Management of human resources in the green economy: Does green labour productivity matter in low-carbon development in China

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Abstract

Environmentally friendly economic development has become a global concern, whereas the existing literature has ignored the human resources management in the green economy. This study utilizes the basic Cobb–Douglas production function and examines the nonlinear effect of labour productivity on the environment in China. Non-linear findings infer that a positive change in labour productivity has a positive and negative change in labour productivity, and has a negative effect on CO₂ emissions in the short run, while results persisted and stable in the long run in China. The crux of this study is that labour productivity is vital for understanding the evolution of a green economy. Conventionally, capital productivity and energy consumption also tend to follow dirty productivity growth and thus, increased environmental pollution. Indeed, research and development is a forceful input to environmental quality. Based on findings, policymakers should need to focus on human resource productivity, green business, and ecosystem protection.

Keywords Human Resource · Labour productivity · Green economy · CO₂ emissions · China · NARDL

Introduction

The concept of “green-productivity” is encouraged by modern researchers and policymakers in Asia as well as China. This

understanding led to the development of green products, which incorporates productivity improvement and environmental protection (Hur et al. 2004). The goal of green productivity is to achieve a higher level of productivity and also protect and improve the quality of the environment. It inspires business to become more innovative as well as more environmentally responsible. Green productivity calls for economies to achieve higher levels of economic productivity and environmental quality through continuous improvement in clean production inputs.

Concerns about environmental pollution are becoming gradually relevant in all domains of economic sectors as agriculture, industry, and service. Essentially, economic activities of human carelessness at work can pay to environmental degradation (Ones and Dilchert 2012). Green human resource practices can be used to encourage the workforce’s responsible behavior to save the environment (Cherian and Jacob 2012). Singh et al. noted that green human resources play a vital role in the sustainability of the environment. They also found that green human resources significantly influence green innovation in industries and significantly impact the sustainability of the environment. Sharma and Gupta (2015) suggest that human resources can increase awareness related to the environment. Human resources are also increasing the

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green labour productivity and thus improve the environmental quality. According to Amjad et al., management of human resources means undertaking such consumers' and producers' activities that enable environmental quality. Ahmad and Zabri (2015) reported that human resource is one of the important assets of an organization that promotes green labour productivity in the industry. They also reported that green labour productivity is one of the most significant elements of environmental sustainability. Green labour productivity plays an important role in the creation of environmental sustainability culture. While normally enterprise has anti-environmental behaviours in industry and used a lot of fossil fuel energy consumption and thus promote the CO₂ emissions in the economy.

Green productivity proposed for sustainable development and human resources can play its role in environmental sustainability. Labour productivity is an engine and key driver of economic growth. Although various theories and empirical literature have been discussed, the various channels of productivity growth, the conventional neoclassical economists are more dependent and emphasized labour, capital and technological innovation in productivity growth. The underlying drivers of productivity growth are more contested and complex. Solow (1956) theory noted that the capital-labour ratio in advanced and developed countries is high compared to developing countries. In contrast, the labour capital ratio is so high in developing economies and they consume more energy consumption in economies and hence increased environmental pollution. Romer (1994) theory of endogenous growth shows that technology is increased economic growth with increasing return to scale and in this process economy small share of labour as well as energy consumption. Therefore, technology innovation is the energy-saving approach and also improved environmental quality. The literature also shows that endogenous growth theories have also indirectly influenced and improved environmental quality.

Green productivity is also required for the national, sub-national, sectoral, and product levels in the economy. Therefore, it is very important to measure and identify the suitable indicators which analyze environmental quality factors in an integrated fashion. Energy consumption is strongly related to economic growth because energy is one of the essential elements of the modern economy. In China, energy and the environmental issue have become a central problem of sustainable development. Since 2006, China has one important aim to decrease energy intensity in the economy. The most effective method to reduce energy intensity in the economy is technological progress. Therefore, labour productivity has also an effect on the environment in different ways. Global warming has very strong increasing trends. The emission of carbon dioxide is a direct consequence of using fossil fuels for utilization by humans. Mostly, developing as well developed

economies want to increase their labour productivity. While historically, labour productivity has been increasing the use of energy consumption and also increase environmental pollution; however, energy policymakers have also admitted such phenomena in the empirical literature (Mirowski 1991; Usman et al. 2020). While energy/labour ratios in rich economies are normally downward as compared to developing economies, this is an important source of green productivity.

