



# Nexus among biomass consumption, economic growth, and CO<sub>2</sub> emission based on the moderating role of biotechnology: evidence from China

Daniel Quacoe<sup>1</sup> · Xuezhou Wen<sup>2</sup> · Dinah Quacoe<sup>3</sup>

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## Abstract

This study seeks to dissect the basic factors that can elucidate the efficiency and innovation in biomass utilization to control carbon dioxide (CO<sub>2</sub>) emission and economic growth nexus particularly at the time that the worldwide CO<sub>2</sub> emission is at an all-time high and COVID-19 is ravaging the world. We use data principally from the World Bank Indicators covering the period 1990–2016 to study the nexus among biomass utilization, economic growth, and CO<sub>2</sub> emission based on the moderating role of biotechnology in China. On the basis of the results of our preliminary tests, we apply the autoregressive distributed lag (ARDL) for this analysis and employ the nonlinear autoregressive distributed lag (NARDL) as a robust check and also deploy the vector error correction model (VECM) to determine the direction of causality. We find that long-run relationship exists among the factors in this study. We additionally find that biotechnology has a critical but negative relationship with CO<sub>2</sub> emission in China. Through hierarchical multiple regression analysis and PROCESS macro for mediation, moderation, and conditional process, we establish that biotechnology significantly moderates the relationship between biomass utilization and CO<sub>2</sub> emission in China. Again, we discover that biomass utilization significantly decreases CO<sub>2</sub> emission in China. Through the ARDL, NARDL, and VECM, we find empirical support for the growth hypothesis in China. We conduct a series of diagnostic tests that prove the robustness of our estimates. Based on our empirical evidence, this study recommends that China seeks sustainable economic development and environmental sustainability simultaneously by prioritizing biomass utilization and biotechnological innovation in the country.

**Keywords** Biomass · Biotechnology · Economic growth · CO<sub>2</sub> emission · Sustainability · Nonlinear autoregressive distributed lag (NARDL)

## Introduction

It will be recalled that the worldwide carbon dioxide continued its 3% yearly ascent of carbon dioxide (CO<sub>2</sub>) outflow for over 10 years until 2013. However, the subsequent years

witnessed a flattened ascent of CO<sub>2</sub> outflow from 2014 to 2016, and this gave an impression that the battle against CO<sub>2</sub> outflow had been won. Notwithstanding, it resumed the ascent pattern in 2017. In 2018, CO<sub>2</sub> outflow was at an unprecedented level, and Jackson et al. (2018) predicted that this ascent in CO<sub>2</sub> outflow will recur in 2019, but it again flattened between 2018 and 2019 (IEA 2020). Interestingly, it has been established that CO<sub>2</sub> outflow increases intensely with fossil-led economic advances (World Bank 2014) and the tremendous CO<sub>2</sub> outflow that comes with fossil-led economic advances imperils living beings (NASA 2018). It has also been predicted that the peril associated with fossil energy will continue to be on the upsurge as fossil energy demand continues to upsurge (Boamah et al. 2017). This has caused immense concerns from international bodies such as the United Nation Framework Convention on Climate Change (UNFCCC) and other stakeholders for the need to tackle the

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- ✉ Daniel Quacoe  
dquacoe@yahoo.co.uk
- ✉ Xuezhou Wen  
xzhwen@jiangnan.edu.cn

- <sup>1</sup> School of Management, Jiangsu University, Zhenjiang 212013, China
- <sup>2</sup> School of Business, Jiangnan University, Wuxi 214122, China
- <sup>3</sup> School of Finance and Economics, Jiangsu University, Zhenjiang 212013, China

monstrous environmental difficulties that comes with fossil energy (Global Bioeconomy Submit 2018). One of the surest ways of curbing these difficulties is the use of clean energy sources (Dong et al. 2018). Thus, most economies are giving tremendous consideration to sustainable economic development (Awuni and Du 2016) with the view of addressing the supplies of the present need without trading the resource and environmental capacity of the future generation (Imperatives 1987). It is therefore obvious that the need to replace fossil raw material is inexorable; thus, a choice for the replacement has to be made. One possible substitute is biomass, and it is for this reason that biomass utilization has become imperative for various countries, hence the focus of this study.

Biomass is a natural material got from living or recently living things. Biomass incorporates woody materials, agriculture harvest buildups, animal dung and body remains, and municipal wastes (Mohammed et al. 2014; Nakada et al. 2014; Mboumboue and Njomo 2018; Jeguirim et al. 2019). At the global level, forest and other wood-related materials are the principal source of biomass (Sánchez et al. 2019). Agriculture ranks second in the order of importance of biomass supply in the world, contributing about 10% of all the biomass feedstock (Kumnamuru 2017; Jeguirim et al. 2019; Sánchez et al. 2019), and its three main biomass sources are energy crops, by-products of other crops, and harvest residues (Kumnamuru 2017; Sánchez et al. 2019). Biomass presents great energy potential that can be reaped to produce energy source with key benefits, including its contribution to economic and social development (Hernández et al. 2018).

To realize the desired duality of sustainable environment and economic growth, numerous studies have explored the link between economic growth and environmental quality (Bilgili et al. 2017; Bekhet and Othman 2018; Li et al. 2018). In any case, the vast majority of the studies explored the relationship among energy utilization, economic growth and environmental quality (Boamah et al. 2017, 2018), emissions trading (Springer et al. 2019), bioeconomy (Wen et al. 2019), etc. Studies have hardly been directed at renewable energy utilization, economic growth, and CO<sub>2</sub> emission (Bekhet and Othman 2018). The dearth of studies on renewable energy utilization, for example, biomass, is likewise observed by Wang (2019). As indicated by Adewuyi and Awodumi (2017), most of the past studies that analyzed the connections between renewable energy and economic growth did not consider the impact of biomass utilization on CO<sub>2</sub> emission. Sadly, the findings from the few studies that considered biomass are not consistent as observed by Adewuyi and Awodumi (2017) and Wang (2019). For instance, Dogan and Ozturk (2017), Hdom (2019), and Shahbaz et al. (2019) find that biomass energy mitigates CO<sub>2</sub> emission, while others, such as Solarin et al. (2018) exhibit opposite discoveries in their studies. Likewise, our review of literature shows that there are restricted studies on

biomass utilization, economic growth, and CO<sub>2</sub> emission in BRICS nations which incorporate China. This position is likewise observed by Wang (2019). It is against this background that our study proves to be useful.

