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Abstract

Understanding the influencing factors of carbon dioxide emissions is an essential prerequisite for pol- icy makers to maintain sustainable low-carbon economic growth. Based on the Autoregressive Distributed Lag Model (ARDL) and Vector Error Correction Model (VECM), we investigate the relationships among economic growth, carbon emission, financial development, renewable energy consumption and technology innovation for China for the period 1965-2018. Our empirical results confirm the presence of a long run relationship among the underlying variables. Our long run estimates show that financial development has negatively significant impacts on carbon emissions, whereas renewable energy and technology innovation have limited impacts on carbon mitigations. In addition, the short run Granger causality analysis reveals that renewable energy consumption has a bidirectional Granger causality with carbon emissions and technology innovations. In the short run, we find that financial development can positively effect China's carbon mitigation indirectly, via the channels of renewable energy sources and technology innovations. Our results have a number of public policy implications for Chinese policy makers to maintain sustainable low carbon economic development: (i) establish a green finance market to mobilize the social capital into green industry; (ii) continue the environmental law enforcement to control for carbon emissions among energy-intensive industries; (iii) provide government fiscal incentives to promote renewable energy sources on both supply and demand sides of the market.

AMS/JEL classification: K32, O13, P28

Keywords: Financial development, Carbon emissions, ARDL, China

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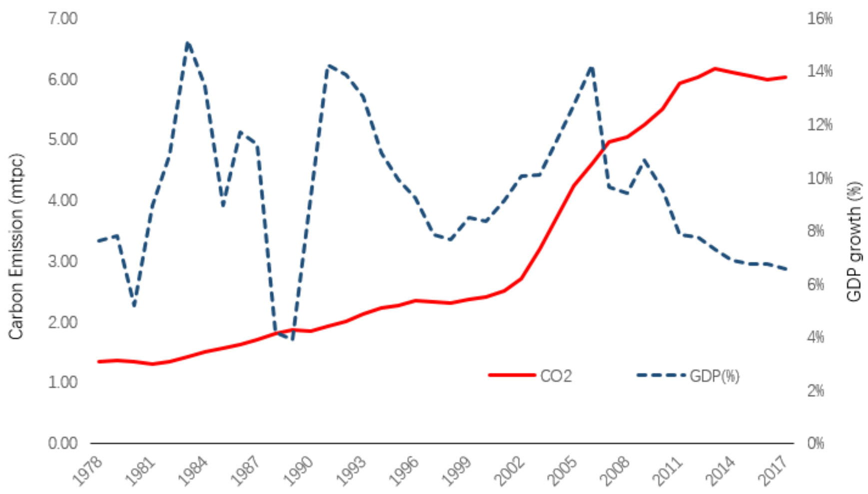
1. Introduction

Along with rapid economic growth, China is facing serious challenges in climate change environmental degradation mainly resulting from its high reliance on fossil fuel consumptions. The rapid economic expansion led China to become the largest carbon emitter in the world in 2006 (Thompson et al., 2016). During the period from 1978 to 2018, according to data published by National Bureau of Statistics of China (NBSC) (2019), the CO_2 emissions in China increased from 1.35 to 6.12 metric tonnes per capita (See Figure 1). In 2018, the human-included CO_2 emissions in China account for approximately 27.8% of global emissions (BP, 2019). Consequently, China is playing a significant role in global carbon reduction and climate change mitigation under the Paris Agreement.

Figure 1: 1978-2018 China carbon emissions and GDP growth



Sources: National Bureau of Statistics of China (2018).

In order to reduce the country's coal dependency, China proposed a target to change the economic development strategy from conventional manufacturing-driven to service-oriented structure based on a clean and low-carbon energy supply system (Song et al., 2018). Along with the transition to low-carbon economic development, the Chinese government has proposed a target to achieve a 60% - 65% reduction in its carbon intensity by 2030 compared with its 2005 levels (Jiao et al., 2018). The accomplishment of the low-carbon economic development in China requires the government to promote public policies leading to significantly lower consumption of fossil fuels. Therefore, an important dilemma arises about how China can achieve a balance between the environmental degradation and economic growth, given the present massive market demand for fossil fuel consumption. In particular, the public finance aspect of this problem will form a significant challenge for the Chinese government. In this context, we review the growth-pollution nexus in China with focuses on financial development, renewable energy and technology innovation. We combine the

Autoregressive Distributed Lag Model (ARDL) and the Vector Error Correction Model (VECM) to conduct the empirical analysis to study the long run and short run relationships among underlying variables. This study contributes to the literature in the following two aspects: (i), we review the growth-pollution nexus for China with a considerably extended database using Markov chain Monte Carlo (MCMC) simulation approach to fill in missing values; (ii), we emphasize the roles of renewable energy sources and technology innovation in reducing carbon emissions in China over the long run and short run. To be more specific, our purpose is to observe whether the pace of renewable energy development and technological progress could accelerate the process of achieving a low-carbon economy in China.

