Energy Mix, Financial Development and Carbon Emissions in China: A Directed Technical Change Perspective

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1 Energy Mix, Financial Development and Carbon Emissions in China:

2 A Directed Technical Change Perspective

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9
10 **Abstract:** Based on a two-sector (clean energy and dirty energy) model of directed technical change,
11 we examine the relationship between carbon emissions, clean energy consumption and financial
12 development in China using the ARDL method. Clean energy consumption reduces carbon emissions
13 effectively but the effect of financial development is opposite, suggesting that financial development
14 increases carbon emissions, contradicting the findings of many existing studies. Then, we decompose
15 financial sector development on carbon emissions into two different effects: the substitution and income
16 effects. The substitution effect reflects more dirty energy consumption as a result of directed technical
17 change promoted by financial development, leading to more carbon emissions. In contrast, the income
18 effect results in a decline of carbon emissions because financial development enables firms to use more
19 clean energy. The empirical results indicate that the net effect of financial development has caused more
20 carbon emissions. The policy implication is also discussed.

21 **Key words:** Carbon emission, Directed technical change, energy mix, financial development, Clean
22 energy, Energy transition.

23 **JEL:** Q01, Q42, Q56

24 25 1. Introduction

26 Global CO₂ (carbon dioxide, or carbon hereafter) emissions has been increasing rapidly since the
27 beginning of the twentieth century. According to BP (2018), we depict the carbon emissions of the world
28 and the major economies during 1965-2017 in Fig. 1. China, the US, India, Russia and Japan are the
29 world's top five emitters. In particular, China and India were the two largest contributors to the rising

amount of global carbon emissions, whose emissions respective rose by 1.6% and 4.4% per year over the sample period. China's carbon emissions growth rate in 2017 was 0.3 percentage points higher than the previous peak in 2014. Together, China and India accounted for nearly half of the global new emissions nowadays (BP, 2018).

Fig. 1. The CO₂ emissions of major countries and the world. Sources: BP (2018)

After the reform and opening-up policy implemented in 1978, China has witnessed a staggering rate of economic growth over the last forty years. This rapid growth has been accompanied with severe environmental degradation. As the largest carbon emitter in the world, China is facing tremendous pressure to reduce carbon emissions. It aims to reduce its carbon emissions per unit of GDP by 60-65% from the 2005 level and promote non-fossil energy accounting for about 20% of the country's primary energy consumption by 2030 (NDRC, 2015). The ability and willingness of China to reduce carbon emissions will have a critical influence on the global natural environment. More and more studies have paid attention to China's carbon emissions and energy policy. Ma et al. (2018) indicate that the mainly carbon emissions in China is from energy consumption of industrial sector. Dong et al. (2018) investigate the dynamic causal impact of renewable energy and nuclear energy consumption on carbon emissions in China, showing that clean energy played an important role in reducing carbon emissions in both the short and long terms. Rong et al. (2020) study the residential energy consumption in Kaifeng China and find that more than 75% carbon emissions is from electricity consumption. Wu et al. (2020) discuss the nonlinear relationship between energy consumption and carbon emissions, indicating that environmental regulation could reduce the carbon emissions in eastern and central China. Moreover, Tamazian et al.

(2009) point out that higher development levels of economy and financial depth reduced carbon emissions in the BRIC countries. Jalil and Feridun (2011) examine the long-run equilibrium relationship between financial sector development and carbon emissions and suggested that financial sector development has led to a reduction in carbon emissions. At the G20 summit in 2016, the heads of states reached an important consensus on ‘green finance’ and set a series of actions to achieve this goal. Zhang et al. (2020) found that credit availability of manufactures results in lower energy efficiency. These findings suggest that financial sector development is a key determinant in environmental protection (Chen et al., 2019).

While many researchers have focused on the impact of various factors, such as renewable energy, nuclear energy or financial sector development on carbon emissions, few studies have comprehensively considered the impact of energy mix, financial sector development, technological change, and foreign trade in the development process. We examine the impacts of financial sector development and clean energy consumption on carbon emissions from a directed technical change perspective following Acemoglu (2002). Using a large dataset spanning a long period of time in China during 1965-2017, it is found that the effect of clean energy consumption on carbon emissions is significantly negative but the effect of financial sector development is opposite, suggesting that financial sector development increases carbon emissions instead of reducing it, which contradict the findings of many existing studies. This implies that China’s energy transition is endogenous to the economy’s industrial structure and the financial sector reform, suggesting that financial sector reform in future should consider its impact on energy structural change as well as carbon emissions. To explain the effect of financial development on carbon emissions, we decompose it into two parts: the substitution effect and income effect. On the one hand, financial sector development may actually direct firms to consume relatively more fossils fuels because it changed the relative prices between fossil fuels clean energy, leading to the so-called substitution effect in favor of fossil fuels. On the other hand, financial sector development also led to faster economic growth and increased capital intensity, which would enable firms to use more clean energy, leading to a reduction in carbon emissions intensity. This is the so-called income effect, which is found to be smaller than the so-called substitution effect, resulting in a net increase in carbon emissions in China over the data period. We will carefully discuss the substitution effect and income effect in last section.

The new contributions of this paper mainly consist of the following three aspects. First, it builds a

81 simple two-sector model embedded with directed technical change and examines the relationships
82 between carbon emissions and clean energy as well as financial sector development using a unified
83 theoretical mechanism. Second, it decomposes financial sector development into two parts following the
84 principle of Slutsky decomposition—the substitution effect and the income effect, because financial
85 sector development can lead to an increase in both technical level and capital intensity. The former results
86 in a reduction in the relative price of dirty energy compared to clean energy in response to technical
87 change, encouraging enterprises to consume more fossil fuels. The latter enables firms to shift energy
88 consumption away from dirty energy towards clean energy sources, and hence reduce carbon emissions.
89 The empirical results in our data period suggest that the former effect outweighs the latter one, leading
90 to a net effect of financial sector development as more carbon emissions. The policy implication is that
91 financial sector development should take into account of its potential impact on energy consumption
92 behavior and carbon emissions as far as environmental protection is concerned. Third, both the shares of
93 manufacture and foreign trade as a proportion of GDP have a positive impact on carbon emissions. In
94 particular, the rapid expansion of carbon emissions after China’s accession to WTO supports the so-
95 called “pollution haven” hypothesis, i.e. more developed countries tend to relocate their polluting
96 industries to the less developed economies such as China.

97 The rest of this paper is organized as follows. Section 2 reviews the related literature on carbon
98 emissions with respect to clean energy consumption and financial sector development respectively, and
99 makes two theoretical propositions. Section 3 discusses data, model and research methodology. Section
100 4 presents the empirical results and explanations. The last section concludes with some policy
101 recommendations.