The transition to a sustainable society poses substantial environmental challenges for economics. Institutional structures, energy and ecological frameworks, and macro-economic relationships all need significant reforms. For environmental sustainability lies the new link between labour productivity, energy consumption, and the environment (Jackson 2009; Victor 2012). The "theory of green economy" has noted that a change in labour productivity is maintaining environmental quality. This study also explores such energy and environmental challenge in economics. Beinhocker (2011) noted that technological innovation is an essential dimension of human activity, driven by a 'natural' human creativity and also improves the environment. They also encouraged technological innovation considered to use expensive labour inputs with cheap inputs material. Labour productivity is a leading role in the modern economy. From an ecological point of view, human resources use fewer polluting emissions inputs (Jackson 2009; Victor 2012). Although, labour productivity is used environmentally unfriendly input that increases the environmental pollution in the production process, the literature considered that labour is one of the basic input of pollution in the modern era.

A couple of previous empirical literature show that labour productivity and capital productivity have influenced environmental pollution (Yuan et al. 2009) because they all noted that capital productivity is used in the energy consumption in productivity, thus capital productivity increased CO₂ emissions. Similarly, Shadbegian and Gray (2005) show that labour is used in small energy consumption and labour productivity increases the environmental quality. In literature, some studies used firm-level data to examine the productivity change with the presence of CO₂ emissions (e.g. Ball et al. 1994; Chung et al. 1997; Färe et al. 2007; Wang 2007). Similarly, Asian Productivity Organization (1992) is more focused on green productivity. The distributional function of Wigner stated that mutual intensity and cross-spectral density have same association due to symmetric information (Zuo et al. 2015; Zuo et al. 2017). For labour, swift long-term care growth desires for population aging in China, Japan and Germany due to noval COVID-19 without daily living activities (Chen and Xu 2020). Lin et al. (2013) noted labour productivity in reducing environmental pollution because it contracts other dirty inputs that are used with labour. The more years of formal education significantly decreases the Subjective health shock (Khelfaoui et al. 2020).

The previous literature has more focused on other predictors of CO₂ emissions. However, it is silent about the impact of labour productivity and the environment. The previous literature is misleading because it is not focused on the productivity input as labour, capital, technology, energy etc., all these inputs are also the basic source of pollution in the production process in the modern economy. Over the last few decades, pollutant economies have not much focused on green labour productivity in the country.

In the last few decades, China has emerged as a world economic power. The Chinese economy is in front in many respects as trade, FDI, economic growth, labour productivity, energy consumption, and environmental pollution. Although China has also the highest labour productivity in global (ILO 2019). As the China is the world's largest carbon emitter and it will reach a peak in pollution emissions by 2030 (World Bank 2019). Labour productivity is important for energy consumption that is closely linked to the environment and economy. Thus, we select the China economy for empirical analysis.

Based on our knowledge, some new relations are getting renewed attention, thus we use the nonlinear ARDL approach of Shin et al. (2014) to assess nonlinear impacts of labour productivity on the environment in China over the period 1991–2019 based on data-set accessibility. Even, this research has entered into a new direction by using nonlinear cointegration and error-correction modelling approach which yields a comparatively more significant and better outcome in analysis. Previous studies have considered the influence of labour productivity on energy consumption and economic growth. While, in this study, we assess its impact on environmental pollution. Moreover, we argue that its impact could be nonlinear, implying that increased labour productivity affects environmental pollution at a different rate than decreased labour productivity.