Regarding the research on influencing factors, numerous studies have examined an inverted U-relationship (known as the environmental Kuznets curve (EKC) hypothesis), between economic growth and carbon emissions. However, the theoretical concept of the EKC hypothesis is more likely to be a country or region-specific issue in empirical research, and there is no universal consensus among scholars regarding the sign, magnitude and significance of the relationship. For instance, the EKC hypothesis is empirically supported for Singapore, Thailand, China, Pakistan, Turkey, Tunisia, Denmark, Italy, the EU countries, and upper-middle and high-income countries (Saboori and Sulaiman, 2013; Li et al., 2016; Jayanthakumaran et al., 2012; Javid and Sharif, 2016; Shafiei and Salim, 2014; Acaravci and Ozturk, 2010; Kasman and Duman, 2015; Al-Mulali et al., 2015; Cetin et al., 2018). In contrast, the EKC hypothesis is invalidated for Russia, the Middle East countries, OECD countries, and low-income economies (Pao et al., 2011; Ozcan, 2013; Dogan and Seker, 2016; Al-Mulali et al., 2015). We could see that some of the regions with different EKC results overlap. The study of Dogan and Seker (2016) among others provides an extensive survey of investigations on influential factors of carbon emissions and points out that economic growth is not the only indicator of carbon emissions in a country; financial development, energy consumption structure, production structure and technology development may also influence carbon pollution.

The literature on the linkage between financial development and carbon emission has been extensively studied in both theoretical and empirical research. However, the previous findings regarding the impact of financial development on environmental performance are inconsistent and inconclusive. For instance, Sadorsky (2010), Javid and Sharif (2016) and Zhang (2011) note that financial liberalization may exacerbate environmental degradation through an increased level of economic activities and energy consumptions. On the contrary, some opposing views hold that a well-established financial development can mobilise public financial resources effectively for investments in green economy-related businesses (Jalil and Feridun, 2011; Tang and Tan, 2013; Saboori and Sulaiman, 2013; Dogan and Seker, 2016). As a result, firms can raise funds effectively for developing environmental-friendly technologies, and eventually require less energy input for productions and emit less greenhouse gases (GHG). For the bank-based financial system, the findings of Shahbaz et al. (2013) confirm the significant role of financial development in combatting carbon emissions as better financial development can support green projects with higher financing at lower costs. Furthermore, Kim and Park (2016) opine that the dependency of renewable energy sectors on banking and credit markets raises disproportionately faster in countries with solid and matured financial markets. In terms of the empirical research, Cetin et al. (2018) for Turkey, Dogan and Seker

(2016) for top renewable countries, and Saidi and Mbarek (2017) for 19 emerging economies reveal that the impact of financial development on carbon reduction is positive and remains statistically significant in the long run.

More recently, many studies investigate the effect of renewable energy and technology on carbon mitigation and empirical analyses predominately claim that there are positive relationships among the three. Tang and Tan (2013) point out that greater technology innovations could create more green energy and energy savings products, which in turn leads to a better quality of environment and economic growth. Using the total factor productivity (TFP) measurement, Ang (2009) argues that technology innovation could be an effective solution for improving environmental performance, only if there is a significant proportion of research focused on pollution abatement and clean technology development.

Renewable energy sources are expected to replace fossil fuels for the purpose of diminishing environmental degradation (Irandoust, 2016; Chen et al., 2019). The positive linkage between renewable energy and carbon migration has also been empirically supported by various studies for many countries and regions, such as Tamazian and Rao (2010) for Malaysia, Apergis and Payne (2014) for Central America and Shafiei and Salim (2014) for OECD countries. By studying a panel of four Nordic countries, Irandoust (2016) finds a significant Granger causality from renewable energy consumption to carbon migrations. Based on vector error correction model (VECM), Chen et al. (2019) reveal that renewable energy consumption was one of the significant contributors for carbon reductions in China over the period 1980 – 2014. Nevertheless, Bhattacharya et al. (2017) opine that the impact of renewable energy on carbon mitigations could be limited if it is not accomplished within a strong and solid institutional governance.

The remaining sections of this paper are structured as follows. Section 2 details data sources, and empirical methodology. Section 3 discusses main empirical results and their policy implications. Section 4 concludes the study.

2. Data descriptions and methodology

2.1. Data

Seven variables were included in this study to examine the impact of renewable energy consumption, technology innovation and financial development on carbon emissions in the case of China. Annual data for China over the period 1965-2018 was collected from the BP, the World Bank Development Indicators (WDI) online databases, National Bureau of Statistics of China, and the Chinese Wind databases. Table 1 summarises a list of variable descriptions, measures and data sources used in our empirical analysis. Note that our sample contains missing values (30% of total sample observations) due to the data limitation. In trying to overcome the issue of

missing data, we use the method of multiple imputation to generate plausible values based on characteristics of the given sample observations. The multiple imputation was implemented in STATA. The imputation method consists of following steps. First, we identify which of the variables in our study contains missing information. Second, we specify the imputation model using an iterative Markov china Monte Carlo (MCMC) procedure to fill in missing data. The procedure generates imputed values based on the assumption that all missing values have a joint multivariate normal distribution. The number of imputations depends on the proportion of missing information (von Hippel, 2018). In this study, we generated 20 imputations, and combined all generated datasets (taken as an average) to obtain one representative set of sample observations for our further empirical analysis. Descriptive statistics of underlying variables are summarized in Table 2. The Jarque-Bera (JB) normality test results suggest that each of these variables follows normal distribution.