103 **2. Literature review and propositions**

104 **2.1. Literature review**

105 Climate change caused by greenhouse gases, especially carbon emissions, has long attracted
106 attention from theoretical and empirical economists since Nordhaus (1977, 1982, 1991) introduced it to
107 economic analysis. More and more studies paid attention to the relationship between clean energy
108 consumption and carbon emissions (Bilgili, et al., 2016; Yao et al., 2019). For example, Dong et al. (2018)
109 indicate that nuclear energy and renewable energy in China play an important role in carbon emissions
110 reduction both in the short and long terms, while Baek (2016) find that renewable energy does so only in

the short term. While almost all the existing studies based on econometric analysis confirm the emissions reduction effect of clean energy employing different data sets, they don't discuss the mechanisms affecting clean energy consumption and thus could not provide a unified framework of economic theory. Therefore, it is imperative to build a unified economic framework for carbon emissions reduction and clean energy promotion.

Another type of literature on carbon emissions reduction focus on the effect of financial sector development. King and Levine (1993) indicate that financial intermediary development may boost the rate of technological innovation in a well-functioning financial institution, thus reducing environmental pollution. Some recent empirical studies (Dasgupta et al., 2004; Liang, 2006; Wang and Jin, 2007; Tamazian et al., 2009; Jalil and Feridun, 2011) reveal that financial sector development improve environmental performance, such as reducing carbon emissions. Tamazian and Rao (2010) argue that financial sector development play a positive role in reducing carbon emissions with a strong institutional framework considering 24 transition economies during 1993-2004. Abid (2017) studies the relationship between institutional quality and carbon emissions, indicating that financial sector development could improve environmental quality. Moreover, Zhao et al. (2021) find that financial sector development measured by different indicators—financial depth and financial efficiency—on environmental pollution were the opposite. Wang et al. (2019) concluded that China's energy structure change was driven by capital deepening and biased technical change towards capital-intensive modern energy in the long run from the new structural economics (NSE) perspective. Adams and Kwame (2018) point out that financial sector development was a significant determinant of environmental degradation after accounting for the political effect. However, Chen et al. (2019) revealed that the effect of financial sector development was limited to energy reduction for OECD countries because their financial systems were mature. Using Turkey's data in 1974-2014, Pata (2018) showed that financial sector development worsened the environmental condition. In addition, Zhang et al. (2020) found that credit availability of manufactures results in lower energy efficiency. Therefore, specific financial reform is required to provide adequate incentives to reduce carbon emissions (Abid, 2016).

Jalil and Feridun (2011) revealed that financial sector development can reduce carbon emissions without considering the energy mix, while Dong et al. (2018) argued that promoting the consumption of clean energy can reach the target of carbon emissions reduction ignoring the effects of other factors such as financial sector development. The existing studies have not paid attention to the combined effect of

clean energy consumption and energy structure change on carbon emissions. To fill this literature gap, we develop a theoretical mechanism to explain the relationship between financial development, clean energy consumption and carbon emissions from a directed technical change perspective. On the one hand, financial sector development would provide abundant funds for firms to avoid dirty industries. On the other hand, it may also encourage firms to expand production size, which will release more carbon emissions. Therefore, the net effect of financial sector development on carbon emissions would depend on the two counteractive forces. To fully understand the exact mechanism, we follow the Slutsky decomposition approach to decompose financial sector development into two parts, the substitution effect and income effect, and suggest that financial sector development may not necessarily lead to carbon emissions reduction because the substitution effect may outweigh the income effect on carbon emissions during the phase of rapid industrialization in China.

Different from some recent studies (Tamazian et al., 2009; Jalil and Feridun, 2011; Wang et al., 2019; Acheampong et al., 2020), our paper shows that financial sector development could not reduce carbon emissions without upgrading the industrial structure and shifting the energy mix in China. That is, the main impact of the current financial sector development has encouraged manufacturers to expand production scale instead of upgrading production technology or shifting energy structure. Our finding is in line with the theories of directed technical change proposed by Acemoglu et al. (2002, 2012, 2016) and the new structural economics by Lin (2011).

2.2. The effects of financial sector development with directed technical change

In the initial analysis of this paper, firms are regarded as producers of a unique final good and consumers of energy, constrained by profit maximization or cost minimization. Our discussion begins with an economy possessing two types of energy, clean energy (renewable energy and nuclear power) and dirty energy (fossil fuels). According to Acemoglu et al. (2012), a unique final good is produced using a combination of two different energy sources (clean energy and dirty energy)¹. Clean energy is a “normal good”, whose demand increases with income. The demand for a clean environment grows as a result of economic expansion and life quality improvement (Grossman and Krueger, 1995; Bilgili, et al., 2016), so the consumption of fossil fuels declines correspondingly. Therefore, fossil fuels are treated as “inferior” goods as far as environmental protection is concerned.

¹ Acemoglu et al. (2012) argue that a unique final good is producing by combining two inputs: dirty input and clean input. It is not impacting the results of analysis by substituting them respectively by dirty energy and clean energy if only considering the carbon emissions instead of other environmental depredations.

The effect of financial sector development on carbon emissions may be different from what has been found in the existing literature once directed technical change is taken into account. Technological change may not be neutral in some specific situations and it may favor some production factors more than others. This phenomenon is called directed technical change according to Acemoglu (2002). Based on a framework of directed technical change, Acemoglu et al. (2012, 2016) make a distinction between dirty innovation and clean innovation and argue that the market size effect encourages innovation towards the larger input sector, such as the fossil fuel market, which still dominates the energy market in China, accounting for more than 80 percent of total energy consumption. Some studies (Blazquez et al., 2018) hold that storage and transport technology were important deterrents to promoting electricity generated by clean energy. Yang et al. (2018) suggest that the production technology of China's industrial sector is biased toward fossil fuels instead of clean energy. Yao et al. (2019) indicate that the energy mix among countries is subject to their different technological conditions and economic development level so that fossil fuels dominated energy consumption in many developing and newly industrializing economies such as China. This would correspond to a low degree of substitution between the two types of energy because more consumption of non-energy commodities using less effective transport technologies would increase the demand for energy. Dirty energy/fossil fuels in our discussion are relatively abundant and not exhaustible in the foreseeable future (Acemoglu et al., 2012).

Financial sector development brings capital accumulation in both the research and production sectors of the economy. More research funding through R&D activities enables the country to improve technologies for energy development and utilization. Lin (2011) suggests that firm performance and the country's comparative advantage were closely related. In a developing economy where advanced technology in the exploitation and utilization of fossil fuels are available in the initial stage of economic development, only research activities focusing on fossil fuels could maintain or increase the country's competitiveness. This will lead to a reduction in fossil fuel prices, implying that technical change is directed to fossil fuels, called the market size effect and initial productivity advantage (Acemoglu, et al., 2012).

In the manufacturing sector, financial sector development encourages firms to expand production scale, leading to more energy consumption, including fossil fuels and clean energy (Sadorsky, 2010; Acheampong, 2019). However, as more advanced technology becoming available with lower fossil fuel prices, firms tend to consume relatively more fossil fuels than clean energy to maximize profits.

Consequently, financial sector development leads to more energy consumption, particularly more consumption of fossil fuels due to cost minimization or profit maximization consideration.

To examine exactly the effect of financial sector development on carbon emissions, we firstly decompose the financial sector development effect into two components following Slutsky's decomposition principle (Nechyba, 2016): (1) the substitution effect directed by technical change due to the price decline of dirty energy relative to clean energy price; and (2) the income effect due to increased demand for clean environment corresponding with rich capital intensity and rising per capita income. Both of these two effects resulting from financial sector development are illustrated in Fig.2.

