the main contributor to the industrialization and economic development of developed and emerging economies. On the other side, this process of modernization and development is not free of cost, and an environmental cost is attached to this process (Chang et al. 2018). Several empirical studies have tried to find the role of energy consumption on the economic development of various countries and regions, and most of them have accounted for the problems of environmental pollution and CO2 emissions (Arouri et al. 2012; Ozturk and Al-Mulali 2015). Moreover, various studies have also highlighted that the adverse effects produced by energy consumption can be countered by increasing energy efficiency (Filippini and Zhang 2016). Therefore, several past studies have considered energy efficiency as a key element in increasing energy security, driving economic growth, and reducing environmental problems.

Given the importance of energy efficiency, many developed and emerging economies have incorporated energy efficiency policy into their energy-related strategies, targets, and overall national agendas. (IEA 2014). To achieve targets of high environmental quality alongside high economic growth, the world has to invest heavily in green technology (Wurlod and Noailly, 2018a; Usman et al., 2021a, b, c; Zhao et al. 2021). Another way to successfully achieve the targets mentioned above is to improve the countries' institutional quality that could effectively contribute to the implementation of energy policies. Although many nations have implemented the energy efficiency policy, the efficacy of these policies largely varies from country to country depending upon the difference in their level of institutions, relative factor prices, degree of specialization, and status of their technological development (Usman et al., 2021a, b, c).

Green innovations have also gained popularity during recent years, and they can help achieve green economic growth, which is the need of the hour (Ullah et al. 2021). One of the most pertinent benefits of green innovations is that they can significantly cut carbon emissions, which is a significant cause of environmental degradation, by increasing energy efficiency and developing more sophisticated and modern technologies (Cantore et al., 2016; Su et al. 2021). Therefore, during the Paris Agreement, various countries have agreed to work together that leads them toward the path of green economic growth. Despite all these efforts, there are several hurdles that still exist in the implementation of green technology not only at the domestic but international level (Maskus 2010). The decision of the countries regarding investment in green technologies will depend on whether the green technology reduces energy inefficiency and increases productivity or not. In this context, empirical studies provided mixed results. Palmer et al. (1995) indicated that green technology might cause energy efficiency and productivity to fall. On the other side, Lin and Moubarak (2014) and Wurlod and Noailly (2018b) highlighted that green technology improves energy efficiency and increases total productivity.

China is the second-largest country, the largest energy consumer, and the most significant contributor to global CO2 emissions (Aslam et al. 2021). China is an emerging economy, which is growing at a great pace. The demand for controlling CO2 emissions in China is on the rise. The pressure is mounting on China domestically and internationally (Yuelan et al., 2019). Energy efficiency and green innovations can help reduce CO2 emissions without compromising economic growth. Not many studies are available that have particularly targeted China in this context. Therefore, in this study, we try to analyze the nexus between energy efficiency, green innovations, and environmental quality in China. This study is different from all previous studies because it relies on the asymmetry assumption, which offers us an opportunity to separately calculate the effect of positive and negative changes in energy efficiency and green innovations on CO2 emissions in China. To that end, the analysis applied linear and nonlinear ARDL models. To the best of our knowledge, this is a first-ever study that tried to capture the asymmetric impact of energy efficiency and green innovations on CO2 emissions in China.

The first and foremost novelty of the study is the asymmetric analysis. The asymmetric examination is closer to reality because macroeconomic variables are subject to external shocks. As a result, the macroeconomic variables move asymmetrically. In recent times, many empirics have analyzed various the asymmetric impact of various variables by using nonlinear ARDL such as Bahmani-Oskooee et al. (2020) for the exchange rate, Usman et al. (2021a, b, c) for exchange rate volatility, Ullah et al. (2019) for industrialization and urbanization, Usman et al. (2019) for renewable energy, and Usman et al. (2021a, b, c) for ICT, among others. However, none of the past studies have focused on the asymmetric impact of green innovations and energy efficiency on CO2 emissions in China. Further, previous studies have relied on panel data analysis, which suffers from the problem of aggregation bias. Nevertheless, we have used time series analysis, free from the glitch of aggregation bias. Moreover, this study opens new theoretical knowledge and finds new practical implications in the context of asymmetric analysis. Lastly, the study significantly contributes to the environmental and cleaner production theory by estimating the positive and negative shocks in green innovations and energy efficiency as separate variables.