Table 1 Variables and data definitions

Variable	Description	Period	Source
$CO_{2,t}$	China's Carbon Emissions per capita in million tons of oil equivalent(mtoe)	1965-2018	NBSC
GDP_t	China's GDP per capita measured in Chinese Yuan	1965-2018	NBSC
SS_t	Stock market scale, represented by the ratio of market capitalization of GDP	1991-2018	Wind Database
FS_t	Financial intermediation scale, represented as the ratio of domestic credit provided by financial sector of GDP	1977-2018	World Bank
FDI_t	Foreign Direct Investment,represented as the ratio of FDI net inflows of GDP	1982-2018	World Bank
REC_t	Renewable energy consumption, measured in million tonnes oil equivalent(mtoe)	1990-2018	BP
TI_t	Technology Innovation, proxied by China's annual spendings on R&D as percentage of GDP	1996-2017	World Bank

NBSC: National Bureau of Statistics of China
Wind Database: A data provider in China with a specific focus on China's economy
BP: British Petroleum
World Bank: World Bank Development Indicators Online Databases

Table 2 Summary statistics

Variable	Obs	Mean	Std.Dev.	Skewness	Kurtosis	JB normality
Ln(CO_2)	54	0.732	0.721	0.040	2.028	2.14(0.3430)
Ln(GDP)	54	7.907	1.923	0.193	1.568	4.951(0.0841)
Ln(SS)	54	-4.065	3.103	-0.127	1.381	6.041 (0.0488)
Ln(FS)	54	-0.135	0.488	0.154	1.863	3.121(0.2100)
Ln(FDI)	54	-4.060	0.840	-0.442	2.298	2.866(0.2385)
Ln(TI)	54	-5.331	0.994	0.124	1.575	4.708(0.0950)
Ln(REC)	54	-2.689	4.304	0.276	1.653	4.765(0.0923)

Notes: We use the Markov chain Monte Carlo (MCMC) simulation apparoch to fill in missing value. We apply the Jarque–Bera (JB) test to normality. The value in parentheses denotes the p-value for test significance

2.2. ARDL bounds testing

To examine the presence of a long run relationship between carbon emissions and its covariates, we use the Autoregressive Distributed Lag (ARDL) bounds testing approach (Pesaran and Shin, 1998; Pesaran et al., 2001) to test the cointegration among the underlying variables. This technique has several advantages in comparison with other conventional cointegration approaches. First, the ARDL has proved to be efficient and it provides unbiased estimates with valid t-statistics for small sample size (Salahuddin et al., 2018). Second, the ARDL estimation does not require the prior classification of variables to be integrated of the same order, the estimation can be carried out regardless of the order of integration among underlying variables. Third, the error correction model (ECM) short-run adjustments can be derived straightforwardly from the ARDL model through a simple linear transformation without losing long-run information (Pesaran and Shin, 1998). An ARDL model is expressed as follows:

$$\begin{aligned}\Delta ln(CO_2)_t = \beta_0 &+ \sum_{i=1}^{n}\beta_{1,i}\Delta ln(CO_2)_{t-i} + \sum_{i=1}^{n}\beta_{2,i}\Delta ln(GDP)_{t-i} + \sum_{i=1}^{n}\beta_{3,i}\Delta ln(SS)_{t-i} \\ &+ \sum_{i=1}^{n}\beta_{4,i}\Delta ln(FS)_{t-i} + \sum_{i=1}^{n}\beta_{5,i}\Delta ln(FDI)_{t-i} + \sum_{i=1}^{n}\beta_{6,i}\Delta ln(TI)_{t-i} \\ &+ \sum_{i=1}^{n}\beta_{7,i}\Delta ln(REC)_{t-i} + \lambda_1 ln(CO_2)_{t-1} + \lambda_2 ln(GDP)_{t-1} \\ &+ \lambda_3 ln(SS)_{t-1} + \lambda_4 ln(FS)_{t-1} + \lambda_5 ln(FDI)_{t-1} \\ &+ \lambda_6 ln(TI)_{t-1} + \lambda_7 ln(REC)_{t-1} + \varepsilon_t\end{aligned} \tag{1}$$

where β_i and λ_i refer to short-run and long-run parameters respectively. The error term ε_t is assumed to be white noise disturbance with zero mean and constant variance. The modelling further proceeds in following two steps. First, we determine the optimal number of lags for each variable based on the Akaike Information Criteria (AIC) and the Schwartz-

Bayesian Criterion (SBC). Second, Eq.(1) is estimated using ordinary least squares (OLS) approach to identify the long-run relationship among the variables by performing an F-test for the joint significance of lagged level variables. The null hypothesis of no cointegration in Eq.(1) is $H_0 : \lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = \lambda_6 = \lambda_7 = 0$, against the alternative hypothesis of presence of cointegration that $H_1 : \lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = \lambda_6 = \lambda_7 = 0$.