Fig.2. Substitution and capital intensity effects with directed technical change.

In Fig.2, C_1 , C_2 and C_3 represent respectively the original budget, the compensated budget and the final budget lines, corresponding with the indifference curves U_1 , U_2 and U_3 as well as the equilibrium points E_1 , E_2 and E_3 . With technological progress in the dirty energy sector, the price of fossil fuels declines, hence the budget line changes to C_3 from C_1 , and the corresponding equilibrium point of energy consumption changes from E_1 to E_3 . Following Slutsky's decomposition principle (Nechyba, 2016), we decompose the changes in the energy consumption mix into two parts, i.e., the substitution effect and the income effect. As previous discussion, financial sector development leads to technological progress, reducing the relative price of fossil fuels and raising the capability of firms to consume clean energy. Yang et al. (2018) and Yao et al. (2019) argue that the developing economies had more available technologies in fossil fuels at the early stage of economic development so that the technical change was

directed to dirty energy, which is called directed technical change in this paper. The price reduction of fossil fuels directed by technical change promotes the demand for dirty energy to accelerate economic growth. That is, the substitution effect is a result of financial sector development. On the other hand, financial sector development enables firms to use more clean energy instead of fossil fuels as higher incomes raise the awareness of environmental protection. This is the so-called income effect of financial sector development in this paper. The income effect is expected to reduce carbon emissions because increased capital intensity and per capita income is a prerequisite for firms to use more clean energy and reduce the consumption of fossil fuels.

Specifically, E_1E_2 in the vertical axis represents the magnitude of the substitution effect, which measures the increased demand for fossil fuels due to the relative price change between the two types of energy. E_2E_3 is the income effect, measuring the reduced demand for fossil fuels under the new budget constraint. These two consumption changes in the opposite directions lead to the net effect on the demand for fossil fuels as a result of financial sector development, represented by E_1E_3 in the figure. The net effect satisfies the equation $|E_1E_3|=|E_1E_2|-|E_2E_3|$. That is, the impact of financial sector development on carbon emissions depends on the absolute value of the sum of these two effects. If the value of E_1E_3 is positive, the financial sector development leads to more fossil fuels consumption and more carbon emissions.

Based on the above theoretical discussion, we put forward two propositions below.

Proposition 1: Promoting clean energy consumption can lead to carbon emissions reduction controlling other factors such as financial sector development.

Proposition 2: Financial sector development bring about more carbon emissions if the substitution effect is larger than the income effect. Financial sector development enables firms to expand production through consuming more fossil fuels and promote energy structural change toward using more clean energy, but the former may dominate the process. Therefore, financial sector development lead to more pollution especially in the early stage of economic development in a developing economy such as China.

3. Data, model and methodology

3.1. Model and data

Following Tamazian et al. (2009), Jalil and Feridun (2011), Dong et al. (2018), we use gross domestic product (GDP) and its quadratic and cubic terms, the share of clean energy consumption as a proportion of total energy consumption, the level of financial sector development, foreign trade,

industrial structure, and CO₂ emissions in a single multivariate regression framework. Using cross-sectional data, Sebri (2016) shows no evidence in favor of an inverted-U shaped environmental Kuznets curve, but in most cases, an evolution into an N-shaped relationship. Yao et al. (2019) and Zhao et al. (2021) suggest that there was an N-shaped relationship instead of the usual inverted U-shaped curve between CO₂ emissions and GDP in China. Based on the previous studies, we specify a log nonlinear model with a cubic term as follows:

$$\ln co_2 = f(\ln gdp, Z) \quad (1)$$

or,

$$\ln co_2 = \alpha_0 + \alpha_1 \ln gdp + \alpha_2 (\ln gdp)^2 + \alpha_3 (\ln gdp)^3 + \alpha_4 \ln scle + \alpha_5 \ln fin + \alpha_6 \ln sind + \alpha_7 \ln stra + \varepsilon \quad (2)$$

Where, *co₂* is per capita CO₂ emissions, *gdp* denotes per capita real GDP. *scle* and *fin* are the main explanatory variables, which represent energy structure and financial sector development respectively. In addition, the model also includes other variables, *sind* and *stra*, controlling industrial structure and economic structure. ε is a random error term. The related variables in Eq. (2) are explained as follows.

(1) Greenhouse gas (CO₂). The carbon dioxide is the primary greenhouse gases, so we use per capita CO₂ emissions (*co₂*) as explained variable to indicate environmental pollution according to the previous studies. *co₂* is the aggregate CO₂ emissions divided by population.

(2) Income level (GDP). *gdp* (per capita real GDP) is used to present income level and economic development. In addition, the squared and cubic terms of *gdp* are also included to examine the N-shaped relationship between environmental pollution and income level according to Sebri (2016), Yao et al. (2019) and Zhao et al. (2021).

(3) Energy structure (clean energy). Compared with fossil fuels, clean energy (including nuclear power) has low or even zero carbon emissions. Using clean energy to replace fossil fuels is an effective way to reduce carbon emissions (Yao et al., 2019; EIA, 2019). Therefore, we employ the share of clean energy consumption to total primary energy consumption (*scle*) to describe energy structure. Clean energy includes nuclear energy, hydroelectric, solar, wind, geothermal, biomass, biofuels and other renewables.

(4) Financial development (*fin*). As discussed in Section 2, financial development influence carbon emission from two perspectives: substitution effect and income effect. Its net effect depends on the two counteractive forces. It is difficult to estimate the value size of substitution effect and income effect for

the availability of data. In order to avoid this inconvenience, we just estimate its net effect instead of estimating substitution effect and income effect respectively. Therefore, the positive coefficient of *fin* means that financial development promotes carbon emission. Beck et al. (2007) point out that there is not a perfect index of financial development. Due to the availability of data, we employ the most commonly proxies of banking sector development (*scrc* and *pcrc*) to indicate financial development (Chakroun, 2020). *scrc* is the share of domestic credit to the private sector as a proportion of GDP and *pcrc* indicates per capita domestic credit.

(5) Economic structure. Energy consumption is closely related to economic structure. The second industry consume more energy than others. In addition, China as the “world factory”, foreign trade accounts for a large proportion of GDP. Therefore, controlling industrial structure (*sind*) and foreign trade (*stra*) could make the estimation more precise. In the empirical sector, *sind* is the share of industry value added as a proportion of GDP, *stra* is the share of foreign trade as a proportion of GDP, which presents the openness of economy.

Table 1

The definition and implication of variables.