#### Model, methods, and data

This study aims to investigate the impact of energy efficiency and green innovation on CO2 emissions in China. Therefore, to analyze the nexus between CO2 emissions, energy efficiency, and green innovation in China, we derived Eq. (1) from the literature.

$$CO_{2,t} = \alpha_0 + \alpha_1 EE_t + \alpha_2 GI_t + \alpha_3 GDP_t + \alpha_4 FDI_t + \mu_t$$
(1)

Where carbon dioxide emissions (CO2) in China depend on the energy efficiency (EE), green innovation (GI), GDP per capita (GDP), foreign direct investment inflows (FDI), and error term ( $\mu_t$ ). Specification (1) is a long-run equation and is only able to provide us with long-run results. In order to get short as well as long-run estimates, we will redefine Eq. (1) in an error correction format as shown below:

$$\Delta CO_{2,t} = \pi + \sum_{p=1}^{n1} \pi_{1p} \Delta CO_{2,t-p} + \sum_{p=0}^{n2} \pi_{2p} \Delta EE_{t-p} + \sum_{p=0}^{n3} \pi_{3p} \Delta GI_{t-p} + \sum_{p=0}^{n4} \pi_{4p} \Delta GDP_{t-p} + \sum_{p=0}^{n5} \pi_{5p} \Delta FDI_{t-p} + \beta_1 CO_{2,t-1} + \beta_2 EE_{t-1} + \beta_3 GI_{t-1} + \beta_4 GDP_{t-1} + \beta_5 FDI_{t-1} + \mu_t$$
(2)

This format of error correction is known as the ARDL model of Pesaran et al. (2001). In this method, we can get short-term as well as long-term estimates at the same time. In Eq. (2) above, estimates of " $\Delta$ " variables offer the short-run outcomes, and the estimates attached to  $\beta_2$ – $\beta_5$  normalized on  $\beta_1$  provide us the long-run outcomes. The soundness of the long-term outcomes relies on the test of cointegration known as the *F*-test for the joint level of significance of the lagged variables. Pesaran et al. (2001) established critical values for the *F*-test. This method has another advantage over other methods. It does not require pre-unit root testing properties and adds a mixture of *I*(0) and *I*(1) variables. Moreover, it can also provide efficient estimates if the number of observations is small (Bahmani-Oskooee et al. 2020).

Apart from the symmetric analysis, we have also performed asymmetric analysis to know whether the effects of energy efficiency and green innovation on CO2 emissions are symmetric or nonsymmetric. To that end, we break the variables of energy efficiency and green innovation into negative and positive components using the partial sum procedure. The process of the partial sum procedure in mathematical form is shown below.

$$EE^{+}_{t} = \sum_{n=1}^{t} \Delta EE^{+}_{t} = \sum_{n=1}^{t} \max (EE^{+}_{t}, 0)$$
(3a)

$$EE_{t}^{-} = \sum_{n=1}^{t} \Delta EE_{t}^{-} = \sum_{n=1}^{t} \min \left( \Delta EE_{t}^{-}, 0 \right)$$
 (3b)

$$GI_{t}^{+} = \sum_{n=1}^{t} \Delta GI_{t}^{+} = \sum_{n=1}^{t} \max \left( \Delta GI_{t}^{+}, 0 \right)$$
 (4a)

$$\operatorname{GI}_{t}^{-} = \sum_{n=1}^{t} \Delta \operatorname{GI}_{t}^{-} = \sum_{n=1}^{t} \min \left( \Delta \operatorname{GI}_{t}^{-}, 0 \right)$$
(4b)

Positive changes in the variables of energy efficiency and green innovations are represented by Eqs. (3a) and (4a); whereas, the negative changes are represented by Eqs. (3b) and (4b). After breaking the variables into twin components, we need to incorporate these partial sum variables in place of original variables in Eq. (2), and the resulting equation will become NARDL as prescribed below.

$$\Delta CO_{2,t} = \omega_0 + \sum_{k=1}^n \pi_{1k} \Delta CO_{2,t-k} + \sum_{k=0}^n \pi_{2k} \Delta EE^+_{t-k} + \sum_{k=0}^n \pi_{3k} \Delta EE^-_{t-k} + \sum_{k=0}^n \pi_{4k} \Delta GI^+_{t-k} + \sum_{k=0}^n \pi_{5k} \Delta GI^-_{t-k} + \sum_{k=0}^n \pi_{6k} GDP_{t-k} + \sum_{k=0}^n \pi_{7k} \text{FDI}_{t-k} + \omega_1 CO_{2,t-1} + \omega_2 EE^+_{t-1} + \omega_3 EE^-_{t-1} + \omega_4 GI^+_{t-1} + \omega_5 GI^-_{t-1} + \omega_6 GDP_{t-1} + \omega_7 FDI_{t-1} + \varepsilon_t$$
(5)

The NARDL is developed by Shin et al. (2014), which is an augmented form of linear ARDL. Therefore, the cointegration and diagnostic tests of the basic ARDL model are equally appropriate for the augmented ARDL model (Usman et al. 2020). However, asymmetric tests are required before we can decide whether the effects of our concerned variables are symmetric or asymmetric. Firstly, to confirm the shortrun impact asymmetry, we need to prove that  $\sum \pi_{2k} \neq \sum \pi_{3k}$ and  $\sum \pi_{4k} \neq \sum \pi_{5k}$  with the help of the Wald-SR test. Then, to confirm the long-run asymmetric effects, we need to prove that  $\frac{\omega_2}{-\omega_1} \neq \frac{\omega_3}{-\omega_1}$  and  $\frac{\omega_4}{-\omega_1} \neq \frac{\omega_5}{-\omega_1}$  with the help of Wald-LR.