The decision about the cointegration test is based on a comparison between the model produced F-statistics and Pesaran et al. (2001) bounds critical values. We can reject the null hypothesis of no cointegration, if the model produced F-statistic is higher than upper-bound critical values (F-statistic > $I(1)_{critical}$). On the other hand, if the computed F-statistic is less than lower-bound critical values (F-statistic < $I(0)_{critical}$), we would have insufficient evidence to reject the null hypothesis. However, if it falls between the upper and lower bound critical values, our cointegration test result will remain inconclusive. If the variables are found to be cointegrated, we can establish an error correction model (ECM) straightforwardly from the ARDL estimation through a simple linear transformation. The long-run and short-run relationships can be estimated as specified by Eqs.(2) and (3), respectively:

$$\begin{aligned} ln(CO_2)_t = \alpha_1 &+ \sum_{i=1}^{n} \gamma_{1,i} ln(CO_2)_{t-i} + \sum_{i=0}^{n} \gamma_{12,i} ln(GDP)_{t-i} + \sum_{i=0}^{n} \gamma_{13,i} ln(SS)_{t-i} \\ &+ \sum_{i=0}^{n} \gamma_{14,i} ln(FS)_{t-i} + \sum_{i=0}^{n} \gamma_{15,i} ln(FDI)_{t-i} + \sum_{i=0}^{n} \gamma_{16,i} ln(REC)_{t-i} \\ &+ \sum_{i=0}^{n} \gamma_{17,i} ln(TI)_{t-i} + \varepsilon_{2t} \end{aligned} \tag{2}$$

$$\begin{aligned} \Delta ln(CO_2)_t = \beta_0 &+ \sum_{i=1}^{n} \beta_{1,i} \Delta ln(CO_2)_{t-i} + \sum_{i=0}^{n} \beta_{2,i} \Delta ln(GDP)_{t-i} + \sum_{i=0}^{n} \beta_{3,i} \Delta ln(SS)_{t-i} \\ &+ \sum_{i=0}^{n} \beta_{4,i} \Delta ln(FS)_{t-i} + \sum_{i=0}^{n} \beta_{5,i} \Delta ln(FDI)_{t-i} + \sum_{i=0}^{n} \beta_{6,i} \Delta ln(REC)_{t-i} \\ &+ \sum_{i=0}^{n} \beta_{7,i} \Delta ln(TI)_{t-i} + \psi ECT_{t-1} + \varepsilon_{3t} \end{aligned} \tag{3}$$

where ψ represents the coefficient of error correction term (ECT_{t-1}), defined as follows:

$$\begin{aligned} ECT_{t-1} = \varepsilon_{2t} = ln(CO_2)_t - \alpha_1 &- \sum_{i=1}^{n} \gamma_{1,i} ln(CO_2)_{t-i} - \sum_{i=0}^{n} \gamma_{12,i} ln(GDP)_{t-i} - \sum_{i=0}^{n} \gamma_{13,i} ln(SS)_{t-i} \\ &- \sum_{i=0}^{n} \gamma_{14,i} ln(FS)_{t-i} - \sum_{i=0}^{n} \gamma_{15,i} ln(FDI)_{t-i} - \sum_{i=0}^{n} \gamma_{16,i} ln(REC)_{t-i} \\ &- \sum_{i=0}^{n} \gamma_{17,i} ln(TI)_{t-i} \end{aligned}$$

2.3. Causality analysis

Although the Pesaran et al. (2001) bounds test reveals the presence or absence of a long run relationship among the underlying variables, it does not indicate the direction of causality. Thus, we apply the vector error correction model (VECM) to conduct the Granger causality analysis. The VECM equations can be expressed as follows:

$$\begin{bmatrix} \Delta Ln(CO_2)_t \\ \Delta Ln(GDP)_t \\ \Delta Ln(SS_t \\ \Delta Ln(FS)_t \\ \Delta Ln(FS)_t \\ \Delta Ln(FDI)_t \\ \Delta Ln(REC)_t \\ \Delta Ln(TI)_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \\ \alpha_5 \\ \alpha_6 \\ \alpha_7 \end{bmatrix} + \sum_{p-1}^{q} \begin{bmatrix} \varphi_{11p} & \varphi_{12p} & \varphi_{13p} & \varphi_{14p} & \varphi_{15p} & \varphi_{16p} & \varphi_{17p} \\ \varphi_{21p} & \varphi_{22p} & \varphi_{23p} & \varphi_{24p} & \varphi_{25p} & \varphi_{26p} & \varphi_{27p} \\ \varphi_{31p} & \varphi_{32p} & \varphi_{33p} & \varphi_{34p} & \varphi_{35p} & \varphi_{36p} & \varphi_{37p} \\ \varphi_{41p} & \varphi_{42p} & \varphi_{43p} & \varphi_{44p} & \varphi_{45p} & \varphi_{46p} & \varphi_{47p} \\ \varphi_{51p} & \varphi_{52p} & \varphi_{53p} & \varphi_{54p} & \varphi_{55p} & \varphi_{56p} & \varphi_{57p} \\ \varphi_{61p} & \varphi_{62p} & \varphi_{63p} & \varphi_{64p} & \varphi_{65p} & \varphi_{66p} & \varphi_{67p} \\ \varphi_{71p} & \varphi_{72p} & \varphi_{73p} & \varphi_{74p} & \varphi_{75p} & \varphi_{76p} & \varphi_{77p} \end{bmatrix}$$