Abb	Definition	Implication
<i>co₂</i>	per capita CO ₂ emissions (Kg)	primary greenhouse gases
<i>gdp</i>	per capita real GDP (Yuan)	income level
<i>scle</i>	the share of clean energy consumption (%)	energy structure
<i>scrc</i>	the share of domestic credit to GDP (%)	financial development
<i>pcrc</i>	per capita domestic credit (Yuan)	
<i>sind</i>	the share of industry value added to GDP (%)	industrial structure
<i>stra</i>	the share of foreign trade to GDP (%)	openness of economy

Table 1 reports the definition and implication of variables in Eq. (2). The data of CO₂ emissions, primary energy consumption, and clean energy consumption are obtained from BP (2018), nominal GDP and population are obtained from the *China Statistical Yearbook* and *China Compendium of Statistics (1949-2008)*, GDP deflator, the share of foreign trade, and domestic credit to the private sector are obtained from the *World Bank Database* (2019). Real GDP is obtained through dividing the nominal GDP by the GDP deflator (2015=100). We employ EViews 10 for the regressions after taking natural logarithms of the relevant data series. Table 2 reports the descriptive statistics of the variables over the

sample period. As shown in Fig.3, the relationship between $lngdp$ and $lnco_2$ looks like an N-shaped curve, consistent with Yao et al. (2019) and Zhao et al. (2021). Therefore, the cubic term of gdp used in model is suitable.

Table 2

Descriptive statistics of variables (1965-2017).

	Mean	Med	Max	Min	S. D.	Ske	Kur
$lnco_2$	7.716	7.660	8.819	6.408	0.711	0.061	2.075
$lngdp$	8.871	8.701	10.940	7.177	1.189	0.230	1.732
$lngdp^2$	80.078	75.70	119.68	51.50	21.451	0.364	1.825
$lngdp^3$	735.35	658.62	1309.3	369.63	293.85	0.497	1.951
$lnind$	3.773	3.798	3.872	3.437	0.091	-1.797	6.317
$lnscre$	4.361	4.437	4.981	3.644	0.381	-0.244	1.690
$lnpcr$	8.626	8.667	11.316	6.293	1.557	0.111	1.695
$lnscl$	1.580	1.435	2.832	0.902	0.469	0.960	3.334
$lnstra$	3.093	3.403	4.166	1.593	0.797	-0.518	1.906

Notes: The unit of CO_2 is kg, the units of gdp and per capita credit (pcr) are RMB, others are per cent (%). Data resources: BP, *China Statistical Yearbook* and *the World Bank Database*.

Fig.3. The N-shaped relationship between $lngdp$ and $lnco_2$

3.2. Methodology

We use the autoregressive distributed lag (ARDL) approach and co-integration methods (including

full modified OLS/FMOLS and dynamic OLS/DOLS) to identify the relationship among the variables. The empirical methodologies in the later section of the paper include the following stages. First, employing the unit root tests to examine the stationarity of the time series. Second, testing the cointegration relationship among the variables using the ARDL approach. Third, estimating the long-run coefficients using FMOLS and DOLS estimators. Fourth, using the Granger causality test to examine the short-run and long-run causalities. The advantages of ARDL method and empirical results are presented in Section 4.

4. Empirical results and discussion

4.1. Unit root tests

In cointegration analyses, it is important to first make sure that all the time series are stationary and integrated of the same order. The unit root test is the most common approach to test the stationarity and integrated order of data (Hu et al., 2018; Yao et al., 2019). This method starts with the time series in level term. If the data are non-stationary in level terms and a unit root exists, we can then derive the first differences of the data and retest them until the results are stationary.

Pesaran and Pesaran (1997) indicate that the ARDL bounds testing procedure can be applied irrespective of whether the variables are $I(0)$, $I(1)$ or fractionally cointegrated. However, Ouattara (2004) argues that the computed F-statistics provided by Pesaran et al. (2001) become invalid in the presence of $I(2)$ variables. That is, the bounds test is based on the assumption that the variables should be $I(0)$ or $I(1)$. It is, therefore, necessary to ensure that none of the variables is integrated at an order of $I(2)$ or beyond in the ARDL procedure. For this purpose, we use the conventional Augmented Dicky Fuller (ADF) tests and Phillips-Perron (PP) tests, which are the common unit root tests in related studies (Danish, et al., 2017). As shown in Table 3, *lnco₂*, *lngdp*, *lnscre*, *lnpcr*, *lnsle*, *lnsind*, and *lnstra*, are level and trend non-stationary, but their first differences are stationary, implying that they are all integrated of order 1, or $I(1)$.

Table 3
Results of unit root tests.

	ADF				PP			
	Level		Difference		Level		Difference	
	<i>I&T</i>	<i>I</i>	<i>I&T</i>	<i>I</i>	<i>I&T</i>	<i>I</i>	<i>I&T</i>	<i>I</i>
<i>lnco₂</i>	-3.233*	-0.827	-3.882**	-3.907***	-1.632	-0.747	-3.285***	-3.321***
<i>lngdp</i>	-3.843**	1.492	-5.307***	-4.822***	-3.452**	2.146	-5.100***	-4.712***
<i>lngdp²</i>	-3.032	2.233	-5.222***	-4.106***	-2.720	3.347	-5.003***	-3.993***
<i>lngdp³</i>	-2.331	2.749	-5.172***	-3.342**	-1.938	4.983	-5.056***	-3.131**

<i>lnscre</i>	-2.990	-0.970	-5.392***	-5.445***	-2.566	-0.966	-5.409***	-5.440***
<i>lnpcr</i>	-3.085	1.476	-5.771***	-5.471***	-2.255	1.327	-5.744***	-5.501***
<i>lnscl</i>	-1.206	1.909	-6.382***	-5.765***	-0.985	2.782	-6.509***	-5.752***
<i>lnsind</i>	-2.080	-2.327	-5.893***	-5.835***	-1.764	-2.531	-5.859***	-5.766***
<i>lnstra</i>	-0.420	-1.342	-5.059***	-4.952***	-0.807	-1.319	-4.770***	-4.780***

Notes: the value is adjusted t-Statistics for PP. Lag Length for ADF: 1 (Automatic - based on SIC, maxlag=10); Bandwidth for PP: 2 (Newey-West automatic) using Bartlett kernel. In addition, *I* is intercept and *I&T* are intercept and trend.

4.2. ARDL bounds test

After identifying the cointegration relationship among the relevant variables, we calculate the long-run and the short-run estimates based on Eq. (2). The ARDL approach is adopted in this section for three reasons that make it superior to others: (1) It does not require the regressors to be integrated at the same order, no matter $I(0)$ or $I(1)$, when examining the long-run relationship among variables; (2) both short-run and long-run parameters of the variables are estimated simultaneously; and (3) the endogeneity problem can be avoided (Pesaran et al., 2001; Jebli and Youssef, 2015; Belaïd and Youssef, 2017). According to Jalil and Feridun (2011), Dong et al. (2018), the complete procedure of the ARDL cointegration test includes three key steps. First, to check for the existence of a long-run relationship among the lagged variables using the ordinary least squares (OLS) method and an F-statistic to estimate Eq. (2) as shown in the following:

$$\begin{aligned} \Delta \ln co_{2t} = & \theta_0 + \sum_{i=1}^p \theta_1 \Delta \ln co_{2t-i} + \sum_{i=1}^p \theta_2 \Delta \ln gdp_{t-i} + \sum_{i=1}^p \theta_3 \Delta \ln gdp_{t-i}^2 \\ & + \sum_{i=1}^p \theta_4 \Delta \ln gdp_{t-i}^3 + \sum_{i=1}^p \theta_5 \Delta \ln scl_{t-i} + \sum_{i=1}^p \theta_6 \Delta \ln fin_{t-i} + \sum_{i=1}^p \theta_7 \Delta \ln sind_{t-i} \\ & + \sum_{i=1}^p \theta_8 \Delta \ln stra_{t-i} + \theta_9 \ln co_{2t} + \theta_{10} \ln gdp_{t-1} + \theta_{11} \ln gdp_{t-1}^2 + \theta_{12} \ln gdp_{t-1}^3 \\ & + \theta_{13} \ln scl_{t-1} + \theta_{14} \ln fin_{t-1} + \theta_{14} \ln sind_{t-1} + \theta_{14} \ln stra_{t-1} + \varepsilon \end{aligned} \quad (3)$$