The study explores the impact of energy efficiency and green innovation on carbon emissions for China for the time period 1991 to 2019. For that purpose, CO2 emission is used as a dependent variable, energy efficiency and green innovation are focused variables, while GDP per capita growth and FDI are control variables in Table 1. CO2 emission is measured by carbon dioxide emissions in kilotons. Energy efficiency is measured as GDP per unit of energy use, and green innovation is measured as the progress of environment-related technologies as a percent of all technologies. GDP per capita growth is taken in annual percentage, and foreign direct investment inflows are taken as a percentage of

| Table 1 Data definitions and sources | Table 1 | Data | definitions | and | sources |
|--------------------------------------|---------|------|-------------|-----|---------|
|--------------------------------------|---------|------|-------------|-----|---------|

| Variables                 | Symbol | Definitions  | Sources    |
|---------------------------|--------|--|------------|
| CO2 emissions             | CO2    | CO2 emissions (kt)   | World Bank |
| Energy efficiency         | EE     | GDP per unit of energy use (constant 2017 PPP \$ per kg of oil equivalent) | World Bank |
| Green innovation          | GI     | Development of environment-related technologies, % all technologies        | OECD       |
| GDP per capita growth     | GDP    | GDP per capita growth (annual %)   | World Bank |
| Foreign direct investment | FDI    | Foreign direct investment inflows (% of the GDP)                           | World Bank |

GDP. All the data to be used in this study is extracted from the World Bank, except green innovation.

### **Results and discussion**

A preliminary analysis, stationarity properties of data have been confirmed by adopting traditional unit root tests. For that purpose, unit root without and with break tests are used to provide for more reliable results, and the outcomes of these tests are presented in Table 2. The findings suggest that all the variables are either stationary at the level I(0) or at the first difference I(1). Moreover, none of the variables is stationary at I(2). Thus, the study adopted the ARDL approach to figure out the dynamics of energy efficiency and green innovation on CO2 emissions in the case of China. The study also continues to investigate the asymmetric impact of energy efficiency and green innovation on CO2 emissions by adopting the NARDL approach.

In Table 3, the long-run findings of the ARDL model reveal that energy efficiency has a negative and significant impact on CO2 emissions revealing that environmental quality improves due to an increase in energy efficiency. The coefficient estimate shows that in response to the 1%upsurge in energy efficiency, CO2 declines by 0.589%. However, green innovation has no significant impact on CO2 emissions in the long run. In terms of control variables, the long-term impact of GDP per capita growth on CO2 emissions is significant and positive in China with an elasticity of 0.074, while FDI produced an insignificant impact. The short-run estimates of the ARDL model demonstrate that energy efficiency, green innovation, and GDP per capita growth produce no significant impact on CO2 emissions; however, the impact of FDI is positively significant on CO2 emissions in China. In the third panel of Table 3, findings of some important diagnostic tests are given, which are imperative to perform to confirm the validity of ARDL estimates. As F-statistics and ECM approve the existence of long-term cointegration among concern variables. No issues of heteroskedasticity and autocorrelation are found in LM and BP tests. The model is correctly specified as confirmed by the findings of the Ramsey RESET test. CUSUM and CUSUMSQ test report that stability exists in the model.

The long-run coefficient estimates of the NARDL model exhibit that positive shock in energy efficiency has a negative significant effect on CO2 emissions confirming that environmental quality is enhanced due to an upsurge in energy efficiency. The findings show that due to the 1% upsurge in positive shock of energy efficiency, CO2 emissions decline by 0.045%. In terms of the negative shock of energy efficiency, findings reveal that a decline in negative shock of energy efficiency results in increasing CO2 emissions in the long run. In other words, due to the 1% decline in negative shock of energy efficiency, CO2 emission increases by 1.573%.

This result is also reliable with Bayar and Gavriletea (20190), who made famous that energy efficiency permits savings of energy in the process of production for goods and services. Energy efficiency and environmental strategy are key factors used by various organizations pursuing to attain sustainability of the environment. Likewise, the energy efficiency contribution is also imperative with a negative coefficient estimate, indicating the significance of energy efficiency in the reduction of carbon emissions in China. Empirical and theoretical literature also supports the findings (Pardo et al. 2011; Wu et al. 2012; Martínez-Moya et al., 2019). Therefore, the proposed contribution of the study is well verified empirically, and energy efficiency can be beneficial toward the growth of China. Furthermore, energy efficiency is beneficial with outstanding market potential, thus facilitating energy security and endorsing sustainable development. Thus, a continuous upsurge in the carbon emissions of China can be controlled by adopting energy efficiency. Energy efficiency is gradually becoming a measure of green growth strategies of governments, aiming to control CO2 emissions by enhancing energy consumption and achieving environmental targets. Energy efficiency is a key measure to attaining decarbonization at a worldwide level (Tajudeen et al. 2018).