$$+ \begin{bmatrix} \Delta Ln(CO_2)_{t-1} \\ \Delta Ln(GDP)_{t-1} \\ \Delta Ln(SS_{t-1} \\ \Delta Ln(FS)_{t-1} \\ \Delta Ln(FS)_{t-1} \\ \Delta Ln(FDI)_{t-1} \\ \Delta Ln(REC)_{t-1} \\ \Delta Ln(TI)_{t-1} \end{bmatrix} + \begin{bmatrix} \psi_1 \\ \psi_2 \\ \psi_3 \\ \psi_4 \\ \psi_5 \\ \psi_6 \\ \psi_7 \end{bmatrix} ECT_{i,t-1} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \\ \varepsilon_{7t} \end{bmatrix} \quad (4)$$

where ECT_{t-1} refers to the lagged error correction term derived from long-run via the ARDL estimation. α_i are constants, and ε_{it} are serially uncorrelated random disturbances with zero mean and constant variance. φ_i represents the speed of adjustment showing the degree to which disequilibrium is corrected within one period. The autoregression lag length, q is determined by the Schwarz information criterion (SBC). The direction of the short-run Granger causality can be identified by accessing the joint significance of coefficients of explanatory variables in each equation.

3. Empirical results and discussions

We perform the augmented Dicky-Fuller (ADF) and Phillips–Perron (PP) test to identify statistical properties of each variables. The results of ADF and PP unit test (See Table 3) reveal that all variables are non- stationary at their levels and are stationary at first differences, which suggests that our variables are integrated of order one.

The results of the cointegration analysis are presented in Table 4. Schwarz-Bayesian Criterion (SBC) is used to determine the optimal lag structure of our ARDL estimation. The final ARDL model is selected based on the fulfilments of all relevant diagnostic tests, including the Jarque–Bera test for normality of residuals,

Table 3 Unit root tests

	Augmented Dicky-Fuller(ADF)		Phillips-Perron		Decision
Variable	Level	First Difference	Level	First Difference	
Ln(CO_2)	-1.585	-3.918***	-9.818	-23.892***	I(1)
Ln(GDP)	-3.472	-3.214*	-6.572	-18.279*	I(1)
Ln(SS)	-2.215	-8.385***	-6.825	-61.058***	I(1)
Ln(FS)	-2.656	-7.986***	-10.198	-55.158***	I(1)
Ln(FDI)	-2.058	-7.206***	-8.148	-49.486***	I(1)
Ln(TI)	-2.892	-7.472***	-11.444	-51.427***	I(1)
Ln(REC)	-2.532	-7.856***	-7.447	-63.145***	I(1)

Note: ***, **, * denotes statistical significance level at 1%, 5% and 10% respectively.

the Augmented Dickey-Fuller test for stationarity of residuals, the Breusch-Godfrey test for serial correlation, the White's test and the ARCH residual test for homoscedasticity, and the portmanteau test for white noise. In addition, we perform the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) tests to assess the stability of the estimated coefficient. Since the calculated F-statistic exceeds the upper-bound critical value at 1% significance level, we have enough statistical evidence to reject the null hypothesis of no cointegration among the variables of Eq.(1). This result indicates the presence of a long-run relationship among economic growth, financial development, renewable energy consumption, technological innovation, and carbon dioxide emissions in China. Given the presence of the cointegration, the long-run and short-run relationships among the variables can be estimated through Eqs. (2) and (3).

Table 4 The Pesaran et al. (2001) Bounds test results

Estimated equation	Eq.(1)	
Optimal lag structure	(2 2 1 0 1 0 2)	
F-statistics	4.704***	
Significance level	Lower bound critical values ⇒I(0)	Upper bound critical values ⇒I(1)
1%	3.15	4.43
5%	2.75	3.99
10%	2.45	3.61

Note: ***, **, * denotes statistical significance level at 1%, 5% and 10% respectively. The optimal lag for model estimation is selected on the basis of the Schwart-Bayesian Criteria (SBC). The critical values for bounds test are obtained from Pesaran et al. (2001).

The estimated short- and long-run results are reported in Table 5. The statistically significant positive long run coefficient of $\ln(GDP)_{t-1}$ confirms that an increase in economic growth leads to an environmental degradation in China. In particular, the magnitude 0.5483 implies that a 1% increase in GDP per capita in China will lead to a 0.5483% increase in carbon emissions per capita in the long run. Similarly, the coefficients of $\Delta Ln(GDP)_t$ is 0.4619 and is statistically significant. This implies that a 1% increase in changes of real GDP per capita will lead to 0.4619% changes in carbon emissions in China, in the short run. From these short-run and long-run elasticity estimates, it can be concluded that economic growth was one of main drivers that lead to an increase in CO_2 emissions in China over the study period. Notice that estimated short-run coefficient on $\Delta \text{Ln(GDP)}_t$ is negative (-0.6316) and statistically significantly at 1%. This may reflect the Chinese government's recent ambition in carbon reduction in the short run.