Where Δ and θ_0 respectively represent the first different operator and the drift component. π_t is an error term. p denotes the maximum lag length. θ_1 — θ_8 depicts the error correction dynamics, and θ_9 — θ_{16} represent the long-run relationships among the variables in the model. The null hypothesis for the non-existence of a long-run relation is $H_0: \theta_9 = \theta_{10} = \theta_{11} = \theta_{12} = \theta_{13} = \theta_{14} = \theta_{15} = \theta_{16} = 0$, against the alternative hypothesis $H_1: \theta_9 \neq 0, \theta_{10} \neq 0, \theta_{11} \neq 0, \theta_{12} \neq 0, \theta_{13} \neq 0, \theta_{14} \neq 0, \theta_{15} \neq 0, \theta_{16} \neq 0$. Based on the Wald tests, this section calculates the F-statistic in order to test the presence of cointegration among the relevant variables. Pesaran et al. (2001) generated the upper and lower critical values for the F-statistic. In general, the null hypothesis of no cointegration will be rejected if the calculated F-statistic value is greater than the critical value of the upper bound, while the null hypothesis will not be rejected if the calculated F-statistic value is smaller than the critical value of the lower bound.

Moreover, we cannot conclude when the F-statistic value is between the upper and lower bounds. In addition, several diagnostic tests, such as the serial correlation test, the normality test, and the heteroskedasticity test are examined to ensure the model's goodness of fit and verify its reliability.

Second, to estimate the long-run parameters employing the ARDL approach according to the R-square (R^2), F-statistic, Durban-Watson statistic (DW), and Akaike information criterion (AIC), we use the SIC criteria to choose the lag length, and a maximum of three lags is proper for our test.

Third, to detect the short-run dynamics of the variables, we estimate the error correction model (ECM) term as shown in Eq. (4).

$$\begin{aligned}
 & \begin{bmatrix} \Delta \ln co_{2t} \\ \Delta \ln gdp_t \\ \Delta \ln gdp_t^2 \\ \Delta \ln gdp_t^3 \\ \Delta \ln scle_t \\ \Delta \ln fin_t \\ \Delta \ln sind_t \\ \Delta \ln stra_t \end{bmatrix} = \begin{bmatrix} \theta_{11,t} & \theta_{12,t} & \theta_{13,t} & \theta_{14,t} & \theta_{15,t} & \theta_{16,t} & \theta_{17,t} & \theta_{18,t} \\ \theta_{21,t} & \theta_{22,t} & \theta_{23,t} & \theta_{24,t} & \theta_{25,t} & \theta_{26,t} & \theta_{27,t} & \theta_{28,t} \\ \theta_{31,t} & \theta_{32,t} & \theta_{33,t} & \theta_{34,t} & \theta_{35,t} & \theta_{36,t} & \theta_{37,t} & \theta_{38,t} \\ \theta_{41,t} & \theta_{42,t} & \theta_{43,t} & \theta_{44,t} & \theta_{45,t} & \theta_{46,t} & \theta_{47,t} & \theta_{48,t} \\ \theta_{51,t} & \theta_{52,t} & \theta_{53,t} & \theta_{54,t} & \theta_{55,t} & \theta_{56,t} & \theta_{57,t} & \theta_{58,t} \\ \theta_{61,t} & \theta_{62,t} & \theta_{63,t} & \theta_{64,t} & \theta_{65,t} & \theta_{66,t} & \theta_{67,t} & \theta_{68,t} \\ \theta_{71,t} & \theta_{72,t} & \theta_{73,t} & \theta_{74,t} & \theta_{75,t} & \theta_{76,t} & \theta_{77,t} & \theta_{78,t} \\ \theta_{81,t} & \theta_{82,t} & \theta_{83,t} & \theta_{84,t} & \theta_{85,t} & \theta_{86,t} & \theta_{87,t} & \theta_{88,t} \end{bmatrix} \times \begin{bmatrix} \Delta \ln co_{2t-1} \\ \Delta \ln gdp_{t-1} \\ \Delta \ln gdp_{t-1}^2 \\ \Delta \ln gdp_{t-1}^3 \\ \Delta \ln scle_{t-1} \\ \Delta \ln fin_{t-1} \\ \Delta \ln sind_{t-1} \\ \Delta \ln stra_{t-1} \end{bmatrix} \\
 & + \dots + \begin{bmatrix} \theta_{11,p} & \theta_{12,p} & \theta_{13,p} & \theta_{14,p} & \theta_{15,p} & \theta_{16,p} & \theta_{17,p} & \theta_{18,p} \\ \theta_{21,p} & \theta_{22,p} & \theta_{23,p} & \theta_{24,p} & \theta_{25,p} & \theta_{26,p} & \theta_{27,p} & \theta_{28,p} \\ \theta_{31,p} & \theta_{32,p} & \theta_{33,p} & \theta_{34,p} & \theta_{35,p} & \theta_{36,p} & \theta_{37,p} & \theta_{38,p} \\ \theta_{41,p} & \theta_{42,p} & \theta_{43,p} & \theta_{44,p} & \theta_{45,p} & \theta_{46,p} & \theta_{47,p} & \theta_{48,p} \\ \theta_{51,p} & \theta_{52,p} & \theta_{53,p} & \theta_{54,p} & \theta_{55,p} & \theta_{56,p} & \theta_{57,p} & \theta_{58,p} \\ \theta_{61,p} & \theta_{62,p} & \theta_{63,p} & \theta_{64,p} & \theta_{65,p} & \theta_{66,p} & \theta_{67,p} & \theta_{68,p} \\ \theta_{71,p} & \theta_{72,p} & \theta_{73,p} & \theta_{74,p} & \theta_{75,p} & \theta_{76,p} & \theta_{77,p} & \theta_{78,p} \\ \theta_{81,p} & \theta_{82,p} & \theta_{83,p} & \theta_{84,p} & \theta_{85,p} & \theta_{86,p} & \theta_{87,p} & \theta_{88,p} \end{bmatrix} \times \begin{bmatrix} \Delta \ln co_{2t-1} \\ \Delta \ln gdp_{t-1} \\ \Delta \ln gdp_{t-1}^2 \\ \Delta \ln gdp_{t-1}^3 \\ \Delta \ln scle_{t-1} \\ \Delta \ln fin_{t-1} \\ \Delta \ln sind_{t-1} \\ \Delta \ln stra_{t-1} \end{bmatrix} \\
 & + \begin{bmatrix} \theta_{01} \\ \theta_{02} \\ \theta_{03} \\ \theta_{04} \\ \theta_{05} \\ \theta_{06} \\ \theta_{07} \\ \theta_{08} \end{bmatrix} + \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \\ \alpha_6 \\ \alpha_7 \\ \alpha_8 \end{bmatrix} \times (ECT_{t-1}) + \begin{bmatrix} \pi_{1t} \\ \pi_{2t} \\ \pi_{3t} \\ \pi_{4t} \\ \pi_{5t} \\ \pi_{6t} \\ \pi_{7t} \\ \pi_{8t} \end{bmatrix}
 \end{aligned} \tag{4}$$

Where ECT_{t-1} is the lagged error correction term generated from Eq. (2) using OLS, which represents the speed at which the dependent variable converges to the long-run equilibrium after a shock

of independent variables in the short run. Moreover, α is the speed of the adjustment coefficient. The sign of the coefficient of ECT_{t-1} must be statistically significant and its value between -1 and 0 (Jebli and Youssef, 2015).