Again, our review of literature reveals that most of the already very limited studies on biomass utilization, economic growth, and CO<sub>2</sub> emission nexus missed a key variable, biotechnological innovation (biotechnology), which may give efficiency to the biomass supply chain and facilitate the influence of biomass to propel economic progress while reducing CO<sub>2</sub> emission. The conceivable variable omission bias in the already limited literature has been demonstrated by Ahmed et al. (2016). The authors find that technological innovation fundamentally facilitates the decrease of CO<sub>2</sub> emissions in the studied European countries. Similarly, Lokko et al. (2017) conclude in their review study that the incorporation of biotechnology in sustainable industrial development can advance the attainment of the Sustainable Development Goals (SDGs). A recent study in China confirms that biotechnological innovation will reduce CO<sub>2</sub> in China. The authors demonstrate that renewable energy technological innovation considerably reduces CO<sub>2</sub> emission in China (Lin and Zhu 2019). However, the authors did not study the moderating role that biotechnology plays in the relationship among biomass utilization, economic progress, and CO<sub>2</sub> emission. Also, in their recommendation, Adewuyi and Awodumi (2017) postulate that CO<sub>2</sub> emission can be curtailed via energy-efficient technologies and biomass utilization. Shockingly, extant literature has, to a great extent, overlooked the role of biotechnology in biomass utilization, economic growth, and CO<sub>2</sub> emission studies. As postulated by Mardani et al. (2018), understanding the nexus between CO<sub>2</sub> emissions and economic growth will help economies in detailing energy policies and developing energy resources in sustainable ways.

Thus, this present study seeks to fill this major knowledge gap, particularly in China. Our study contributes to extant literature by fusing biotechnological innovation into the equation of biomass utilization, economic growth, and CO<sub>2</sub> emission in an attempt to study the critical factors that can elucidate the efficiency in biomass utilization to control the carbon dioxide emission associated with economic growth especially at the time that global CO<sub>2</sub> emission is at an unsurpassed high and COVID-19 is ravaging the world.

This present study is of critical importance in an attempt to propel sustainable economic growth and plunge carbon dioxide emission in China. As far as we could possibly know, no study has considered the moderating role that biotechnology plays in directing the relationship among biomass utilization, economic growth, and CO<sub>2</sub> in China. Our study likewise adds to literature by utilizing the recently developed nonlinear autoregressive distributed lag (NARDL) by Shin et al. (2014) in our analysis. Kocaarslan and Soytaş (2019) show that disregarding nonlinearity in time series study could end in wrong estimates and deluding inferences. Shockingly,

most studies, for example, Bilgili and Ulucak (2018), Wen et al. (2019), and Kim et al. (2020), disregarded nonlinearity in their time-series studies.

For several good reasons, we conduct our study in China. China is, at present, the biggest energy user and CO<sub>2</sub> emitter on earth (Meng et al. 2017; Ma et al. 2019), and simultaneously, the nation has the highest renewable energy capacity and a significant user of biomass energy (Aydin 2019a, b). Nonetheless, there is a dearth of research on biomass utilization, GDP growth, and CO<sub>2</sub> emission in the whole of BRIC nations including China (Aydin 2019a, b; Wang 2019). These attributes make China an awesome candidate for this study. At the 2015 UN Climate Conference, China assured 60–65% drop of its carbon emission in 2030 based on the 2005 level. China needs to be laborious in its effort to achieve this targeted drop (Lin and Zhu 2019), and thus studies in China such as the one presented in this paper is worthwhile. According to the World Bank (2020), China’s most present challenge is related to economic, social, and public health impacts of the COVID-19 pandemic. Nonetheless, China needs to be involved in global environmental engagement. Given China’s size as the second largest economy, the largest emitter of greenhouse gases, the biggest energy user, highest renewable energy capacity, and a significant user of biomass energy, China is central to important regional and global development issues, hence our decision to conduct our study in China.

The rest of the paper is organized as follows: Section two presents the materials and methods for this study. Section three presents the results and discussions, while section four concludes the study.

## Materials and methods

### Data source

This study uses data primarily from the World Bank Indicators. The study utilizes updated data contrasted with the vast previous studies. The study time frame ranges from 1986 to 2016 which is the most recent available data. This study examines the relationship among biomass utilization, CO<sub>2</sub> emission, and economic growth based on the moderating role of biotechnological innovation. Biomass utilization is estimated as a 1000 extraction from farm produce, biotechnological innovation is proxied as biotechnological patent grants, CO<sub>2</sub> is proxied as carbon dioxide emission per capita, and economic growth is proxied as GDP growth per capita. The source of data and variable definition are in Table 1.

### Methods

As indicated by Cutcliffe and McKenna (1999), any attempt to model a given time-series data must be preceded by precise

fundamental examination to completely assess the issues that can distort the result. Subsequently, we initially assess the stationarity within our time-series data to decide on the fitting analytical techniques to employ.

### Stationarity tests

The most famous stationarity tests are the augmented Dickey-Fuller test (ADF) and the Phillips-Perron test (PP). This study utilizes the ADF test for stationarity testing and the PP test as a robust check.

**Augmented Dickey-Fuller test (ADF) unit root test** The ADF test is specified as follows:

$$\Delta y_t = \mu_0 + \alpha t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \dots + \delta_{i-1} \Delta y_{t-i+1} + v_t \tag{1}$$

where  $\mu$  is a constant,  $\alpha$  is the coefficient of the time trend  $t$ , and  $i$  is the lag order of the autoregressive process (for more, see Dickey and Fuller (1981)).

**The Phillips-Perron (PP)** The Phillips-Perron (PP) unit root test differs from the ADF test mainly in how it deals with serial correlation and heteroskedasticity in the errors. Formulation:

$$\Delta y = \alpha_0 + \delta_{i-1} \Delta y_{t-1} + v_t \tag{2}$$

One advantage of the PP test over the ADF test is that the PP test is robust to general forms of heteroskedasticity in the error term. Another advantage is that the user does not have to specify a lag length for the test regression (Phillips and Perron 1988).

**Kruse test** Beyond the conventional unit root tests, our study employs a recent unit root test to confirm our estimates. Recent unit root tests include Kapetanios et al. (2003) and Kruse (2011). One major shortcoming in Kapetanios et al. (2003) unit root test is that it is too restrictive for variables where the threshold value may be different from zero. Thus, we employ Kruse (2011) which extends the unit root test of Kapetanios et al. (2003) and overcome its shortcoming (see Kruse (2011) for details).