The signs of financial development indicators (Ln(SS)_{t-1} and Ln(FS)_{t-1}) show negative and statistically significant impacts on carbon emissions, in the long run. This finding of negative effect of financial development on carbon emission in the long run is consistent with the study of Jalil and Feridun (2011). Given that the estimated coefficient of Ln(FDI)_{t-1} is 0.119 in the long run, it implies that a 1% increase in net flows of foreign direct investment will lead to a 11.9% increase in carbon emissions.

An interesting finding is that the long run coefficient of technology innovation is significant with a positive sign. The positive coefficient of Ln(TI)_{t-1} indicates that a 1% increase in national expenditures on technology innovation will lead to a 0.5% increase in carbon emissions in the case of China. The result of the positive technology-pollution relationship is controversial in the literature, as discussed by Blanford (2009) and Irandoust (2016). This is mainly because the share of green technology innovation in China is relatively small in comparison with other strategic emerging sectors. As stated by Ang (2009) and Tang and Tan (2013), the impact of technology innovation on carbon emissions would be statistically observable only if there is a significant proportion of research focused on green-related projects. In addition, Zhang and Du (2017) emphasize that most of the core technologies in China's clean energy development are imported from the U.S. and the EU market. Hence, the statistical impact of technology innovation on China's carbon emissions in our model went against the expectations.

Table 5 The estimated long run coefficients using ARDL (2, 2, 1, 0, 1, 0, 2) estimation

Variable	Coefficient	Standard Errors	t-statistics
Long-Run Relationship			
ln(GDP)$_{t-1}$	0.5483	0.2503	2.19**
ln(SS)$_{t-1}$	-0.1504	0.0365	-4.12***
ln(FS)$_{t-1}$	-0.3065	0.1352	-2.27**
ln(FDI)$_{t-1}$	0.1190	0.0653	1.82*
ln(TI)$_{t-1}$	0.4995	0.2171	2.30**
ln(REC)$_{t-1}$	-0.0792	0.0698	-1.13
Short-run Relationship			
$\Delta ln(CO_2)_t$	0.4619	0.097	4.769***
$\Delta Ln(GDP)_t$	0.4645	0.112	4.14***
$\Delta Ln(GDP)_{t-1}$	-0.6316	0.105	-6.02***
$\Delta Ln(SS)_t$	0.0397	0.013	3.13***
$\Delta Ln(FDI)_t$	-0.6917	0.206	-3.36***
$\Delta Ln(REC)_t$	0.0217	0.023	0.95
$\Delta Ln(REC)_{t-1}$	0.0368	0.017	2.14**
ECM$_{t-1}$	-0.4211	0.085	-4.97***

$ECM_{t-1} = ln(CO_2)_t - 0.5483 ln(GDP)_t + 0.1504 ln(SS)_t + 0.3065 ln(FS)_t - 0.1190 ln(FDI)_t - 0.4995 ln(TI)_t + 0.0792 ln(REC)_t$

Note: ***, **, * indicate statistical significance at the 1%, 5% and 10% respectively. The maximum lag to be used is two, and the optimal lag length is chosen by Schwartz information criterion(SBC). All computations are carried out by STATA.

The estimated long run coefficient on renewable energy consumption is negative with a lack of statistical significance, revealing that an increase in renewable consumption has limited impact on emission management in China. This is mainly because the proportion of renewable energy consumption in China energy supply mix is low with respect to other conventional energy sources (Chen et al., 2019). Although China has achieved a remarkable progress on clean energy development, fossil fuels continue to dominate (85.4% of total primary energy consumption) China's energy consumption mix (BP, 2019). Thus, the impact of renewable energy consumption on carbon mitigation in China is likely to remain limited. The insignificant long-run clean energy – pollution nexus also reveals that despite efforts of the Chinese central government to promote renewable energy sources in the energy supply system, the target for reducing emissions is far below the expectation.

Table 6 Diagnostic tests

Test	Statistics	Test	Statistics
R^2	0.8110	$Adj R^2$	0.7395
Jarque–Bera Normality	2.284(0.3192)	Portmanteau test	30.5997(0.1657)
ADF stationarity	-7.363 (0.00)	Breusch-Godfrey	0.049(0.8243)
White's homoscedasticity	52.00(0.4347)	ARCH LM test	1.370 (0.2418)

Note: Diagnostic tests include the Jarque–Bera test for normality of residuals, the Augmented Dickey-Fuller test for stationarity of residuals, the Breusch-Godfrey test for serial correlation, the White's test and the ARCH residual test for homoscedasticity, and the portmanteau test for white noiseThe value in parentheses denotes the p-value for test significance.