In the case of green innovation, it is found that positive shock of green innovation produces no significant effect on CO2 emissions, while a decline in negative shock of green innovation produces a positive significant effect on CO2

|     | Unit root without break |              |              | Unit root with break |            |              |            |              |  |
|-----|-------------------------|--------------|--------------|----------------------|------------|--------------|------------|--------------|--|
|     | <u>I(0)</u>             | <i>I</i> (1) |              | <i>I</i> (0)         | Break date | <i>I</i> (1) | Break date |              |  |
| CO2 | -0.638                  | -3.105**     | <i>I</i> (1) | -5.155               | 2002       |              |            | <i>I</i> (0) |  |
| EE  | -1.264                  | -3.047       | <i>I</i> (1) | -2.102               | 2006       | -4.356       | 2003       | <i>I</i> (1) |  |
| GI  | -1.372                  | -6.215       | <i>I</i> (1) | -3.142               | 2000       | -8.235       | 2001       | <i>I</i> (1) |  |
| GDP | -1.712                  | -6.145       | <i>I</i> (1) | -3.023               | 2007       | -6.015       | 2010       | <i>I</i> (1) |  |
| FD  | -4.156                  |              | <i>I</i> (0) | -6.695               | 2004       |              |            | <i>I</i> (0) |  |

\*\*\*p < 0.01; \*\*p < 0.05; and \*p < 0.1

Table 2 Unit root testing

Table 3ARDL and NARDLestimates

|               | ARDL           |            |        |       | NARDL          |            |        |       |
|---------------|----------------|------------|--------|-------|----------------|------------|--------|-------|
|               | Coefficient    | Std. error | t-Stat | Prob. | Coefficient    | Std. error | t-Stat | Prob. |
| Short-run     |                |            |        |       |                |            |        |       |
| D(EE)         | -0.023         | 0.093      | 0.243  | 0.812 |                |            |        |       |
| D(EE(-1))     | -0.061         | 0.111      | 0.554  | 0.590 |                |            |        |       |
| D(EE(-2))     | -0.195***      | 0.074      | 2.629  | 0.024 |                |            |        |       |
| D(EE_POS)     |                |            |        |       | -0.094         | 0.103      | 0.909  | 0.390 |
| D(EE_POS(-1)) |                |            |        |       | -0.339         | 0.122      | 2.786  | 0.024 |
| D(EE_NEG)     |                |            |        |       | -1.056***      | 0.339      | 3.118  | 0.014 |
| D(EE_NEG(-1)) |                |            |        |       | 0.956***       | 0.358      | 2.673  | 0.028 |
| D(GI)         | -0.007         | 0.010      | 0.723  | 0.485 |                |            |        |       |
| D(GI_POS)     |                |            |        |       | 0.001          | 0.018      | 0.035  | 0.973 |
| D(GI_NEG)     |                |            |        |       | -0.132***      | 0.046      | 2.896  | 0.020 |
| D(GI_NEG(-1)) |                |            |        |       | -0.152**       | 0.069      | 2.201  | 0.059 |
| D(GDP)        | 0.009          | 0.006      | 1.568  | 0.145 | 0.031***       | 0.011      | 2.977  | 0.018 |
| D(GDP(-1))    | -0.001         | 0.008      | 0.136  | 0.894 | 0.016          | 0.012      | 1.345  | 0.216 |
| D(GDP(-2))    | -0.024         | 0.007      | 3.248  | 0.008 |                |            |        |       |
| D(FDI)        | 0.144***       | 0.054      | 2.671  | 0.022 | -0.224*        | 0.133      | 1.693  | 0.129 |
| D(FDI(-1))    | 0.038          | 0.043      | 0.890  | 0.393 |                |            |        |       |
| D(FDI(-2))    | 0.073*         | 0.039      | 1.879  | 0.087 |                |            |        |       |
| Long-run      |                |            |        |       |                |            |        |       |
| EE            | $-0.589^{***}$ | 0.101      | 5.842  | 0.000 |                |            |        |       |
| EE_POS        |                |            |        |       | -0.045*        | 0.024      | 1.875  | 0.089 |
| EE_NEG        |                |            |        |       | -1.573**       | 0.733      | 2.145  | 0.064 |
| GI            | -0.017         | 0.020      | 0.837  | 0.420 |                |            |        |       |
| GI_POS        |                |            |        |       | -0.001         | 0.018      | 0.035  | 0.973 |
| GI_NEG        |                |            |        |       | -0.168 ***     | 0.028      | 5.956  | 0.000 |
| GDP           | 0.074***       | 0.024      | 3.129  | 0.010 | 0.003          | 0.012      | 0.226  | 0.827 |
| FDI           | 0.108          | 0.094      | 1.146  | 0.276 | 0.724***       | 0.125      | 5.812  | 0.000 |
| С             | 10.02***       | 1.880      | 5.334  | 0.000 | $-2.747^{***}$ | 3.116      | 0.881  | 0.404 |
| Diagnostics   |                |            |        |       |                |            |        |       |
| F-test        | 4.252*         |            |        |       | 3.954*         |            |        |       |
| ECM(-1)       | $-0.426^{***}$ | 0.142      | 3.009  | 0.012 | 0.692*         | 0.407      | 1.700  | 0.100 |
| LM            | 1.654          |            |        |       | 2.512          |            |        |       |
| BP            | 0.689          |            |        |       | 0.721          |            |        |       |
| RESET         | 1.845          |            |        |       | 1.234          |            |        |       |
| CUSUM         | S              |            |        |       | S              |            |        |       |
| CUSUM-sq      | S              |            |        |       | S              |            |        |       |
| Wald-SR-EE    |                |            |        |       | 1.235          |            |        |       |
| Wald-LR-EE    |                |            |        |       | 6.655***       |            |        |       |
| Wald-SR-GI    |                |            |        |       | 0.265          |            |        |       |
| Wald-LR-GI    |                |            |        |       | 5.654***       |            |        |       |