### Co-integration test

This study deploys autoregressive distributed lag (ARDL) bounds test to research the relationship that exists among the factors under investigation. Our choice to deploy ARDL is fundamentally premised on the fact that the variables in our dataset are integrated in order

**Table 1** Data source and variable definition

Variable	Definition	Source
CO <sub>2</sub>	Carbon dioxide emission (metric tons per capita)	World Bank ( <a href="http://data.worldbank.org">http://data.worldbank.org</a> )
Y	Economic growth (real GDP per capita)	World Bank ( <a href="http://data.worldbank.org">http://data.worldbank.org</a> )
E	Biomass utilization (1000 tons of used agric. extraction)	( <a href="http://www.materialflows.net/home/">http://www.materialflows.net/home/</a> ) <sup>a</sup>
T	Biotechnology (biotechnology patent granted per year)	WIPO ( <a href="https://www.wipo.int/portal/en/">https://www.wipo.int/portal/en/</a> ) <sup>b</sup>

<sup>a</sup> Materialflows.net is hosted by WU Vienna in collaboration with Commonwealth Scientific and Industrial Research Organization and Nagoya University

<sup>b</sup> WIPO is World Intellectual Property Organization

I(0) and I(1) as revealed by our preliminary tests. Notwithstanding the appropriateness of the ARDL procedure in this study, we also deploy nonlinear autoregressive distributed lag (NARDL) as a robust test. The ills of earlier studies that deployed only the ARDL model is that if the relationship among their variables is not linear, then all those studies may have produced wrongful estimates about the actual relationships among their variables (Kocaarslan and Soytas 2019). To defeat this potential risk, we follow Shin et al. (2014) and utilize their newly created asymmetric NARDL model that captures conceivable long- and short-run nonlinearities. Both the ARDL and NARDL offer the malleability to initiate a co-integration test for factors that are integrated in order I(0) and I(1) such as the one presented in this study. Moreover, ARDL and NARDL produce more effective evaluations for a small sample size. Finally, ARDL and NARDL can evaluate both short-run and long-run nexus in contrast to the conventional co-integration strategies. This study utilizes Akaike's information criterion (AIC) and Schwarz criterion (SC) among others to choose the ideal lag order of our models. We perform the ARDL first then the NARDL. To perform the ARDL bounds test for co-integration, we specify the models as follows:

$$\begin{aligned} \Delta CO_{2t} = & \beta_0 + \sum_{i=1}^p \beta_1 \Delta CO_{2t-i} + \sum_{i=1}^q \beta_2 \Delta Y_{t-i} \\ & + \sum_{i=1}^q \beta_3 \Delta E_{t-i} + \sum_{i=1}^q \beta_4 \Delta T_{t-i} + \lambda_1 CO_{2t-1} \\ & + \lambda_2 Y_{t-1} + \lambda_3 E_{t-1} + \lambda_4 T_{t-1} + \varepsilon_{it} \end{aligned} \quad (3)$$

$$\begin{aligned} \Delta Y_{t-1} = & \beta_0 + \sum_{i=1}^p \beta_1 \Delta Y_{t-1} + \sum_{i=1}^q \beta_2 \Delta CO_{2t} \\ & + \sum_{i=1}^q \beta_3 \Delta E_{t-1} + \sum_{i=1}^q \beta_4 \Delta T_{t-1} + \lambda_1 CO_{2t-1} \\ & + \lambda_2 Y_{t-1} + \lambda_3 E_{t-1} + \lambda_4 T_{t-1} + \varepsilon_{it} \end{aligned} \quad (4)$$

$$\begin{aligned} \Delta E_{t-1} = & \beta_0 + \sum_{i=1}^p \beta_1 \Delta E_{t-1} + \sum_{i=1}^q \beta_2 \Delta CO_{2t} \\ & + \sum_{i=1}^q \beta_3 \Delta Y_{t-1} + \sum_{i=1}^q \beta_4 \Delta T_{t-1} + \lambda_1 CO_{2t-1} \\ & + \lambda_2 Y_{t-1} + \lambda_3 E_{t-1} + \lambda_4 T_{t-1} + \varepsilon_{it} \end{aligned} \quad (5)$$

$$\begin{aligned} \Delta T_{t-1} = & \beta_0 + \sum_{i=1}^p \beta_1 \Delta T_{t-1} + \sum_{i=1}^q \beta_2 \Delta CO_{2t} \\ & + \sum_{i=1}^q \beta_3 \Delta Y_{t-1} + \sum_{i=1}^q \beta_4 \Delta E_{t-1} + \lambda_1 CO_{2t-1} \\ & + \lambda_2 Y_{t-1} + \lambda_3 E_{t-1} + \lambda_4 T_{t-1} + \varepsilon_{it} \end{aligned} \quad (6)$$

where  $\beta_0$  is the constant and  $\varepsilon_{it}$  is the white noise. The terms with the summation sign,  $\Sigma$ , represent the short-run dynamics where the terms with lambda,  $\lambda$ , represent the long-run dynamics of the model. The null hypothesis is  $H_0: \lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = 0$  against the alternate hypothesis  $H_1: \lambda_1 \neq \lambda_2 \neq \lambda_3 \neq \lambda_4 \neq 0$ .

We specify the general form of the NARDL as follows:

$$y_t = \beta^+ X_T + \beta^- X_t^- + \mu_t \quad (7)$$

where  $y_t$  and  $x_t$  refer to  $CO_{2t}$ ,  $Y_t$ ,  $E_t$ , and  $T_t$  and in the case of Eq. (7) above.  $\beta^+$  and  $\beta^-$  represent the associated long-run parameters.  $x_t$  is a  $k \times 1$  vector of regressors defined as  $x_t = x_0 + x_t^+ + x_t^-$  where  $x_0$  is the initial value. The NARDL model employs the decomposition of the exogenous variables into their negative and positive partial sums for decreases and increases as follows.

$$x_t^+ = \sum_{i=1}^t \Delta x_i^+ = \sum_{i=1}^t \max(\Delta x_i, 0) \quad (8)$$

$$x_t^- = \sum_{i=1}^t \Delta x_i^- = \sum_{i=1}^t \min(\Delta x_i, 0) \quad (9)$$

We adjust the symmetric ARDL in Eqs. (3) and (4) to include the asymmetric NARDL in line with Shin et al. (2014) and present in Eqs. (10) and (11) when carbon dioxide emission and economic growth are the dependable variables,

respectively. Subsequent variables follow in a similar fashion. We specify the models as follows:

$$\Delta CO_{2t} = \beta_0 + \chi CO_{t-1} + \omega_1^+ y_{t-1}^+ + \omega_1^- y_{t-1}^- + \omega_2^+ E_{t-1}^+ + \omega_2^- E_{t-1}^- + \omega_3^+ T_{t-1}^+ + \omega_3^- T_{t-1}^- + \sum_{i=1}^{p-1} \tau \Delta CO_{2t-i} + \sum_{i=0}^{q-1} \phi_1^+ \Delta y_{t-i}^+ + \sum_{i=0}^{q-1} \phi_1^- \Delta y_{t-i}^- + \sum_{i=0}^{q-1} \phi_1^+ \Delta E_{t-i}^+ + \sum_{i=0}^{q-1} \phi_1^- \Delta E_{t-i}^- + \sum_{i=0}^{q-1} \phi_1^+ \Delta T_{t-i}^+ + \sum_{i=0}^{q-1} \phi_1^- \Delta T_{t-i}^- \tag{10}$$