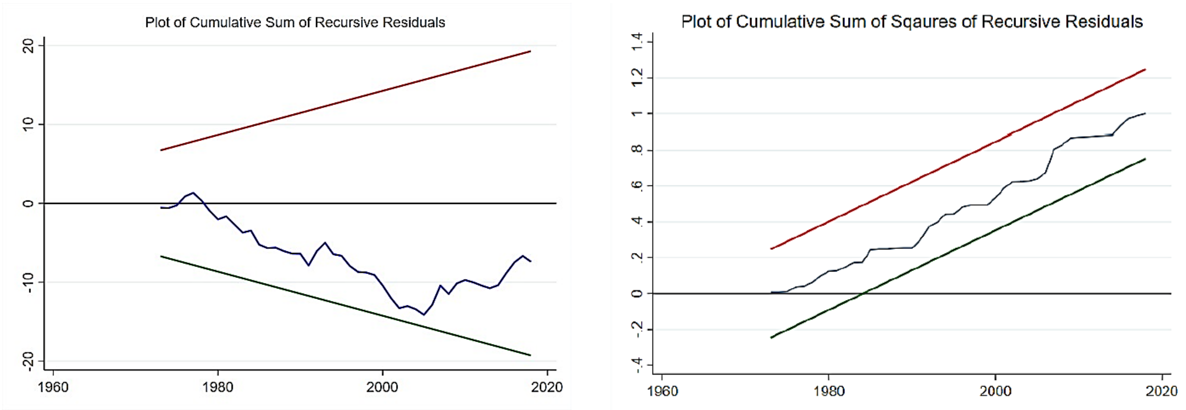
As shown in the lower part of Table 5, the short-run coefficient of financial development $\Delta Ln(SS)_t$ is 0.0397 suggesting a positive correlation between financial development and carbon emissions in the short-run. This effect has been observed because the Chinese stock market may support the public listed enterprises by offering the larger financing channels to implement new project within a relatively short time period; consequently leading to increased energy consumption and carbon emissions. In addition, according to the arguments of Sadorsky (2010) and Zhang (2011) who highlight that a well-developed financial market seems benefit consumers for personal loans to purchase energy intensive products such as cars, air conditioners refrigerators, and houses, and consequently increase energy consumption and carbon emissions in the short run. In short, an increase in financial development will lead to increased carbon emissions in the short-run and improved environmental condition in the long-run. The negative and significant coefficient of $\Delta ln(FDI)_t$ suggests that FDI drives CO_2 reductions in the short-run. It is noted that renewable energy consumption and technological innovation have limited impacts on carbon emissions in the short run.

The estimated coefficient of the error correction term ECM_{t-1} is -0.4211 with statistical significance at the 1% level, implying a convergence from the short-run dynamics to the long-run equilibrium. Given negative sign of the error correction term, the short-run deviations are being corrected by 42.11% each year towards the long-run equilibrium.

The statistical results of our diagnostic tests are summarized in Table 6 and they suggest our ARDL estimation is correctly specified with the absence of serial correlation and heteroscedasticity. The residuals are found to be stationary and they are normally distributed with the presence of the white noise process. Figure 2 displays the stability tests of CUSUM and CUSUM squares. Since all CUSUM and CUSUM squares statistics lie between the upper and lower critical bounds, our model estimation satisfies the stability condition.

Figure 2 Plots of model stability tests

(a) Cumulative sum of recursive residuals (b) Cumulative sum of squares of recursive residuals

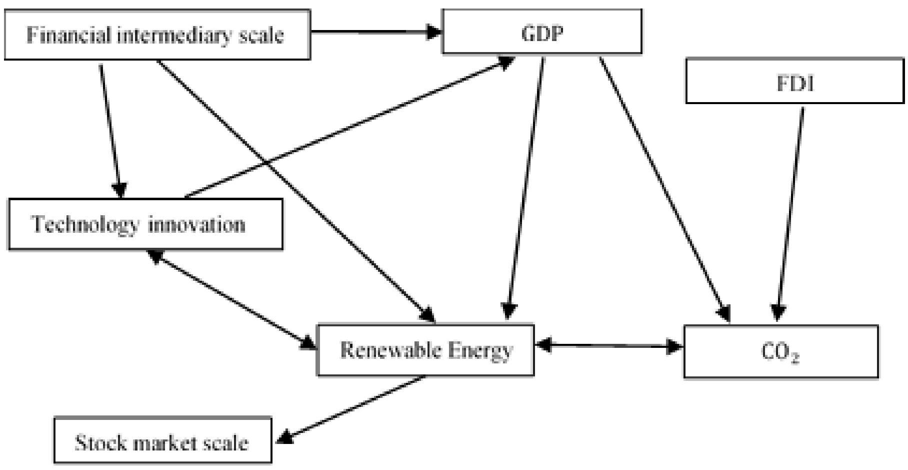


To check the robustness of the short-run causal relationship among the underlying variables, we perform the estimation of VECM as shown by Eq.(4) to detect the direction of causality. Figure 3 plots the results of the short-run Granger causality tests within the framework of VECM estimation.