This study provides the attention and new thinking, whether inputs matter in pollution. Based on this study, we can revise the production policies. Modern studies used the green productivity approach as a reduction for pollution activities. This study has also enriched the energy and environmental policies that are based on human resources. The study also has high relevance for other low-labour productive countries in terms of policy implications. Green labour productivity in the economy is much essential for environmental quality. Findings in the literature have shown diverse and limited outcomes. This study is more important in the context of green human resources management in China.

Model and methods

It is a fact that human resource is one of the most important assets of organizational activities that plays a significant role in managing green labour productivity. Von Arnim and Rada

(2011) noted that labour and capital productivity can be considered to be a driving force of energy consumption in Egypt and they reported that there is a strong correlation between labour productivity and energy consumption. Similarly, Ryan (2018) employed the dataset of manufacturing plants in India and he noted that skilled labour is increasing output and thus is resulting in higher energy consumption. Based on these empirical findings, we can assess the impacts of labour productivity on environment. We employ the basic Cobb–Douglas production function for the CO₂ emissions and we used labour and capital as basic determinants of environmental pollution. Therefore, our model is based on Lin et al. (2013) and yields us

$$\text{CO}_{2,t} = \alpha_0 + \alpha_1 \text{Lp}_t + \alpha_2 \text{Kp}_t + \alpha_3 \text{RD}_t + \alpha_4 \text{EC}_t + \mu_t \quad (1)$$

Where CO₂ is the output that is CO₂ emissions, Lp and Kp are basic labour and capital productivity inputs, RD is a research and development expenditure, and EC is the energy consumption, which may affect the environment. As such, we amend the production function estimated by Shadbeigian and Gray (2005) so that it conforms to the output level of CO₂ emissions. Eq. (1) of interest is showing long-run associations between the variables of concentration. To incorporate the short-run in combined with long-run effects, Eq. (1) can be modified in a vector error-correction presentation by Pesaran et al. (2001) as shown in Eq. (2) as follows:

$$\begin{aligned} \Delta \text{CO}_{2,t} = & \gamma + \sum_{p=1}^{n1} \gamma_{1p} \Delta \text{CO}_{2,t-p} + \sum_{p=0}^{n2} \gamma_{2p} \Delta \text{Lp}_{t-p} \\ & + \sum_{p=0}^{n3} \gamma_{3p} \Delta \text{Kp}_{t-p} + \sum_{p=0}^{n4} \gamma_{4p} \Delta \text{RD}_{t-p} \\ & + \sum_{p=0}^{n5} \gamma_{5p} \Delta \text{EC}_{t-p} + \pi_1 \text{CO}_{2,t-1} + \pi_2 \text{Lp}_{t-1} \\ & + \pi_3 \text{Kp}_{t-1} + \pi_4 \text{RD}_{t-1} + \pi_5 \text{EC}_{t-1} + \mu_t \end{aligned} \quad (2)$$

In Eq. (2), all variables capturing the short run are shown through the coefficients γ_{1p} – γ_{5p} by considering their sign and significance. The long-run effects are through the coefficients of π_2 – π_5 which are normalized on π_1 . In comparison to other approaches to measure cointegration, the symmetry autoregressive distributive lag technique is more advantageous because used variables can be integrated either I(0) or I(1) (Li et al. 2021). The most important benefit is that we can get effects short-run and long-run, of explanatory variables on the explained variable at the same time and one model in a single step. A basic and main assumption behind Eq. (2) is that labour productivity has symmetric effects on the environment. However, we assumed that an increase in labour productivity has a different effect on the environment compared to a decrease in labour productivity, thus we can establish asymmetric effects of labour productivity on the environment and

following Shin et al. (2014). We construct two new variables as follows:

$$Lp^+_t = \sum_{n=1}^t \Delta Lp^+_t = \sum_{n=1}^t \max(\Delta Lp^+_t, 0) \quad (3)$$

$$Lp^-_t = \sum_{n=1}^t \Delta Lp^-_t = \sum_{n=1}^t \min(\Delta Lp^-_t, 0) \quad (4)$$