$$\Delta y_t = \beta_0 + \chi y_{t-1} + \omega_1^+ CO_{2t-1}^+ + \omega_1^- CO_{2t-1}^- + \omega_2^+ E_{t-1}^+ + \omega_2^- E_{t-1}^- + \omega_3^+ T_{t-1}^+ + \omega_3^- T_{t-1}^- + \sum_{i=1}^{p-1} \tau \Delta y_{t-i} + \sum_{i=0}^{q-1} \phi_1^+ \Delta CO_{2t-i}^+ + \sum_{i=0}^{q-1} \phi_1^- \Delta CO_{2t-i}^- + \sum_{i=0}^{q-1} \phi_1^+ \Delta E_{t-i}^+ + \sum_{i=0}^{q-1} \phi_1^- \Delta E_{t-i}^- + \sum_{i=0}^{q-1} \phi_1^+ \Delta T_{t-i}^+ + \sum_{i=0}^{q-1} \phi_1^- \Delta T_{t-i}^- \tag{11}$$

Similar to the ARDL models, we employ the F-statistic to test the null hypothesis of no asymmetric co-integration relationship that

$$\chi = \omega_1^+ = \omega_1^- = \omega_2^+ = \omega_2^- \dots \omega_4^+ = \omega_4^- = 0$$

We instigate the long-run nonlinearities by testing the null hypothesis of long-run asymmetry that is:

$\beta^+ = \beta^-$  where  $\beta^+ = -\omega_j^+ / \chi$  and  $\beta^- = -\omega_j^- / \chi$  with  $j = 1$  to 4. We assess the short-run relationships by testing the null hypothesis that:

$$\sum_{i=0}^{q-1} \phi_k^+ = \sum_{i=0}^{q-1} \phi_k^- \text{ where } k = 1 \text{ to } 4$$

**Causality test**

Granger (1969) contends that the certainty of the existence of at least a single directional causality between two or more variables is accentuated by the establishment of co-integration relationship among those variables. Subsequent to the above co-integration tests, we test the bearing of the causality among our variables. We utilize the vector error correction model (VECM) for this purpose. We use the statistical significance of the *t* test for the lagged error correction term ( $ECT_{t-1}$ ) to examine the long-run causal relationships of the model and the F-tests applied to the joint significance of the sum of the lags of each explanatory variable in their first differences to examine the short-run causal effects in the system. We specify the VECM Granger causality modules transformed from Eqs. (3) to (6) above as follows:

$$\Delta CO_{2t} = \beta_0 + \sum_{i=1}^p \beta_1 \Delta CO_{2t-i} + \sum_{i=1}^q \beta_2 \Delta Y_{t-i} + \sum_{i=1}^q \beta_3 \Delta E_{t-i} + \sum_{i=1}^q \beta_4 \Delta T_{t-i} + ECT_{t-1} + \varepsilon_{it} \tag{12}$$

$$\Delta Y_{t-1} = \beta_0 + \sum_{i=1}^p \beta_1 \Delta Y_{t-1} + \sum_{i=1}^q \beta_2 \Delta CO_{2t} + \sum_{i=1}^q \beta_3 \Delta E_{t-1} + \sum_{i=1}^q \beta_4 \Delta T_{t-1} + \lambda_1 ECT_{t-1} + \varepsilon_{it} \tag{13}$$

$$\Delta E_{t-1} = \beta_0 + \sum_{i=1}^p \beta_1 \Delta E_{t-1} + \sum_{i=1}^q \beta_2 \Delta CO_{2t} + \sum_{i=1}^q \beta_3 \Delta Y_{t-1} + \sum_{i=1}^q \beta_4 \Delta T_{t-1} + \lambda_1 ECT_{t-1} + \varepsilon_{it} \tag{14}$$

$$\Delta T_{t-1} = \beta_0 + \sum_{i=1}^p \beta_1 \Delta T_{t-1} + \sum_{i=1}^q \beta_2 \Delta CO_{2t} + \sum_{i=1}^q \beta_3 \Delta Y_{t-1} + \sum_{i=1}^q \beta_4 \Delta E_{t-1} + \lambda_1 ECT_{t-1} + \varepsilon_{it} \tag{15}$$

where  $ECT_{t-1}$  represents the error correction model indicating long-run causality among the variables. All the other terms are as defined above.

**Moderation analysis**

We use hierarchical multiple regression analysis and the recently created PROCESS macro for mediation, moderation, and conditional process by Hayes (2013) as a robust check to study the moderation effect of biotechnology

**Table 2** Result of lag length selection criterions

Lag	LogL	LR	FPE	AIC	SC	HQ
0	59.8	NA	2.50	- 3.84	- 3.66	- 3.78
1	198	230	5.25	- 12.3	- 11.3	- 12.0
2	235*	50.20*	1.38*	- 13.7*	- 12.0*	- 13.2*

on the relationship between biomass consumption and CO<sub>2</sub> emission in China.

## Results and discussions

We begin our analysis with the lag selection to determine the appropriate lag length to be used for our study. Like Akalpler and Hove (2019), we use the VAR for the variable at levels for this analysis. The result in Table 2 shows that all the lag selection criterions including the Akaike's information criterion (AIC) suggest lag 2 for our study. Thus, this study uses lag 2 for our estimations.

### Unit root test

This study conducts an ARDL bound test to examine the long- and short-run relationship among the variables. Literature shows that ARDL bound test will produce spurious estimates if any of the variables in the study is integrated in order two. Thus, we employ the widely used ADF unit root test for this analysis, and then we use the PP and Kruse (2011) as a robust check as stated above.

According to our results, the F-statistics in each variable in the ADF test is less than their respective critical value when we test for unit root at level. However, the F-statistics in each variable in the ADF test is greater than their respective critical value when we test for unit root after the first difference. Thus, according to the ADF unit root test, biomass utilization, biotechnological innovation, economic growth, and CO<sub>2</sub> emission all have unit root at level. These variables, however, show no evidence of unit root after the first difference. The PP test is consistent with the ADF result except in the case of biotechnological innovation. According to the PP result, the F-statistic of biotechnological innovation is greater than its critical value at level, and this means the variable has no unit root at level. The results of the Kruse (2011) test are consistent with the PP test. We conclude from these tests that the variables in this present study are all integrated at most in order 1 (see Table 3).