The short-run Granger causality analysis shows a significant bidirectional causal relationship between renewable energy consumption and carbon emissions in China. Given the insignificant long-run clean energy – pollution nexus (See Table 5), the significant short-run bidirectional Granger causality between the two suggests that adoption of renewable energy sources can lead to environmental improvements in China, in the short run. The finding of the significant short-run clean energy – pollution nexus is consistent with those of Apergis et al. (2010) for 19 developed and developing countries.

In the short run, there exists a unidirectional causality in Granger sense running from financial intermediary scale to renewable energy consumption and technology innovation. Moreover, we find a significant causality from renewable energy consumption to stock market scale. This relationship is observed because China's banking and financial institution have remained remarkably strong in corporate lending and loan market since the economic reform of 1970s. The financing of green companies encompasses R&D processes and technology innovations in renewable energy sources, which leads to a reduction in carbon emissions through raising renewable energy consumption in the country. Moreover, we find a significant causality running from renewable energy consumption to stock market scale, suggesting that the public development and utilization of renewable energy sources would provide a chance for green companies to seek further financial resources from stock markets. Given the presence of significant causalities among technology innovation, renewable energy consumption, carbon emissions and financial development, we conclude that financial development can positively effect China's carbon mitigation indirectly, via the channels of renewable energy consumption and technology innovation.

Figure 3: Short run causalities Granger among variables



4. Conclusions and policy implications

Understanding the influencing factors of carbon dioxide emissions is an essential prerequisite for policy makers to maintain sustainable low-carbon economic growth. Although previous research has extensively studied the emission-growth nexus, those studies did not incorporate the impact of renewable energy development and technological innovations on the carbon emissions. Therefore, using the ARDL bounds test and error correction model, this paper explores the long-run and short-run casual influence of China's financial development, renewable energy consumption and technological innovation on carbon emissions over the period from 1965 to 2018. The cointegration test result, based on the ARDL bounds test procedure developed by Pe- saran et al. (2001), confirms a long-run relationship among the carbon emissions, economic growth, financial development, renewable energy consumptions and technological innovations.

The empirical results reveal that both short-run and long-run coefficients of economic growth are positive and significant, suggesting that past economic development had led to increase in environmental pollutions in China. On the contrary, financial development in China is found to have a significant impact on decreasing carbon emissions in the long run. In addition, a temporary improvement in financial development may stimulate enterprises to obtain higher profit through additional project implementations, and consequently, lead to increase in carbon emissions. It is concluded that carbon emissions are mainly determined by economic growth, foreign direct investment and technological progress in the long run. Moreover, the impact of renew- able energy consumption on carbon emissions is found to be weak and insignificant in China, mainly because the proposition of renewable energy consumption is relatively weak with regard to the total energy consumption level. In terms of the short run Granger causality analysis, we find that renewable energy consumption has a bidirectional

Granger causality with carbon emissions and technology innovations. Given the presence of short run causalities among technology innovation, renewable energy consumption, carbon emissions and financial development, our results suggest that financial development can have a positively effect on China’s carbon mitigation indirectly in the short run, via the channels of renewable energy development and technology innovation.

The empirical results enable us to suggest a number of policy implications regarding low carbon economic development in China. First, the government should continue to take actions to ascertain further financial development in terms of the market scale and operational efficiency. Given the significant role of the Chinese stock market in determining carbon emissions, establishing a systematic and effective green finance market may allow the government to mobilize the private capital and funds effectively into green industry through the channel of financial derivatives. In this respect, the establishment of a green finance market will encourage private green investors, banks, securities, insurance, funds and other financial institutions to actively participate in the low-carbon economic development.

Second, given the fact of weak effect of renewable energy consumption on environmental improvement, the government should pay more attention to promote renewable energy sources on both supply and demand side of China’s economy. On the supply side, the government may provide green enterprise with supports from aspects of fiscal incentives, technology consultancy, legal and policy implementation. Since the energy sector is mainly owned and operated by state-owned companies, government direct interventions remain one of the most effective strategies to increase the proportion of renewable energy sources in China’s energy supply portfolio (Reboredo and Wen, 2015). In terms of the demand side, positive price discriminations of clean energy electricity encourage public adoption of clean energy sources effectively among households. In addition, the government should continue to enforce environmental laws. As stated by Jalil and Feridun (2011), the government proactive laws have not been beneficial to environmental protections over the past two decades due to ineffective supervisory monitoring system and inefficient compliance measures. Therefore, the government should introduce more stringent legislation and efficient compliance measuring scheme for controlling carbon emissions among energy-intensive industries. Furthermore, carbon credit rating scheme and carbon allowance trading may also be effective strategies to accelerate the process of energy transformations among energy- intensive industries, as enterprises are expected to behave eco-friendly with regard to the impacts of price signalling and policy enforcement.

Finally, our results show a positive relationship between technological innovations and carbon emissions which is principally because the percentage of clean energy innovations of total national research projects is relatively small comparing with other strategic emerging sectors. Considering the potential impacts of the U.S.-China trade wars, we strongly recommend the Chinese government to undertake an aggressive investment strategy in cultivating talents to enhance science research in green technologies in order to achieve successful technological innovations in renewable energy sources and energy efficiency.

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