We estimate Eq. (3) by the ARDL method for the long-run estimates during 1965-2017, including five separate models. The related literature employs the adjusted R^2 criterion, Hannan Quinn Criterion, AIC Criterion and SBC Criterion to find the coefficients of the level variables. Following Jalil and Feridun (2011), we present only the results of the model that are selected on the basis of SBC because it is known to select the most parsimonious model, where the smallest possible lag length is selected and the loss of freedom degree is minimized. Table 4 presents the results of the ARDL method. It is clear that the results of the five models support the N-shaped relationship, showing that the econometric model with a cubic term is appropriate.

The coefficient of *lnscl* is significantly negative, indicating that promoting clean energy consumption can improve environmental performance. This finding is consistent with the existing literature. More specifically, the value of the coefficient ranging between -0.233/-0.283 implies that improving the share of clean energy to total energy consumption by 10% will lead to a reduction of per capita carbon emissions by up to 2.83% in the long run, supporting Proposition 1 proposed in Section 2.

As description in section 3.1, we use two indicators measuring financial development—*lnscre* in model 1 to model 4 and *lnpcr* in model 5 for robustness test. All the coefficients of the variables measuring financial sector development are positive and significant (except the results in model 2), showing that financial sector development leads to more air pollution rather than reducing it. In other word, the substitution effect of financial development on carbon emissions is larger than the income effect, which support the theoretical analysis in Section 2. The coefficient ranges between 0.45-0.69, implying that a 10% rise in financial sector development will lead to a 4.5%-6.9% increase in per capita carbon emissions. This result is in sharp contrast to Tamazian et al. (2009), Jalil and Feridun (2013), who suggested that financial sector development can lead to a reduction in air pollution. The empirical results in Table 4 support Proposition 2 presented in last Section.

The sign of *lnsind* is significant and positive in models 3-5, indicating a higher share of manufacturing in the national economy causes more carbon emissions. It is clear that the manufacturing industry is the main source of environmental pollution. Fortunately, the share of this industry to GDP remains stable over time with a declining trend in the most recent years of the data period in China.

The coefficients of *lnstra* in Table 4, are statistically significant and positive, confirming that an increase in foreign trade also leads to more carbon emissions. These results are in line with the “pollution haven” hypothesis: a large amount of emissions in the developing countries is embodied in export commodities of the developing countries to be consumed by the developed economies. In fact, China’s carbon emissions experienced rapid growth after joining the WTO in 2001 (see Fig.1). Similarly, the significant and positive coefficients of *lnsind* show that an increase in the manufacturing industry leads to environmental degradation. Therefore, we can conclude that manufacturing is the main resource of carbon emissions as well as the main resource of exports.

In Table 4, the coefficient of ECT_{t-1} shows the speed of the adjustment back to the long-run equilibrium after a short run shock. The lagged error correction coefficients, ECT_{t-1} are correct in sign, and significant at the 1% level in all cases. This verifies the established cointegration relationship among the related variables. The values of the coefficients range between -0.395 and -0.652.

All the diagnostic tests show no evidence of serial correlation, normality and heteroscedasticity. The last stage of ARDL estimation is to test the stability of the models. All the plots of the CUSUM and CUSUMSQ statistics shown in Fig.4 are well within the critical bounds, confirming that all the coefficients in the ECM model are stable.

Table 4

The effects of variables on CO₂ emissions during 1965-2017 (ARDL).

	Model 1	Model 2	Model 3	Model 4	Model 5
<i>Cointegration tests</i>					
<i>F-statistic</i>	6.878	7.615	8.003	11.50	9.897
<i>ARDL estimate</i>					
<i>Constant</i>	-46.569** [-2.454]	-29.942** [-2.144]	-34.280*** [-2.231]	-33.972*** [-2.865]	-38.978*** [-3.110]
<i>lngdp</i>	17.323*** [2.805]	12.966*** [2.873]	12.062** [2.316]	12.678*** [3.107]	14.720*** [3.487]
<i>lngdp</i> ²	-1.871*** [-2.838]	-1.545*** [-3.311]	-1.446** [-2.770]	-1.531*** [-3.672]	-1.780*** [-4.309]
<i>lngdp</i> ³	0.067*** [2.896]	0.063*** [3.891]	0.057*** [3.231]	0.061*** [4.233]	0.070*** [4.852]

<i>lnscre</i>	/	0.087	0.790**	0.614**	/
		[0.579]	[2.549]	[2.613]	
<i>lnpcr</i>	/	/	/	/	0.450*
					[1.992]
<i>lnscl</i>	/	-0.729***	/	-0.233**	-0.283***
		[-6.236]		[-2.588]	[-2.898]
<i>lnsind</i>	/	/	1.208***	0.920***	0.807***
			[4.672]	[4.494]	[3.941]
<i>lnstrade</i>	0.234**	0.326***	0.289***	0.307***	0.278***
	[2.472]	[4.512]	[4.027]	[5.598]	[5.114]
<i>Error correction coefficient</i>					
<i>ECT_{t-1}</i>	-0.029***	-0.395***	-0.572***	-0.632***	-0.652***
	[-6.893]	[-8.696]	[-9.240]	[-11.954]	[-11.167]
<i>A-R²</i>	0.863	0.941	0.931	0.962	0.962
<i>Diagnostic test</i>					
χ^2_{sc}	0.389	5.636	0.890	0.093	1.131
	(0.177)	(0.228)	(0.641)	(0.761)	(0.345)
χ^2_{nor}	0.992	0.860	2.163	0.367	0.226
	(0.609)	(0.650)	(0.339)	(0.832)	(0.893)
χ^2_{het}	0.6595	23.292	27.661	34.933	1.594
	(0.956)	(0.225)	(0.429)	(0.141)	(0.207)

Notes: the F-statistics of the bounds test are against the critical values reported in Pesaran et al. (2001).

The t-statistics are presented in square brackets and p-values in parentheses. ** Variable interpreted as

$Z = Z(-1) + D(Z)$. Bartlett kernel, Newey-West fixed bandwidth = 4.0.

Model 1

Model 2

Model 3

Model 4

Model 5

Fig.4. Plots of the cumulative sums of square recursive residuals.