**Table 3** Summary of unit root test

Variable	ADF	PP	KRUSE	Decision
CO <sub>2</sub>	I(1)	I(1)	I(1)	I(1)
E	I(1)	I(1)	I(1)	I(1)
Y	I(1)	I(1)	I(1)	I(1)
T	I(1)	I(0)	I(1)	I(0)

### Co-integration test

After the unit root test, we then test the presence of co-integration relationship among the variables in this study. The results, showing ARDL bounds test and NARDL bounds test, are presented in Table 4. The table has two parts, (a) and (b). According to our results, the 5% critical computed F-statistic value which includes trend and constant terms is 5.69. In the model with constant and trend Pesaran table, I(0) value is 4.01, while the I(1) is 5.07 at 5% critical value. According to Pesaran et al. (2001) criterion, this result indicates that there is co-integration among CO<sub>2</sub> emission, biomass utilization, biotechnological innovation, and economic growth at 5% significant level.

(a) presents ARDL bounds test result when CO<sub>2</sub> emission is the dependent variable. (b) presents NARDL bounds. The computation includes trend and constant terms. Critical values are taken from Pesaran et al. (2001).

For robustness, we verify this result within the NARDL framework and report the result in Table 4 (b). It can be seen that the computed F-statistic, which also includes trend and constant terms, is 4.62, and this is greater than the corresponding Pesaran et al. 5% critical I(1) value of 4.57. This indicates that the NARDL result confirms that of the ARDL result. We conclude that co-integration exists among CO<sub>2</sub>, utilization, biotechnological innovation, and economic growth at 5% significant level in China.

### ARDL and NARDL short- and long-run estimates

First, we start our analysis by estimating Eq. (3) to (6) in the linear form. We use the autoregressive distributive lag (ARDL) model to examine the relationship among economic growth, biomass utilization, biotechnology, and CO<sub>2</sub> emissions in the short and long run. The findings of the symmetry ARDL (p, q) models are illustrated in Table 5. We discuss the short- and long-run results of each variable in turn. We study

**Table 4** Co-integration test when CO<sub>2</sub> is dependent variable

(a) ARDL bounds test			I(0)	I(1)
F-statistic	5.68712	10%	3.47	4.45
K	3	5%	4.01	5.07
		2.50%	4.52	5.62
		1%	5.17	6.36
(b) NARDL bounds test			I(0)	I(1)
F-statistic	4.624746	10%	3.03	4.06
K	4	5%	3.47	4.57
		2.50%	3.89	5.07
		1%	4.4	5.72

**Table 5** ARDL short- and long-run estimates

Short run								
EV	CO <sub>2</sub>		E		T		Y	
	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.
ΔCO <sub>2</sub>	-	-	- 0.20	0.13	- 5.97	0.52	0.14	0.00
ΔE	- 0.32	0.09	-	-	- 2.06	0.52	0.04	0.09
ΔE <sub>t-1</sub>	- 0.15	0.50	0.17	0.43	-	-	0.35	0.06
ΔE <sub>t-2</sub>	- 0.44	0.03	-	-	-	-	-	-
ΔY	0.86	0.01	0.12	0.50	5.97	0.03	-	-
ΔY <sub>t-1</sub>	- 0.87	0.07	-	-	-	-	1.13	0.00
ΔY <sub>t-2</sub>	0.55	0.09	-	-	-	-	- 0.7	0.00
ΔT	- 0.01	0.07	0.01	0.83	-	-	0.01	0.49
ΔT <sub>t-1</sub>	-	-	-	-	0.22	0.16	-	-
C	- 2.42	0.09	- 0.50	0.62	0.06	0.02	3.08	0.00
TREND	- 2.42	0.05	0.01	0.57	0.70	0.02	0.03	0.00
CointEq(- 1)	- 0.27(0.000)							
Long run								
CO <sub>2</sub>	-	-	0.04	0.69	- 4.85	0.00	0.25	0.00
E	- 3.34	0.041	-	-	- 2.68	0.52	0.7	0.00
Y	1.97	0.003	0.15	0.479	7.75	0.02	-	-
T	- 0.04	0.046	- 0.00	0.828	-	-	0.01	0.47
Diagnostics								
R <sup>2</sup>	0.99	-	0.99	-	0.99	-	0.99	-
Adj. R <sup>2</sup>	0.98	-	0.98	-	0.98	-	0.98	-
F-stat.	836	0.00	416	0.00	299	0.00	1829	0.00
SC	1.26	0.1	0.75	0.12	2.79	0.50	1.26	0.4
Heter.	1.18	0.3	1.72	0.32	2.75	0.20	1.18	0.7
JB	0.48	0.6	0.3	0.67	0.79	0.30	0.46	0.7

EV denotes the explanatory variables. CO<sub>2</sub>, E, Y, and T denote carbon dioxide emission, biomass utilization, economic growth, and biotechnological innovations, respectively. The subscripts t-1 and t-2 represent the time lag measured in years. R<sup>2</sup>, Adj. R<sup>2</sup>, DW, F-stat, SC, Heter. and JB represent the R squared, adjusted R squared, F-statistics, serial correlation LM test, heteroskedasticity test and Jarque-Bera normality test. Maximum lag length is determined by Akaike information criteria (AIC). Estimations include trend and constant terms

whether an increase in biomass utilization under the moderating effect of biotechnology will result in a decrease in CO<sub>2</sub> per capita in China, all else being the same. We also study whether an increase in biomass utilization in the presence of biotechnology will result in an increase in economic growth (GDP per capita) in China, all else being the same. The result is presented in Table 5 below.

Table 5 shows that 1% percent increase in biomass utilization is associated with a 0.32% decrease in carbon emissions in the short term, and this is significant at 10%, all else being the same. This result provides evidence that biomass utilization leads to a reduction of CO<sub>2</sub> emission in China; albeit this evidence is at best a weak evidence. We also find that the first lag of biomass utilization (E) leads to a reduction in CO<sub>2</sub>, but this is completely insignificant. However, the second lag of biomass utilization shows that a 1% increase in biomass

utilization will result in a significant decrease in CO<sub>2</sub> emission by 0.44%. In the long run, we find that biomass utilization has a higher and more significant negative impact on CO<sub>2</sub> emission in China. The sum effect of these results is that biomass utilization decreases CO<sub>2</sub> emission in China. Our finding is similar to that of Jaforullah and King (2015), Ahmed et al. (2016), Chen et al. (2019), Hdom (2019), Shahbaz et al. (2019), and Kim et al. (2020). For instance, Shahbaz et al. (2019) find that the nexus between biomass energy use and carbon emissions is negative and significant. According to Chen et al. (2019), the finding that renewable energy use such as the one presented in this study is a key solution in reducing CO<sub>2</sub> emissions over time in China. Our result from China is similar to a recent study from the USA (Kim et al. 2020). The impacting mechanism of biomass energy utilization on CO<sub>2</sub> reduction is that carbon dioxide released from biomass energy