In Eqs. (3) and (4), Lp^+_t , Lp^-_t are the two partial sums of both positive and negative changes. The positive change shows an increased in labour productivity while the negative change indicates a decline in labour productivity. Shin et al. (2014) proposed a nonlinear ARDL approach by using the positive and negative changes in Eq. (5) and a new model is:

$$\Delta CO_{2,t} = \gamma + \sum_{p=1}^{n1} \gamma_{1p} \Delta CO_{2,t-p} + \sum_{p=0}^{n2} \gamma_{2p} \Delta Lp^+_{t-p} + \sum_{p=0}^{n3} \gamma_{3p} \Delta Lp^-_{t-p} + \sum_{p=0}^{n4} \gamma_{4p} \Delta Kp_{t-p} + \sum_{p=0}^{n5} \gamma_{5p} \Delta RD_{t-p} + \sum_{p=0}^{n6} \gamma_{6p} \Delta EC_{t-p} + \pi_1 CO_{2,t-1} + \pi_2 Lp^+_{t-1} + \pi_3 Lp^-_{t-1} + \pi_4 Kp_{t-1} + \pi_5 RD_{t-1} + \pi_6 EC_{t-1} + \mu_t \quad (5)$$

To get the nonlinear ARDL model estimates, we employ Eq. (5) and called asymmetric ARDL model. Linear or nonlinear estimated through OLS and F-test and ECM are used to determine the cointegration. Linear diagnostic estimates will remain the same in the NARDL model. Besides, the nonlinear model has also several asymmetry hypotheses tested for the short and long run. We employ the Wald test for this purpose.

Sample-set

The labour market plays an important role in the green economy. China used more than 70% of energy consumption in industry and the energy share in pollution is relatively more in the economy. However, we employ the Cobb–Douglas production function as key indicators for carbon emissions. Therefore, we used labour productivity, capital productivity, technological progress, and energy consumption in the carbon emissions model from 1991 to 2019 based on data

accessibility. All the dataset has been retrieved from the World Bank (2020). The detailed descriptive statistics of the dataset are given in Table 1. The results also show that the model is free of multicollinearity problems.

Results and discussion

The primary step is to examine the order of integration of all the variables before employing the cointegration procedure to avoid spurious regression. Besides the many economic variables, the integration order is one. Thus, the mixed order of integration is acceptable such as $I(1)$ or $I(0)$ but none of the variables should not be the order is $I(2)$ (Ahmed et al. 2019). We employed ADF and PP unit root tests to investigate the integration order and the Schwarz information criteria and optimal lag selection used. The turnouts are represented in Table 2. The empirical results demonstrate that most of the variables have been stationary after taking the first difference, and some variables are stationary at the level. So, the mixed order of integration. Both tests give similar results. These tests improve the reliability and validity of the outcomes. The BDS test also reported the non-linearity in CO_2 and labour productivity variables and thus we can apply the NARDL. ARDL is most useful for the small data set variables (Aslam et al. 2021; Ahmed et al. 2019) (Table 3).

This study used ARDL and non-linear ARDL to inspect both the long-run and short-run estimates after examining the integration order. However, panel A demonstrates the short-run estimates. On the other hand, panel B depicts the long-run dynamics. Besides, panel C highlights the various statistical tests. The empirical results from both the estimates explored that NARDL gives better results compared to the ARDL dynamics. The results from non-linear ARDL and ARDL are offered in Table 4.