\*\*\*p < 0.01; \*\*p < 0.05; and \*p < 0.1

emissions. It reveals that due to a 1% decline in negative shock of green innovation, CO2 emissions rise by 0.168% in the long run. Green innovation helps in reducing energy consumption and resultantly reduces energy use that leads to the achievement of sustainable growth. Therefore, green innovation is found to be favorable in reducing carbon emissions in China (Hussain et al. 2020). Green innovation is such technology that is used in the processing or production of goods without any damage to the environment. Hussain and Dogan (2021) highlighted the contribution of green innovation in the execution of efficiency-based models to attain sustainable societies. Furthermore, sustainable growth via green innovation is also supported by growing investment in the environmental research and development sector (Ulucak 2020). The findings confirm the encouraging contribution of green technologies in green growth environmental targets (Mensah et al. 2019; Ullah et al. 2021). Moreover, consumption-based carbon emissions are controlled due to the adoption of green innovations and energy efficiency in China, thus providing smooth measures of sustainable growth (Hussain et al. 2020). Furthermore, energy efficiency and green innovation can contribute a significant role in correcting environmental pollution. Furthermore, green innovations are imperative for sustainable growth of economic, social, and energy systems and carbon mitigation of the economies.

In terms of control variables, findings reveal that GDP growth produces an insignificant impact on CO2 emissions, while the long-term impact of FDI on CO2 emissions is positively significant in China with an elasticity of 0.724. The short-run results of the NARDL model validate that positive shocks in energy efficiency and green innovation produce no significant impact on CO2 emissions; however, negative shocks in energy efficiency and green innovation have a significant and positive impact on CO2 emissions in China. In terms of control variables, findings reveal that GDP produces a significant positive impact on CO2 emissions, while FDI produces a significant and negative impact on CO2 emissions in the short run. The long-run cointegration is also confirmed by F-stat and ECM. The results of LM, BP, and RESET tests confirm that the model is free from severe problems. The stability condition is also fulfilled in the model as shown by findings of CUSUM and CUSUMSQ tests. The asymmetries are only observed in the long run. Table 4 reports the symmetric and nonsymmetric causality results. Findings show that energy efficiency has a bidirectional causality relationship with CO2 emissions, which implies that energy efficiency significantly causes CO2 emissions. The existence of unidirectional Granger causality running from CO2 to green innovation indicates that there is green innovation enhances during high carbon emissions in China.

### **Conclusion and implications**

Although the industrial revolution has raised the living standard of the people, its contribution to global warming and climate change cannot be ignored. Environmentalists have singled out GHG emissions, mainly carbon, as the leading cause of environmental degradation. Therefore, recently, academics and empirics have turned their attention to the factors that can contribute to the sustainable economic development of the country. Despite rising interest in energy efficiency and green innovation as a mitigating factor of CO2 emissions; however, the literature in this context is at the infancy stage. Therefore, an in-depth study on the nexus between energy efficiency, green innovation, and CO2 emissions is the need of the hour, and this analysis is a step in that direction. Moreover, the asymmetric effect of energy efficiency and green innovation on CO2 emission has not attracted previous empirics. Therefore, our study considers the asymmetric impact of energy efficiency and green innovation on CO2 emissions of China selected from 1991 to 2019 by controlling GDP and FDI in empirical analysis. For empirical investigation, we have chosen the linear and nonlinear ARDL models. The cointegration outcomes confirm that there is a longrun relationship between energy efficiency, green innovation, and CO2 emissions.