**Table 6** NARDL short and long-run estimates

Short run								
EV	CO <sub>2</sub>		E		T		GDP	
	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.
CO <sub>2</sub> <sup>+</sup>	-	-	-0.01	0.89	1.71	0.53	0.21	0.07
CO <sub>2t-1</sub> <sup>-</sup>	-	-	1.43	0.02	- 2.0	0.52	0.06	0.05
E <sub>t-1</sub>	- 0.22	0.01	-	-	23.5	0.11	0.17	0.03
E <sup>+</sup>	- 0.27	0.01	-	-	1.71	0.53	0.18	0.08
E <sub>t-1</sub> <sup>+</sup>	- 0.17	0.56	-	-	- 2.0	0.52	0.04	0.09
E <sub>t-2</sub> <sup>+</sup>	- 0.46	0.02	-	-	23.5	0.11	0.27	0.04
E <sup>-</sup>	- 1.84	0.18	-	-	- 61.1	0.00	- 0.89	0.35
T	- 0.02	0.05	- 0.00	0.88	-	-	0.01	0.41
Y	0.97	0.03	0.134	0.47	2.61	0.02	-	-
Y <sub>t-1</sub>	- 0.95	0.09	-	-	0.43	0.06	-	-
Y <sub>t-2</sub>	0.52	0.06	- 0.00	0.83	0.42	0.03	-	-
C	- 2.94	0.02	- 0.48	0.67	0.23	0.16	2.5	0.00
TREND	1.87	0.01	0.008	0.43	2.12	0.02	2.10	0.01
Long run								
E <sup>+</sup>	- 8.72	0.020	-	-	1.54	0.53	0.99	0.07
E <sup>-</sup>	- 4.34	0.025	-	-	- 33.9	0.00	- 0.12	0.06
T	- 0.10	0.056	0.156	0.47	-	-	0.01	0.04
Y	2.54	0.043	- 0.003	0.82	2.36	0.28	-	-
CO <sub>2</sub>	-	-	-	-	- 0.38	0.73	0.26	0.00
Diagnostics								
R <sup>2</sup>	0.99	-	0.99	-	0.99	-	0.99	-
Adj. R <sup>2</sup>	0.98	-	0.98	-	0.99	-	0.98	-
F-stat.	837	0.00	348	0.00	370	0.00	125	0.00
SC	1.76	0.20	1.22	0.34	2.02	0.16	2.77	0.09
Heter.	1.58	0.19	0.89	0.52	1.71	0.15	2.35	0.05
JB	0.45	0.60	0.09	0.95	1.91	0.38	0.36	0.83

EV denotes the explanatory variables. CO<sub>2</sub>, E, Y, and T denote carbon dioxide emission, biomass utilization economic growth, and biotechnological innovations, respectively. The subscripts t-1 and t-2 represent the time lag measured in years. The superscripts “+” and “-” refer to positive and negative partial sums, respectively; R<sup>2</sup>, Adj. R<sup>2</sup>, DW, F-stat, SC, Heter. and JB represent the R squared, adjusted R squared, F-statistics, serial correlation LM test, heteroskedasticity test, and Jarque-Bera normality test. Maximum lag length is determined by Akaike information criteria (AIC). Estimations include trend and constant terms

utilization is compensated by the carbon dioxide captured in the photosynthesis process (Payne 2011). It is noteworthy that our study is consistent with Solarin and Bello (2019) who have shown strong evidence of substitution possibilities between biomass and fossil fuels indicating that sustainable development could be achieved with continued use of more biomass and lesser fossil fuels in their studied country. Nonetheless, other authors such as Adewuyi and Awodumi (2017) have found varied results relating to the relationship between biomass utilization and CO<sub>2</sub> emission in different countries. Similarly, Nguyen and Kakinaka (2019) show that for low-income countries, renewable energy utilization such as biomass is positively associated with carbon emissions,

while they show that renewable energy utilization such as biomass is negatively associated with carbon emissions in high-income countries. The varied finding among these empirical studies could be attributed to differences in variables used and country characteristics.

Our study also finds that biotechnology reduces CO<sub>2</sub> emission in China. The finding shows that a 1% increase in biotechnology will reduce CO<sub>2</sub> emission by 0.01 percent also statistically significant at 10%. We find that the long-run negative effect of biotechnology on CO<sub>2</sub> emission is higher and more significant than its short-run effect on CO<sub>2</sub> emission in China, all things being the same. A recent study in China confirms this study’s finding that biotechnology reduces



CO<sub>2</sub> emission in China even though different variables were used in the various studies. The authors demonstrate that renewable energy technological innovation (RETI) significantly reduces CO<sub>2</sub> emission in China (Lin and Zhu 2019). In their recommendation to curtail carbon emission, Adewuyi and Awodumi (2017) postulate that there is the need to reduce energy intensity of output via the adoption of energy-efficient technologies and to find alternative clean energy sources to reduce carbon emissions associated with biomass use to promote growth. Also similar to our finding, Ahmed et al. (2016) find that technological progress helps to reduce CO<sub>2</sub> emissions by promoting energy efficiency. Our finding implies that as China uses better biotechnology in their production progress, economic growth is taking place and that CO<sub>2</sub> emissions are being reduced. This finding is also consistent with a study by Sohag et al. (2015) who indicate that technological innovation improves energy efficiency and reduces CO<sub>2</sub> intensity.

Relative to economic growth, it can be seen from Table 5 that biomass utilization has a positive effect on GDP, and this is significant in both the short and long run. Biomass utilization based on the moderating effect of biotechnology has a significant effect both in the short and long run on economic growth due to the efficiency that biotechnology brings to biomass production, process, and usage. Thus our study supports the growth hypothesis in China. Some previous authors who did not include biotechnology in their studies find different result. For instance, Tuna and Tuna (2019) recently studied the relationship between renewable energy utilization and economic growth. The authors confirmed the neutrality hypothesis for Indonesia, Malaysia, Singapore, and Thailand. For Philippines, the authors confirmed conservation hypothesis. In other words, renewable energy utilization in their five studied countries does not cause economic growth. Aydin (2019a, b) analyzed the relationship between economic growth and biomass energy utilization within the framework of the production function in BRICS countries. The author confirmed that the conservation hypothesis is valid in China and South Africa indicating that renewable energy utilization which includes biomass utilization does not have a significant impact on economic development.