Notes: Straightlines represent critical bounds at 5% significant level; models 1-4 with *scre* while model 5 with *pcr*.

4.3. The results of VECM Granger causality tests

Table 5 represents both the short-run and long-run Granger causality relationships among the variables and their causal directions thereof. The short-run causality tests state that there is a significant bidirectional relationship between clean energy consumption and carbon emissions. Similarly, clean energy consumption has a significant impact on economic growth, which in turn has a significant effect on the former. Financial sector development has a significant effect on carbon emissions through industrial structure change. The relationship between financial sector development and carbon emissions is unidirectional. Fig.5 summarizes the short-run Granger causalities between the related variables.

From the long-run causality test results, the coefficients of the error correction terms (ECT) in all the models are statistically significant based on Eq. (4). The estimated coefficients are all within the range of $(-1, 0)$, revealing a moderate speed of adjustment from the short run to the long-run equilibrium. Looking into the short-run dynamics causality in Fig.5 and the long-run dynamics causality in Table 5, we can highlight the main causal relationships.

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Fig.5. Pairwise Granger causality results.

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Table. 5
Granger causality tests

Dependent variable	Short-run								Long run
	$\Delta \ln co_2$	$\Delta \ln gdp$	$\Delta \ln gdp^2$	$\Delta \ln gdp^3$	$\Delta \ln scre$	$\Delta \ln scle$	$\Delta \ln stra$	$\Delta \ln sind$	$ECT(-1)$
$\Delta \ln co_2$	-	5.188 [1.006]	-0.570 [-0.986]	0.023 [1.079]	-0.037 [-0.383]	-0.228*** [-3.295]	0.054 [1.204]	0.612*** [2.932]	-0.296*** [-2.314]
$\Delta \ln gdp$	0.002 [0.371]	-	0.112*** [95.103]	-0.004*** [-49.368]	0.002 [0.649]	0.004* [1.754]	-0.003*** [-2.244]	0.014** [2.310]	-0.189* [-1.957]
$\Delta \ln gdp^2$	-0.015 [-0.400]	8.874*** [94.374]	-	0.037*** [99.861]	-0.012 [-0.477]	-0.039* [-1.868]	0.027** [2.453]	-0.111* [-1.990]	-0.195** [-2.020]
$\Delta \ln gdp^3$	0.543 [0.543]	-237*** [-48.708]	26.82*** [99.281]	-	0.245 [0.358]	1.160** [2.048]	-0.789** [-2.635]	2.583* [1.689]	-0.208** [-2.119]
$\Delta \ln scre$	0.076 [0.393]	4.313 [0.659]	-0.420 [-0.574]	0.014 [0.528]	-	-0.131 [-1.470]	-0.018 [-0.308]	-0.996*** [-3.716]	-0.529*** [-4.068]
$\Delta \ln scle$	-0.768*** [-3.362]	15.253* [1.791]	-1.756* [-1.852]	0.070* [1.993]	-0.016 [-0.097]	-	0.138* [1.847]	-0.408 [-1.079]	-0.815*** [-5.673]
$\Delta \ln stra$	0.699 [1.605]	-35.117** [-2.443]	4.242*** [2.662]	-0.167*** [-2.862]	-0.504* [-1.706]	0.546*** [2.665]	-	-1.037 [-1.511]	-0.459*** [-3.331]
$\Delta \ln sind$	0.255*** [3.141]	6.981** [2.447]	-0.710** [-2.207]	0.024* [1.966]	-0.215*** [-3.899]	-0.047 [-1.153]	-0.014 [-0.512]	-	-0.312*** [-3.070]

Table. 6

The results of FMOLS, DOLS and CCR (1965-2017).

	Model I			Model II			Model III			Model IV		
	FMOLS	DOLS	CCR	FMOLS	DOLS	CCR	FMOLS	DOLS	CCR	FMOLS	DOLS	CCR
C	-55.38*** [-7.904] 21.410***	-62.31*** [-4.940] 23.608***	-53.60*** [-7.611] 20.815***	-60.83*** [11.703] 23.195***	-83.07*** [-10.359] 30.289**	-59.69*** [-11.139] 22.830**	-48.96*** [-7.642] 18.528**	-82.45*** [-8.768] 30.149**	-49.10*** [-6.944] 18.676**	-50.03*** [-8.453] 14.152***	-84.86*** [-9.603] 22.993***	-49.88*** [-7.359] 14.779***
<i>lngdp</i>					*	*	*	*	*			
<i>lngdp</i> ²	[9.018] -2.462*** [-9.211]	[5.909] -2.684*** [-6.475]	[8.647] -2.397*** [-8.763]	[13.181] -2.614*** [-13.265]	[11.939] -3.317*** [-12.782]	[12.536] -2.574*** [-12.636]	[7.955] -2.151*** [-8.631]	[9.430] -3.306*** [-10.292]	[7.235] -2.162*** [-7.848]	[4.251] -1.642*** [-4.461]	[5.813] -2.485*** [-5.688]	[4.516] -1.707*** [-4.697]
<i>lngdp</i> ³	0.096*** [9.620]	0.104*** [7.271]	0.093*** [9.095]	0.101*** [13.624]	0.123*** [14.105]	0.099*** [12.989]	0.085*** [9.394]	0.123*** [11.355]	0.085*** [8.547]	0.065*** [4.843]	0.093*** [5.852]	0.068*** [5.052]
<i>linscle</i>	-0.931*** [-11.123]	-1.002*** [-5.737]	-0.940*** [-11.214]	-0.812*** [-11.842]	-0.598*** [-4.888]	-0.828*** [-11.802]	-0.655*** [-7.953]	-0.567*** [-4.167]	-0.689*** [-7.504]	-0.663*** [-8.717]	-0.715*** [-4.880]	-0.694*** [-8.240]
<i>linscre</i>	-	-	-	-0.313*** [-3.259]	-0.578*** [-5.097]	-0.330*** [-3.463]	-0.006 [-0.046]	-0.641** [-2.626]	-0.053 [-0.377]	3.434* [1.663]	5.343* [1.891]	2.959 [1.417]
<i>linsind</i>	-	-	-	-	-	-	0.613** [2.798]	0.004 [0.015]	0.540** [2.335]	4.341* [1.917]	6.427** [2.110]	3.801* [1.660]
<i>linscre*ln sind</i>	-	-	-	-	-	-	-	-	-	-0.957*	-1.683**	-0.837
<i>lnstra</i>	0.301*** [4.798]	0.234** [2.186]	0.313*** [4.994]	0.271*** [5.800]	0.224*** [3.941]	0.283*** [5.908]	0.303*** [6.652]	0.280*** [4.099]	0.310*** [6.710]	0.318*** [7.157]	0.281*** [4.588]	0.318*** [7.210]
<i>A- R</i> ²	0.992	0.996	0.991	0.993	0.998	0.993	0.994	0.998	0.994	0.995	0.998	0.994

Notes: for FMOLS, with lags=2 from SIC maxlags = 3, Bartlett kernel, Newey-West fixed bandwidth = 4. For DOLS, Fixed leads and lags specification (lead=1, lag=1).