Generally, our findings show that energy efficiency and green innovation have an asymmetric effect on CO2 emissions in China in the short and long run. An increase in energy efficiency stimulated environmental quality, but a decrease in energy efficiency promoted environmental quality in China in the long run. The effect of positive change in green innovation has negative insignificant, while a negative change in green innovation has a positive significant impact on CO2 emissions in the long run in China. Energy efficiency and green innovation have also asymmetrically influenced CO2 emissions in the short run. The coefficients on positive shock in energy efficiency and green innovation indicate insignificant effects on CO2 emissions, while negative shocks coefficient have also positive impacts on CO2 emissions in the short run. The estimate of negative shocks in energy efficiency and green innovation is greater than positive shocks in nonlinear models. The results show that energy efficiency and green innovation significantly reduce CO2 emissions and improve environmental quality in the long run.

Policy instruments such as subsidies, rebates, feed-in tariffs, and incentives can be used in order to promote and inspire green investments without compromising the environment and economic growth. Authorities must change their strategic approaches in order to meet growing clean energy demands. China should redesign and implement green growth policies and programs to achieve carbon neutrality. The government should allocate a large share of green public spending on green environmental innovation. China can promote environmental awareness by using smart technologies. China should have more investments in environmental technology to clean its environment. In the end, this study did not examine the impact of energy efficiency and green innovation on green growth in the context of China. Future research can reflect the role of energy efficiency and green innovation in influencing green growth. Authors should also conduct the same research for other high carbon emitter economies and conducted at the provincial level is needed. Future studies can yield more consistent parameter estimates with alternative indicators, datasets,

Table 4Symmetric andasymmetric causality tests

| Symmetric causality                     |        |       | Asymmetric causality  |        |       | Decision            |                              |
|---|--------|-------|---|--------|-------|---------------------|------------------------------|
| Null hypothesis                         | F-stat | Prob. | Null hypothesis   | F-stat | Prob. | Symmetric causality | Asym-<br>metric<br>causality |
| $EE \rightarrow CO2$                    | 2.290  | 0.125 | $\text{EE}\_\text{POS} \to \text{CO2}$                          | 3.153  | 0.064 | No                  | Yes                          |
| $\rm CO2 \rightarrow \rm EE$            | 5.105  | 0.015 | $CO2 \rightarrow EE_POS$  | 3.970  | 0.035 | Yes                 | Yes                          |
| $\text{GI} \rightarrow \text{CO2}$      | 3.237  | 0.059 | $\text{EE}\_\text{NEG} \rightarrow \text{CO2}$                  | 0.925  | 0.412 | Yes                 | No                           |
| $\rm CO2 \rightarrow GI$                | 0.283  | 0.756 | $CO2 \rightarrow EE\_NEG$                                       | 3.575  | 0.046 | No                  | Yes                          |
| $\mathrm{GDP} \to \mathrm{CO2}$         | 2.069  | 0.150 | $GI_{POS} \rightarrow CO2$                                      | 5.335  | 0.013 | No                  | Yes                          |
| $\rm CO2 \rightarrow \rm GDP$           | 2.437  | 0.111 | $CO2 \rightarrow GI_POS$  | 0.772  | 0.475 | No                  | No                           |
| $\mathrm{FDI} \rightarrow \mathrm{CO2}$ | 0.368  | 0.696 | $\text{GI\_NEG} \rightarrow \text{CO2}$                         | 0.057  | 0.945 | No                  | No                           |
| $\rm CO2 \rightarrow FDI$               | 5.060  | 0.016 | $CO2 \rightarrow GI\_NEG$                                       | 1.731  | 0.202 | Yes                 | No                           |
| $\mathrm{GI}  ightarrow \mathrm{EE}$    | 0.161  | 0.852 | $\text{GDP} \rightarrow \text{CO2}$                             | 2.069  | 0.150 | No                  | No                           |
| $\rm EE \rightarrow GI$                 | 0.992  | 0.387 | $\rm CO2 \rightarrow \rm GDP$                                   | 2.437  | 0.111 | No                  | No                           |
| $\text{GDP} \rightarrow \text{EE}$      | 0.148  | 0.863 | $FDI \rightarrow CO2$   | 0.368  | 0.696 | No                  | No                           |