The ARDL estimation technique's short-run outcomes revealed that labour productivity and capital productivity have an insignificant effect on carbon emissions in the short run. Meanwhile, the results demonstrate that green innovation has significantly reduced environmental pollution in the short run. The results indicate that a 1% increase in green innovation leads to a decline in carbon emissions to about 0.71% at a 10% significance level in China's short run. The empirical results indicate the energy consumption has significantly contributed to carbon emissions and responsible for environmental pollution in the short run. Results depict a 1% increase in energy consumption and increase the carbon emissions by 0.85% by approximately at the 5% significance level in China in the short run. Panel B offered the long-run estimates. The long-run turnouts from ARDL depict that labour productivity and capital productivity have an insignificant impact on environmental pollution in the long run. The results confronted that research and development lead to reduce

Table 1 Data description

	CO_2	Lp	Kp	RD	EC
Descriptive statistics					
Mean	15.52	4.912	4.612	1.273	7.190
Std. Dev.	0.513	0.723	0.678	0.676	0.413
Min	14.75	3.657	3.436	0.164	6.602
Max	16.14	5.999	5.636	2.383	7.713
Correlation matrix					
CO_2	1				
Lp	0.918	1			
Kp	0.947	1	1		
RD	0.674	0.397	0.597	1	
EC	0.977	0.474	0.573	0.470	1

Table 2 Unit root testing

	ADF			PP		
	I(0)	I(1)	Decision	I(0)	I(1)	Decision
CO ₂	−1.080	−2.736***	I(1)	−1.120	−2.836***	I(1)
Lp	−3.298***		I(0)	−3.455***		I(0)
Kp	−3.293***		I(0)	−3.373***		I(0)
RD	−0.192	−4.927***	I(1)	−1.012	−4.209***	I(1)
EC	−0.827	−2.805***	I(1)	−1.032	−2.997***	I(1)

Note: *** indicates the 1 % significance level

carbon emissions in the long run. Also, the results show that energy use has significantly stimulated carbon emissions in the long run.

Besides, panel C represents the various diagnostic test statistics to examine the model's reliability and stability. The value of F-statistics in the bound test is greater than the upper bound and indicates cointegration. Further, the coefficient of ECM is negative and statistically significant and shows the speed of adjustment towards the long-run equilibrium. To investigate the stability and good fitness of the model, we employed the Ramsey RESET test. This test shows that the model is a good fit and free from all the statistical issues. Non-linear ARDL outcomes are offered in Table 4. Panel A indicates the short-run dynamics. On the contrary, panel B depicts the long-run dynamics. However, panel C highlights statistical analysis. The empirical turnout elaborates that the partial sum of positive change in labour productivity has a statistically significant and positive effect on carbon emissions in the short run. Thus, the results demonstrate that a 1% increase in labour productivity leads to an increase in the carbon emissions by 0.015% at the 1% significance level.

Table 3: BDS test

	Dimension	BDS Stat	S.E	Z-Stat	Prob.
CO ₂	2	0.188***	0.009	21.755	0.000
	3	0.312***	0.014	22.267	0.000
	4	0.392***	0.017	23.008	0.000
	5	0.439***	0.018	24.178	0.000
	6	0.463***	0.018	25.809	0.000
Lp	2	0.201***	0.008	26.257	0.000
	3	0.336***	0.012	26.960	0.000
	4	0.426***	0.015	28.132	0.000
	5	0.488***	0.016	30.297	0.000
	6	0.532***	0.016	33.465	0.000

Note: *** indicates the 1 % significance level

On the other hand, the partial sum of negative change in labour productivity falls the carbon emissions; for instance, decrease 0.011% and significance level is 10%. Furthermore, the results for capital productivity have an insignificant impact on carbon emissions. The research and development results show a statistically significant and negative effect of carbon emissions in China's short run, i.e., the results revealed that a 1% increase in research and development expenditure reduces carbon emissions by 0.011%. A 1% increase in energy use enhances the carbon emissions to about 0.530% at a 5% significance level.

Long-run NARDL estimates are depicted in panel B. Besides, the results indicate that a partial sum of positive change in labour productivity is positively associated with environmental pollution; for instance, the outcome elaborates that a 1% increase in the positive component of labour productivity increases the carbon emissions 0.015% at a 1% significance level. Besides, labour productivity increases the energy/labour ratio in the economy, which in turn increases environmental pollution. These results are in the same line with Devaraj and Kohli (2000); Neves and Sequeira (2018); Hall and Helmers (2010); Geels et al. (2004); and Dewan and Kraemer (2000). Thus, the results demonstrate that a 1% decrease in the partial sum of negative change in labour productivity leads to reduced carbon emissions by 0.011% and causes environmental quality. The link between labor productivity and CO₂ emissions dynamics is important (Marin and Mazzanti 2013) because the size of the CO₂/labour ratio declines.