In addition to the above estimations, we also examine a series of diagnostic tests to ensure that our estimates are not spurious. The diagnostic results are shown in the lower part of Tables 5 and 6. First,  $R^2$  and the adjusted  $R^2$  show that our data have a good fit to the respective models. The F-statistics show that there is statistical significance in the overall relationship in our models. The serial correlation LM, heteroskedasticity, and Jarque-Bera tests show that we do not have problems of serial correlation, heteroskedasticity, or normality issues in our respective models. Figures 1 and 2 below also show that our models are free from instability issues. Figures 3 and 4 also show there is no autocorrelation or partial autocorrelation

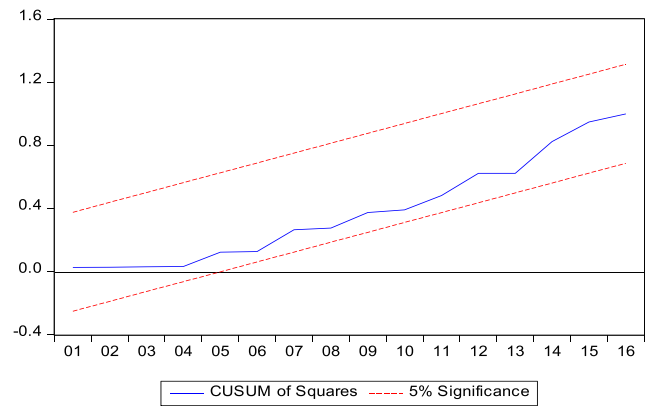


Fig. 1 Cusum of Squares for ARDL model

associated with our model. Thus, our models are robust and that statistical inference could be made from our estimations.

Again, for robustness, we examine the relationship among our variables in the NARDL framework, and the result is presented in Table 6. First, it can be seen from the result that a positive change (+) in CO<sub>2</sub> emission has a negative effect on biomass utilization, but this is highly insignificant ( $p$  value = 0.89). More important to our study is the effect of biomass utilization and biotechnology on both CO<sub>2</sub> emission and economic growth. It can be seen that biomass utilization negatively influences CO<sub>2</sub> emission in the short and long run in such a way that the larger impact of biomass utilization on the CO<sub>2</sub> is resulting from a positive change in biomass utilization, which significantly decreases the CO<sub>2</sub> at 5% significant level, rather than a negative change in the biomass utilization. We also find that biotechnology negatively impacts CO<sub>2</sub> emission in China with a larger impact seen in the long run than the short run. The sum effect is that the findings in the NARDL largely confirm that of the above ARDL findings that biomass utilization and biotechnology contribute to CO<sub>2</sub> emission reduction, thus consistent with previous studies such as Jaforullah and King (2015), Ahmed et al. (2016), Chen et al. (2019), Hdom (2019), and Shahbaz et al. (2019).

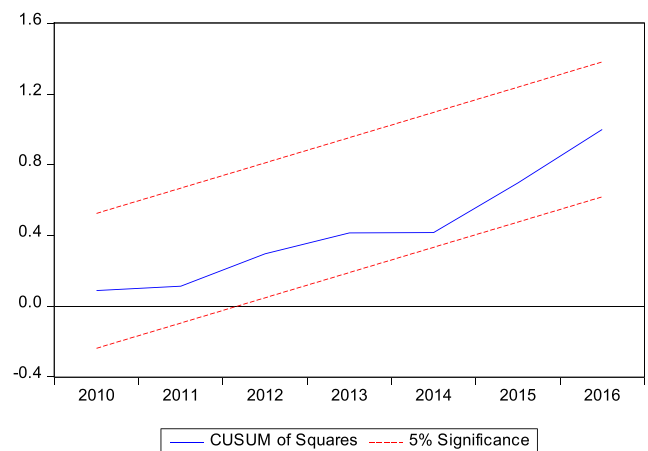


Fig. 2 Cusum of Squares for NARDL model

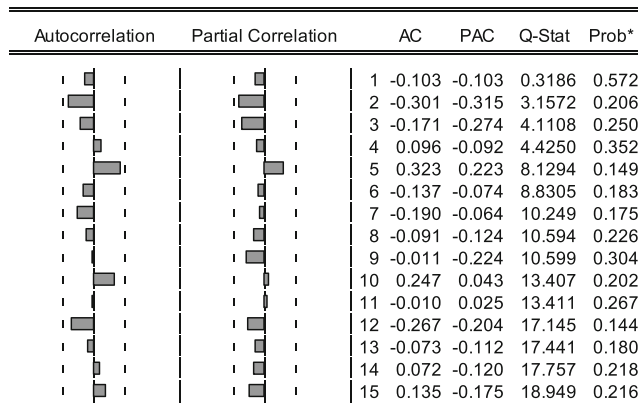


Fig. 3 Autocorrelation and partial autocorrelation

Relative to economic growth in the NARDL framework, it can be seen that biomass utilization has a positive effect on GDP growth in the short and long run in such a way that the larger impact of biomass utilization on GDP is resulting from a positive change in lag 2 of biomass utilization, rather than a negative change in the biomass utilization in the short run. Our NARDL result is largely similar to that of the ARDL result in direction but not in magnitude.

**VECM estimates**

A local Ghanaian adage states “there is no smoke without fire.” Consistent with this adage, Granger (1969) argues that once there is co-integration relationship among variables studied, there is bound to be at least, a one-way causality.

Thus, we investigate the causal relationship among variables by applying the Granger causality test based on vector error correction model (VECM). The result is presented in Table 7. The result indicates that all the error correction terms (ECT) are negative and also statistically significant. This implies that the system can return to its equilibrium level in the long-term at yearly adjustment speed of 27%, 82%, 57%, and 77% when CO<sub>2</sub> emission, biomass utilization, economic growth, and biotechnological advancements are used as dependent variables, respectively.

In the short run, we find bi-causality running from biomass utilization to CO<sub>2</sub> emission and vice versa. This result shows a

Table 7 Results of VECM

	ΔCO <sub>2</sub>	ΔE	ΔY	ΔT	ECT
ΔCO <sub>2</sub>	-	- 0.3 [0.1] <sup>a</sup>	0.8 [0.3] <sup>b</sup>	- 0.01 [01] <sup>c</sup>	- 0.27 [0.05] <sup>c</sup>
ΔE	0.2[0.1] <sup>a</sup>	-	0.1 [0.1] <sup>c</sup>	- 0.01 [0.1]	- 0.82 [0.18] <sup>c</sup>
ΔY	0.1[0.1] <sup>c</sup>	0.3 [0.1]	-	0.01 [0.1]	- 0.57 [0.06] <sup>c</sup>
ΔT	12[5.3] <sup>b</sup>	- 2 [3.1]	5 [2.6] <sup>b</sup>	-	- 0.77 [0.13] <sup>c</sup>

Coefficient std error and sig. level. a, b, and c denote 10%, 5%, and 1% significant levels