| $\text{EE} \rightarrow \text{GDP}$      | 2.206  | 0.134 | $\rm CO2 \rightarrow FDI$                                       | 5.060  | 0.016 | No                  | Yes                          |
| $FDI \rightarrow EE$                    | 2.242  | 0.130 | $\rm EE\_NEG \rightarrow \rm EE\_POS$                           | 2.113  | 0.146 | No                  | No                           |
| $\text{EE} \rightarrow \text{FDI}$      | 0.490  | 0.619 | $EE_{POS} \rightarrow EE_{NEG}$                                 | 2.457  | 0.110 | No                  | No                           |
| $\mathrm{GDP}\to\mathrm{GI}$            | 0.223  | 0.802 | $\text{GI\_POS} \rightarrow \text{EE\_POS}$                     | 0.314  | 0.734 | No                  | No                           |
| $\text{GI} \rightarrow \text{GDP}$      | 0.183  | 0.834 | $EE_{POS} \rightarrow GI_{POS}$                                 | 3.347  | 0.055 | No                  | Yes                          |
| $FDI \rightarrow GI$                    | 1.004  | 0.382 | $GI\_NEG \rightarrow EE\_POS$                                   | 0.434  | 0.653 | No                  | No                           |
| $\mathrm{GI}  ightarrow \mathrm{FDI}$   | 3.232  | 0.059 | $EE_{POS} \rightarrow GI_{NEG}$                                 | 3.307  | 0.056 | Yes                 | Yes                          |
| $FDI \rightarrow GDP$                   | 0.630  | 0.542 | $GDP \rightarrow EE_POS$  | 0.174  | 0.842 | No                  | No                           |
| $\text{GDP} \rightarrow \text{FDI}$     | 6.512  | 0.006 | $EE_{POS} \rightarrow GDP$                                      | 2.307  | 0.124 | Yes                 | No                           |
|   |        |       | $FDI \rightarrow EE_POS$  | 2.172  | 0.139 |                     | No                           |
|   |        |       | $EE_{POS} \rightarrow FDI$                                      | 1.448  | 0.258 |                     | No                           |
|   |        |       | $GI_POS \rightarrow EE_NEG$                                     | 8.945  | 0.002 |                     | Yes                          |
|   |        |       | $EE_NEG \rightarrow GI_POS$                                     | 0.140  | 0.870 |                     | No                           |
|   |        |       | $GI_NEG \rightarrow EE_NEG$                                     | 7.535  | 0.003 |                     | Yes                          |
|   |        |       | $EE_NEG \rightarrow GI_NEG$                                     | 0.319  | 0.731 |                     | No                           |
|   |        |       | $GDP \rightarrow EE_NEG$  | 0.799  | 0.463 |                     | No                           |
|   |        |       | $EE_NEG \rightarrow GDP$  | 0.577  | 0.570 |                     | No                           |
|   |        |       | $FDI \rightarrow EE_NEG$  | 1.540  | 0.238 |                     | No                           |
|   |        |       | $EE_NEG \rightarrow FDI$  | 3.618  | 0.045 |                     | Yes                          |
|   |        |       | $\overline{\text{GI NEG}} \rightarrow \overline{\text{GI POS}}$ | 1.213  | 0.317 |                     | No                           |
|   |        |       | $GI_{POS} \rightarrow GI_{NEG}$                                 | 10.264 | 0.001 |                     | Yes                          |
|   |        |       | $GDP \rightarrow GI_POS$  | 1.328  | 0.287 |                     | No                           |
|   |        |       | $GI_{POS} \rightarrow GDP$                                      | 0.293  | 0.749 |                     | No                           |
|   |        |       | $FDI \rightarrow GI_POS$  | 1.147  | 0.337 |                     | No                           |
|   |        |       | $GI_POS \rightarrow FDI$  | 0.781  | 0.471 |                     | No                           |
|   |        |       | $GDP \rightarrow GI_NEG$  | 0.514  | 0.605 |                     | No                           |
|   |        |       | $GL_NEG \rightarrow GDP$  | 0.472  | 0.630 |                     | No                           |
|   |        |       | $FDI \rightarrow GI NEG$  | 1.848  | 0.182 |                     | No                           |
|   |        |       | $GI_NEG \rightarrow FDI$  | 0.869  | 0.434 |                     | No                           |
|   |        |       | $FDI \rightarrow GDP$   | 0.630  | 0.542 |                     | No                           |
|   |        |       | $GDP \rightarrow FDI$   | 0.000  | 0.012 |                     |                              |