In environmental pollution, labour productivity substitutes with capital productivity, increasing energy use and degrading ecological quality. Additionally, the outcome revealed that research and development expenditures reduce carbon emissions and improve environmental quality. The results show that a 1% increase in the research and development expenditures declines the carbon emission by 0.530% approximately in the long run. Moreover, many studies in the previous literature used the research and development expenditures as a proxy of technological innovation. For example, Kunapatarawong and Martínez-Ros (2016) and Cole et al.

Table 4 Long-run and short-run estimates

Variable	Coefficient	ARDL			NARDL			
		S.E	t-Stat	Prob.	Coefficient	S.E	t-Stat	Prob.
Short-run								
D(LP)	−12.37	12.90	0.959	0.362				
D(LP(-1))	−30.04**	14.68	2.046	0.071				
D(LP(-2))	16.62**	7.598	2.189	0.056				
LP_POS					0.014***	0.005	3.049	0.004
D(LP_POS(-1))					0.010	0.031	0.332	0.741
LP_NEG					−0.233***	0.089	2.612	0.010
D(LP_NEG(-1))					−0.010	0.007	1.396	0.167
D(KP)	11.38	12.27	0.928	0.378	−1.032	0.685	1.506	0.149
D(KP(-1))	27.99**	12.43	2.252	0.051	1.620**	0.749	2.163	0.044
D(KP(-2))	−14.15**	6.911	2.048	0.071				
D(RD)	−0.710*	0.433	1.641	0.135	−0.130	0.152	0.855	0.403
D(RD(-1))	−0.239	0.225	1.066	0.314				
D(EC)	0.856**	0.411	2.082	0.067	0.763***	0.147	5.178	0.000
Long-run								
LP	3.466	4.539	0.764	0.465				
LP-POS					0.015***	0.004	3.890	0.000
LP-NEG					−0.011*	0.006	1.680	0.098
KP	3.238	4.700	0.689	0.508	0.425*	0.269	1.582	0.130
RD	−0.109*	0.173	0.628	0.546	−0.530*	0.283	1.873	0.077
EC	0.700***	0.209	3.351	0.009	1.077***	0.129	8.372	0.000
C	8.494***	1.030	8.243	0.000	9.018***	1.151	7.834	0.000
Diagnostic								
F TEST	3.400**				5.110***			
ECM	−1.926***	0.705	2.730	0.023	−0.708***	0.103	6.816	0
Adj. R2	0.865				0.912			
RESET	1.987				0.891			
LM	2.774				0.235			
CUSUM	S				S			
CUSUMSQ	S				S			
Wald-SR					4.689***			
Wald-LR					5.356***			

Note: The coefficient estimates are the significance levels at 10%, 5%, and 1% (1.64), (1.96), and (2.58)

(2013) findings revealed that technological innovation has a negative linkage with carbon emissions. As for us, Cole et al. (2005) found and concluded that investment in research and development expenditure statistically significantly mitigates the carbon emissions for Japan's case. Similarly, Yin et al. (2015) indicate that technological advancement plays a vital role in reducing carbon emissions in China. Additionally, Song et al. (2018) also inspect similar findings. The results elaborate that energy consumption is also positively associated with China's environmental pollutions in the long run; for example, a 1% increase in energy use contributes to carbon emissions to about 1.077% at a 1% significance level. This outcome is in line with the study of Hafeez et al. (2019a).

Energy consumption is significantly uplifting the environmental degradation in 12 out of 16 regions across the globe (Hafeez et al. 2019a, 2019b). Similarly, environmental degradation is paddled up by energy consumption in the Belt and Road region (Hafeez et al. 2019b).