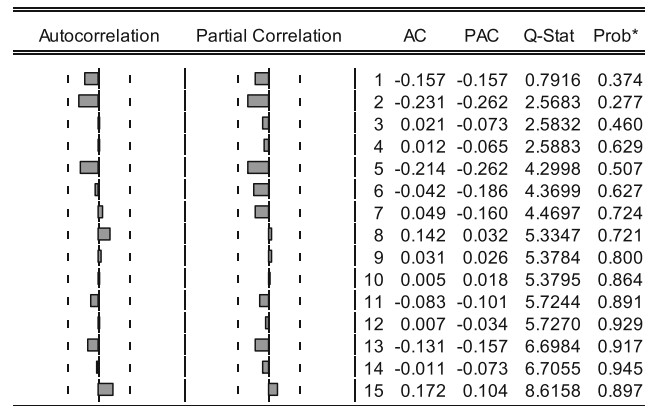


Fig. 4 Autocorrelation and partial autocorrelation

negative coefficient for biomass utilization, and this indicates that biomass utilization in the presence of biotechnology can be used to reduce CO<sub>2</sub> emission in China. This is a confirmation of the ARDL and NARDL findings above. This result is also confirmed by prior studies such as Jaforullah and King (2015), Ahmed et al. (2016), Chen et al. (2019), Hdom (2019), and Shahbaz et al. (2019). We also find that biotechnology has a negative relationship and causal effect of CO<sub>2</sub> emission, but it is only at 10% significant level. Biotechnology is expected to bring efficiency to the biomass processes and usage and thus facilitate biomass utilization’s influence on CO<sub>2</sub> emission. Our finding is similar to prior studies (Ahmed et al. 2016; Lin and Zhu 2019). Similarly, we find that biomass utilization and biotechnology have causal effect on GDP in China.

**Moderation analysis**

To test the hypothesis that biotechnology moderates the relationship between biomass utilization and CO<sub>2</sub> emission in China, we conduct a hierarchical multiple regression analysis. The result is presented in Table 8 below. First, we center our variables to satisfy the assumption of no multicollinearity with the interaction term, and then we create the interaction term. We include biomass utilization and biotechnology as our predictor variables, and we find that these variables account for a significant amount of variance in CO<sub>2</sub> emission in China, R<sup>2</sup> = 0.396, F(1, 35) = 22.946, p = 0.000.

Next, we include the interaction term in the regression model and find that it has a significant impact on the regression model. Specifically, ΔR<sup>2</sup> = 0.058, ΔF (1, 34) = 3.587, and p = 0.067. The 5.8% change in R<sup>2</sup> among other changes after the introduction of the interaction term provides empirical evidence of the moderation effect of biotechnology on biomass utilization and CO<sub>2</sub> emission nexus in China. We confirm our result by using the PROCESS macro for mediation, moderation, and conditional process introduced by Hayes (2013). The PROCESS macro has become increasingly

**Table 8** Moderation analysis

Model summary									
Model	R	R square	Adj. R square	SE	Change statistics				
					R square change	F change	df1	df2	Sig. F change
1	0.629 <sup>a</sup>	0.396	0.379	0.10961822	.396	22.946	1	35	0.000
2	0.674 <sup>b</sup>	0.454	0.421	0.10577863	.058	3.587	1	34	0.067

<sup>a</sup> Predictors: (Constant), biomass, biotechnology

<sup>b</sup> Predictors: (Constant), biomass, biotechnology, biomass\*biotechnology

popular in a variety of journal publications and academic conferences (Hayes et al. 2017). The PROCESS macro result is similar to that of the hierarchical multiple regression analysis.

### Conclusion and policy implications

Understanding the nexus between CO<sub>2</sub> emissions and economic growth will help countries in formulating policies in sustainable ways. Thus, we study the relationship among biomass utilization, economic growth, and CO<sub>2</sub> emission based on the moderating role of biotechnology which hitherto has been ignored in literature.

First, we test the stationarity of our variables and find that our variables are integrated, at most, in order 1. Next, we employ symmetric ARDL bounds testing approach and the asymmetric NARDL bounds testing approach as a robust check. Both methods prove the existence of co-integration among our variables. We thus study the short- and long-run symmetric and asymmetric relationships among the variables. The short- and long-run results of both methods show that there is a short- and long-run relationship among biomass utilization, economic growth, CO<sub>2</sub> emission, and biotechnology. The estimated models indicate that increasing biomass utilization decreases CO<sub>2</sub> emission and increases economic growth in China. We find that biomass utilization has a statistically significant negative relationship with CO<sub>2</sub> emission in China. We also find that biotechnology also has a statistically significant negative relationship with CO<sub>2</sub> emission in China. However, economic growth in the presence of biomass utilization and biotechnology has a positive relationship with CO<sub>2</sub> emission in China. Again, we find that both biomass utilization and biotechnology have a positive relationship with economic growth in China.

The VECM-based Granger causality test was also employed to study the causal link among the variables. The result shows that there exists a long-run Granger causality for all our models. For instance, the results show VECM-based Granger causality running from biomass utilization, economic growth, and biotechnology to CO<sub>2</sub> emission in the long run. In

the short run, we find that both biomass utilization and biotechnology have a causal relationship with CO<sub>2</sub> in China with a negative relationship. Our result also showed support for the growth hypothesis in China. Through hierarchical multiple regression analysis and the recently created PROCESS macro for mediation, moderation, and conditional process, we established that biotechnology significantly moderates biomass utilization and CO<sub>2</sub> emission in China.

Our empirical results have important policy implications. First, because biomass utilization and biotechnology have negative and significant relationships with CO<sub>2</sub> emission and because biotechnology significantly moderates the relationship between biomass utilization and CO<sub>2</sub> emission in China, the country should pay more attention to the development and utilization of biomass in various forms, and this ought to be done in tangent with biotechnological innovation to give efficiency to biomass usage in China. Second, because biomass utilization and biotechnology show positive relationship with economic growth and negative relationship with CO<sub>2</sub> emission, China can thus achieve economic growth and environmental sustainability simultaneously. China must, therefore, continue to make all the necessary policies and investments in biomass production and encourage biomass usage with the aim of achieving both economic growth and environmental sustainability.

**Authors' contributions** D.Q. (1st author) conceived and designed the paper; he also analyzed the data, interpreted the results, and wrote the paper; X.W. supervised the paper; D.Q. (3rd author) collected and processed the data for analysis. All authors read and approved the final manuscript.

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**Data availability** The datasets generated and analyzed during the current study are available in the World Bank Indicator, [Materialflows.net](http://materialflows.net), World Intellectual Property Organization repository, <http://data.worldbank.org>,

<http://www.materialflows.net/home>, and <https://www.wipo.int/portal/en> respectively (see Table 1 above for details).

## Compliance with ethical standards

**Competing interests** The authors declare that they have no competing interests.

**Ethics approval and consent to participate** Not applicable.

**Consent for publication** Not applicable.

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