\*\*\*p < 0.01; \*\*p < 0.05; and \*p < 0.1

and econometric methods that can substantially enrich our empirical findings.

**Data availability** The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Author contribution This idea was given by Yue Li. Yue Li, Chuan Zhang, and Ahmed Usman analyzed the data and wrote the complete paper. While Shixiang Li read and approved the final version.

#### Declarations

Ethics approval Not applicable.

**Consent to participate** I am free to contact any of the people involved in the research to seek further clarification and information.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

# References

- Al-Mulali U, Ozturk I, Solarin SA (2016) Investigating the environmental Kuznets curve hypothesis in seven regions: the role of renewable energy. *Ecological indicators* 67:267–282
- Arouri MEH, Youssef AB, M'henni, H., & Rault, C. (2012) Energy consumption, economic growth and CO2 emissions in Middle East and North African countries. *Energy policy* 45:342–349
- Aslam B, Hu J, Majeed MT, Andlib Z, Ullah S (2021) Asymmetric macroeconomic determinants of CO 2 emission in China and policy approaches. *Environmental Science and Pollution Research*:1–14
- Bahmani-Oskooee M, Akhtar P, Ullah S, Majeed MT (2020) Exchange rate risk and uncertainty and trade flows: asymmetric evidence from Asia. Journal of Risk and Financial Management 13(6):128
- Cantore N, Calì M, te Velde DW (2016) Does energy efficiency improve technological change and economic growth in developing countries? *Energy Policy* 92:279–285
- Dinda S (2004) Environmental Kuznets curve hypothesis: a survey. *Ecological economics* 49(4):431–455
- Filippini M, Zhang L (2016) Estimation of the energy efficiency in Chinese provinces. *Energy Efficiency* 9(6):1315–1328
- Grossman, G. M., & Krueger, A. B. (1991). Environmental impacts of a North American Free Trade Agreement. NBER Working Paper, (w3914).
- Hussain M, Dogan E (2021) The role of institutional quality and environment-related technologies in environmental degradation for BRICS. *Journal of Cleaner Production 304*:127059
- Hussain, M., Mir, G. M., Usman, M., Ye, C., & Mansoor, S. (2020). Analysing the role of environment-related technologies and carbon emissions in emerging economies: a step towards sustainable development. *Environmental Technology*, 1-9.
- Lin B, Moubarak M (2014) Renewable energy consumption–economic growth nexus for China. *Renewable and Sustainable Energy Reviews* 40:111–117
- Martínez-Moya J, Vazquez-Paja B, Maldonado JAG (2019) Energy efficiency and CO2 emissions of port container terminal equipment: evidence from the Port of Valencia. *Energy Policy* 131:312–319
- Maskus, K. (2010). Differentiated intellectual property regimes for environmental and climate technologies. OECD Environment Working Papers, (17).

- Mensah CN, Long X, Dauda L, Boamah KB, Salman M (2019) Innovation and CO2 emissions: the complimentary role of eco-patent and trademark in the OECD economies. *Environmental Science and Pollution Research* 26(22):22878–22891
- Ozturk I, Al-Mulali U (2015) Investigating the validity of the environmental Kuznets curve hypothesis in Cambodia. *Ecological Indicators* 57:324–330
- Pardo N, Moya JA, Mercier A (2011) Prospective on the energy efficiency and CO2 emissions in the EU cement industry. *Energy* 36(5):3244–3254
- Patterson MG (1996) What is energy efficiency?: concepts, indicators and methodological issues. *Energy policy* 24(5):377–390
- Pesaran MH, Shin Y, Smith RJ (2001) Bounds testing approaches to the analysis of level relationships. *Journal of applied econometrics* 16(3):289–326
- Shin, Y., Yu, B., & Greenwood-Nimmo, M. (2014). Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. In *Festschrift in honor of Peter Schmidt* (pp. 281-314). Springer, New York, NY.
- Su CW, Xie Y, Shahab S, Faisal C, Nadeem M, Hafeez M, Qamri GM (2021) Towards achieving sustainable development: role of technology innovation, technology adoption and CO2 emission for BRICS. *International Journal of Environmental Research and Public Health* 18(1):277
- Tajudeen IA, Wossink A, Banerjee P (2018) How significant is energy efficiency to mitigate CO2 emissions? Evidence from OECD countries. *Energy Economics* 72:200–221
- Ullah S, Ozturk I, Majeed MT, Ahmad W (2021) Do technological innovations have symmetric or asymmetric effects on environmental quality? Evidence from Pakistan. *Journal of Cleaner Production 316*:128239
- Ulucak R (2020) How do environmental technologies affect green growth? Evidence from BRICS economies. *Science of the Total Environment* 712:136504
- Usman, A., Bahmani-Oskoee, M., Anwar, S., & Ullah, S. (2021a). Is there J-curve effect in the trade between Pakistan and United Kingdom? Asymmetric evidence from industry level data. The Singapore Economic Review, 1-21.
- Usman A, Ozturk I, Hassan A, Zafar SM, Ullah S (2021b) The effect of ICT on energy consumption and economic growth in South Asian economies: an empirical analysis. *Telematics and Informatics* 58:101537
- Usman A, Ozturk I, Ullah S, Hassan A (2021c) Does ICT have symmetric or asymmetric effects on CO2 emissions? Evidence from selected Asian economies. *Technology in Society* 67:101692
- Wu F, Fan LW, Zhou P, Zhou DQ (2012) Industrial energy efficiency with CO2 emissions in China: a nonparametric analysis. *Energy Policy* 49:164–172
- Wurlod JD, Noailly J (2018a) The impact of green innovation on energy intensity: an empirical analysis for 14 industrial sectors in OECD countries. *Energy Economics* 71:47–61
- Wurlod JD, Noailly J (2018b) The impact of green innovation on energy intensity: an empirical analysis for 14 industrial sectors in OECD countries. *Energy Economics* 71:47–61
- Yuelan P, Akbar MW, Hafeez M, Ahmad M, Zia Z, Ullah S (2019) The nexus of fiscal policy instruments and environmental degradation in China. *Environmental Science and Pollution Research* 26(28):28919–28932
- Zhao S, Hafeez M, Faisal CMN (2021) Does ICT diffusion lead to energy efficiency and environmental sustainability in emerging Asian economies? *Environmental Science and Pollution Research*:1–10

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