Panel C elaborated the various statistical and diagnostic tests to inspect the model's good fitness and stability for the non-linear ARDL. The F-statistics critical value from the bound test is greater than the upper bound value, and the turnout confirms the presence of cointegration. Hence, the ECM value is negative and statistically significant that shows the speed of adjustment toward long-run equilibrium. Besides, ECM estimates revealed the presence of cointegration in the

carbon emissions model for China. The ECM indicates that carbon emissions adjust vastly toward the long-run equilibrium, with a rate of 70% in a year and occurrence and variables quantified. Hence, the NARDL is the most reliable approach because the non-linear model has passed by various substantial tests such as RESET, R2, and LM tests. The LM test results indicate that the model feels free from serial correlation, and Ramsey RESET suggests that the model has a correct functional form. The short-run and long-run asymmetric results are denoted in Panel C. The Wald test statics confirms the presence of both the short-run and long-run nonlinear nexus in China.

Conclusion and policy

The evolution to a low-carbon economy signifies an enormous challenge. Such a challenge is faced by China. This study is to detect the dynamic relationship between labour productivity and CO₂ emissions by Cobb–Douglas production function in which labour productivity, capital productivity, technological progress, and energy consumption are taken as independent variables. Therefore, this study uses the non-linear ARDL approach for the time series dataset over the period 1991–2019. As the environmental issue has received more attention nowadays, this study aims to show green labour productivity that might contribute to achieving low-carbon economy targets of China. However, the “green productivity” literature shows that labour productivity is a vital input to the environment because it is the source of economic activities. As labour productivity maintains and improves environmental activities more than capital productivity, labour is the source of productivity to have a positive effect on environmental quality because it has also less use energy consumption.

Regarding our empirical findings, we find that positive change in labour productivity has positive and significant impacts on CO₂ emissions, which implies that there exist a robust relationship between labour productivity and the environment in the economy. This implies that our results do not coincide with the “green growth theory”. Concurrently, a negative change in labour productivity has negative effects on CO₂ emissions in long run, which indicates that small use of labour also reduces capital as well energy consumption and hence reduce the environmental pollution in the economy. While the positive change in labour productivity leads to an increase in CO₂ emissions, negative change in labour productivity is also falling the pollution in the short term. Labour productivity results are also stable and consistent in the long run. The empirical results also confirmed that capital productivity also increases environmental pollution. This means that capital productivity is not beneficial for air quality in the long term because it is a lot of energy use in production and

mitigates the environment. This finding has also outweighed the influence of clean energy on the environment because the clean energy share in total energy is relatively small in China. Therefore, energy consumption has a positive impact on CO₂ emissions in the long run. The result is also indicating that research and development spending is more important for a low-carbon economy.

Based on these outcomes, we draw the implications for the policy. The authorities should increase labour productivity by using clean technology and clean energy consumption. The transition of labour market policies and structural economic change is also very important in achieving environmental targets. China should reduce the energy/labour ratios to labour productivity in the economy. Such a reduction is so good for green productivity and the environment. The key policy is that China should introduce clean technology in green productivity. The present study has some limitations from theoretical as well as empirical sides. Labour and capital productivity variables model in the environment pollution production function for theoretical understanding. This study only focused on non-linear dynamic impacts of labour productivity on pollution ignoring the nonlinear effects of capital productivity. It is essential to understand the working mechanisms of labour productivity in the environment at different time horizons in different political regimes. Environmental productivity indicators at the micro-level should be introduced to get more accurate and rich empirical results. Further work is necessary to explore the connotations of the green productivity model for other economies.

Data and materials 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 Mansoor Mumtaz Soomro and Yanqing Wang. Mansoor Mumtaz Soomro, Raza Ali Tunio, Khamida Aripkhanova, analyzed the data and wrote the complete paper. While Mohammad Ibrahim Ansari read and approved the final version.

Declarations

Ethics approval and 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.

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