4.4. Cointegration analysis

We further employ three different cointegration methods, such as the fully modified least squares (FMOLS), the dynamic least squares (DOLS) and the canonical cointegration regressions (CCR) to estimate Eq. (2) and test the validity and reliability of the results following Baek (2016) and Danish et al. (2017). The results of the four different models are reported in Table 6. The results of models I-IV all show that the coefficients of both $\ln gdp$ and $(\ln gdp)^3$ are statistically significant and positive, while the coefficients of $(\ln gdp)^2$ are negative and significant. That is, the relationship between GDP and carbon emissions in China during 1965-2017 is N-shaped rather than inverted U-shaped, which is consistent with the results presented in Fig.2 and the ARDL regressions.

While the coefficient of $\ln scre$ in models II and III is negative and significant, it is positive in model IV when we control the interaction term of $\ln scre * \ln sind$. The term of $\ln scre * \ln sind$ is to examine the interaction effect of financial development and industrial structure on carbon emission intensity. Financial sector development has a positive effect on carbon emissions like the results in section 4.2. That is, financial sector development could affect environmental quality through changing industrial structure. This is because the cost of capital becomes lower than before as a result of financial sector development, which allows firms to invest in research on new technologies and to develop renewable energy as well as nuclear power. Renewable energy and nuclear power belong to the so-called capital-intensive industries. Our research finding supports Grossman and Krueger (1995) and Halicioglu (2009) who argued that more funding opportunities for private firms enable them to reduce their dependence on dirty energy.

The coefficients of $\ln scle$ and $\ln stra$ in the models are negative and positive respectively. They respectively indicate that increasing renewable energy consumption share in total energy consumption could reduce carbon emissions. In contrast, increasing foreign trade may lead to more carbon emissions. This finding also supports Grossman and Krueger (1995) who suggested that developing countries tend to develop dirty industries with a heavy share of pollutants due to their desire for fast industrialization despite knowing the significant cost of environmental pollution. As shown in Fig.1, the growth rate of carbon emissions has accelerated significantly after China's accession to the WTO in 2001. However, the total amount of carbon emissions in America remains almost unchanged. This phenomenon is consistent with the "pollution haven" hypothesis as explained before.

5. Conclusions and policy implications

Based on a two-sector model from a directed technical change perspective, this paper examines the relationship between carbon emissions, clean energy and financial sector development in China during 1965-2017 using the ARDL and the dynamic cointegration models. It tests the impacts of clean energy consumption, financial sector development, and economic growth on carbon emissions controlling the main related factors such as industrial structure and international trade. It is found that the effect of clean energy consumption on carbon emissions is significantly negative but the effect of financial sector development, measured by the proxies of banking sector development, is opposite. It suggests that financial sector development promote carbon emissions instead of reducing it, contradicting the findings of many existing studies (Tamazian et al., 2009; Jalil and Feridun, 2011; Acheampong et al., 2020). To explain this puzzle, we build a theory by decomposing the effect of financial sector development on carbon emissions into two components: the substitution effect and the income effect following the Slutsky decomposition principle (Nechyba, 2016). Given dirty energy as an “inferior” good, the theory built in Section 2 show that the substitution effect outweighs the latter so that financial sector development in China lead to more carbon emissions. For the availability of data, it is difficult to estimate the substitution effect and income effect, respectively. For simplicity, we just estimate the net effect of substitution and income effect. Fortunately, the coefficient of financial development is positively significant in the empirical analysis. That is, the net effect of financial development increases carbon emissions. In other words, the size of substitution effect is greater than income effect, which is consistent with theoretical analysis. This finding has some important policy implications as it implies that energy structural change should incorporate industrial structural transformation and finance sector reform to reduce carbon emissions more effectively.

The main findings of this paper include the following: (i) It proves the existence of the environmental Kuznets curve (EKC) hypothesis with a shape of N after controlling clean energy consumption, financial sector development and other related factors. (ii) Clean energy has a significantly negative effect on carbon emissions in both the short and long runs. (iii) The effect of financial sector development on carbon emissions is positive, leading to more carbon emissions instead of reducing it. (iv) The manufacturing sector has a positive impact on carbon emissions, suggesting that the secondary industry is the most important carbon emitter among all the industrial sectors of the Chinese economy. (v) The impact of foreign trade on carbon emissions is significantly positive, supporting the “pollution

haven” hypothesis. (vi) Financial sector development affects environmental quality due to its impact on industrial structural change and firm revenue-generating capability.

Some latest studies such as Xu et al. (2020) quantified the progress towards the 17 United Nations Sustainable Development Goals (SDGs) at the national and regional levels in China. It was found that SDG 13 (climate action) showed the greatest decline, while SDG 17 (affordable and clean energy) presented the greatest improvement. It implies that shifting the energy consumption mix away from fossil fuels toward using more and more clean energy takes time although the process in China has long begun (Yao et al., 2019). The results of our paper suggests that the share of clean energy as a proportion of total energy consumption has gradually increased and clean energy consumption is shown to have had a significant impact on carbon emissions reduction although its impact has not been large enough to prevent total carbon emissions from rising. Therefore, promoting clean energy consumption through financial sector development is an important policy instrument helping China to achieve its ambitious goal of containing carbon emissions. In light of the two counteractive effects of financial sector development on carbon emissions discussed in the paper, energy structural change depends on a rising income effect and a declining substitution effect of financial sector development. In the case of China, the following policy recommendations can be made based on the theoretical and empirical analyses in this paper.

First, permanent policy intervention is required to prevent a climate disaster for the low substitution between the dirty and clean energy sectors. Second, promoting the efficiency of transportation and storage is an important way to increase the substitution between the two energy sectors. Third, using appropriate and differential tax policies to accelerate the energy structure shift away from fossil fuels to clean energy sources. Finally, research subsidies or profit taxes should be used to guide the direction of research in favor of the clean energy sector. Once the two energy sectors become highly substitutable, carbon taxes or research subsidies for a temporary period would be sufficient to induce technical change in favor of clean energy and to avoid climate disasters.

Ethical Approval

Not applicable

Consent to Publish

Not applicable

Consent to Participate

Not applicable

Competing Interests

The authors declare that they have no competing interests.

Availability of data and materials

The datasets used or analysed during the current research are available from the corresponding author on reasonable request.

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Authors Contributions

Conceptualization: [Shujie Yao, Shuai Zhang]; Methodology: [Shuai Zhang]; Formal analysis and investigation: [Shuai Zhang]; Writing - original draft preparation: [Shuai Zhang]; Writing - review and editing: [Shujie Yao]; Funding acquisition: [Shujie Yao, Shuai Zhang]; Resources: [Shujie Yao]; Supervision: [Shujie Yao]. All authors read and approved the final manuscript.

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Figures

Figure 1

The CO2 emissions of major countries and the world. Sources: BP (2018)

Figure 2

Substitution and capital intensity effects with directed technical change.

Figure 3

The N-shaped relationship between lngdp and lnco2

Model 2

Model 3

Model 4

Model 5

Figure 4

Plots of the cumulative sums of square recursive residuals. Notes: Straightlines represent critical bounds at 5% significant level; models 1-4 with scre while model 5 with pcre.

Figure 5

Pairwise Granger causality results.