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The Impact of Financial Development on Carbon Emission: Evidence from China

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Abstract: This paper studies the impact of financial development on carbon emissions in China from 1997 to 2016. First, this paper uses the entropy method to construct a synthetical index to measure the financial development. Meanwhile, a two-dimensional panel framework is introduced to group provinces in the panel analysis. The estimation results of the time series autoregressive distributed lag model show that for China as a whole, there is a weak carbon emissions reduction effect of financial development, whether it is a long-term effect or a short-term effect. The estimation results of the panel autoregressive distributed lag model also support that an increase in financial development suppresses carbon emissions. Although financial development inhibits carbon emissions both in the short run and in the long run, the absolute value of the long-term coefficient of financial development is significantly greater than that of the short-term coefficient.

Keywords: carbon emission; financial development; time series autoregressive distributed lag model; panel autoregressive distributed lag model; China

1. Introduction

Global warming is undoubtedly one of the most serious challenges facing all countries today. The greenhouse effect has led to frequent catastrophic events, such as cyclones in the Philippines and the United States, long drought in Chile, bushfires in Russia, devastating floods in Pakistan, tsunami in Japan and earthquakes in Haiti. Carbon emissions (CE) become the biggest culprit of climate warming. Under the severe environmental situation, human beings have also made their own efforts. The task of improving the global climate and truly realizing a low-carbon economy remains long and arduous. The long-term extensive economic development model also makes China bear great environmental costs. Green development has become an important requirement for the construction of a new era. Achieving clean and low-carbon development is an urgent need for economic and social transformation. Faced with arduous environmental problems and energy reform, China has put forward a new vision of innovative, coordinated, green, open and inclusive development. China demonstrates its determination to protect the ecology and build a green and beautiful country.

Finance is of great importance in a modern economy. It is also an important indicator to measure the development of a country or region. At the same time, its effect on CE cannot be ignored. The role of financial development (FD) in the process of energy conservation and emissions reduction is worth exploring. On the one hand, FD may promote the expansion of production and commercial activities, increase energy demand and consumption and then lead to an increase in carbon emissions. On the other hand, FD may directly affect the development of a low-carbon economy. FD may indirectly affect the process of energy conservation and carbon emissions by influencing economic development, industrial structure, technological innovation and other aspects (Wang et al. [1]; Chang [2]; Ziaei [3]; Nasreen et al. [4]).

The development of China's financial market has gradually matured, with various indicators of the financial market improving by different degrees. From 1997 to 2016, the total balance of deposits and loans of financial institutions rose from 157,306.86 billion yuan in 1997 to 2,571,903.89 billion yuan in 2016, with a drastic increase. This is mainly because FD is encouraged, and the loose and safe financial environment is provided by the government. The change of market value and trading volume of listed companies is particularly obvious, which fully proves the fast development of China's securities market. In addition, the issue of climate change has attracted more and more attention from China. As a large economy and a major carbon emitter, China is actively taking responsibility and participating in the governance of global climate issues. However, the development level and economic conditions of China's provinces are different. It is very important to clarify the impact of FD on CE. This can not only provide policy suggestions and a theoretical basis for China to deal with global climate issues, but also provides reference for China to reasonably formulate financial policies and deal with international relations.

In recent years, more and more scholars have studied the impact of FD on CE. No consistent conclusions have been reached on the impacts of FD on CE. Some scholars found that FD reduced CE (Nasreen et al. [4]; Dogan and Seker [5]; Riti et al. [6]). Some scholars found that FD promoted CE (Bekhet et al. [7]; Shahbaz et al. [8]; Shahzad et al. [9]). Some scholars found that FD had no impacts on CE (Salahuddin et al. [10]). This paper makes up for some deficiencies in previous studies from the following aspects:

Firstly, in this paper, we conduct a systematic and comprehensive analysis of the impact of China's FD on CE from both national and provincial levels. Secondly, in terms of variable selection, this paper uses the improved entropy method to synthesize the sum of deposit and loan balances of financial institutions/GDP, non-state sector credit/GDP, listed company's market value/GDP and stock trading volume/GDP into an indicator to comprehensively measure the FD of China and its provinces. Thirdly, previous studies usually grouped panel data by a single economic indicator or carbon emissions indicator. This paper introduces a two-dimensional panel framework to group panel data. These two dimensions are FD and CE. After grouping according to the quadrant, 30 provinces are divided into 4 regions, namely: high level of both FD and CE (Quadrant I, panel 1), low level of FD and high level of CE (Quadrant II, panel 2), low level of both FD and CE (Quadrant III, panel 3) and high level of FD and low level of CE (Quadrant IV, panel 4). The two-dimensional quadrant grouping method not only provides the basis for exploring the relationship between FD and CE in different regions, but also provides the basis for analyzing regional carbon emission factors. Finally, this paper uses both time series autoregressive distributed lag (ARDL) and panel ARDL to study the long-term and short-term effects of FD on CE in different data sets.

The structure of this paper is as follows: Section 2 reviews the literature. Section 3 describes the models, variables and data used in this paper. Section 4 conducts an empirical analysis and discusses the empirical results. Section 5 gives conclusions.

2. Literature Review

In recent years, more and more scholars have taken FD into consideration, studying the impact of FD on CE. Many scholars choose different research objects to conduct research and draw different conclusions.

Some scholars found that FD reduced CE and improved the environment. Adams and Klobodu [11] showed that after joining political factors, FD significantly reduced the CE of 26 African countries from 1985 to 2011. Anees et al. [12] studied the relationship between FD and CE in Asia-Pacific Economic Cooperation (APEC) countries from 1990 to 2016. They found that FD was negatively correlated with CE. Charfeddine and Kahia [13] found FD had a weak CE reduction in 24 countries of the Middle East and North Africa. Some scholars have reached the opposite conclusion and found that FD increased CE. Kayani et al. [14] selected the ten countries with the largest CE as the research object and found that FD significantly promoted CE. Nguyen et al. [15] selected 13 representative countries from the G20 and found that FD increased CE.

Some scholars have conducted more detailed research and found that the impact of FD on CE was different due to the choice of research sample and the indicators of FD. Xiong et al. [16] found that FD was negatively and positively correlated with CE in developed and underdeveloped regions of China, respectively. Huang and Zhao [17] proved that the carbon emission reduction effects of FD in different regions of 30 provinces in China are different. Reddy et al. [18] showed that the stock markets of developed countries significantly reduced CE, while the stock markets of emerging market countries significantly increased CE. Liu and Song [19] paid attention to the impact of FD on CE after the global financial crisis. They showed that FD reduced CE in general. Wasif et al. [20] measured FD of the banking industry and found there was a positive correlation between the FD and CE of G-7 countries, but a negative correlation between FD and CE of N-11 countries.

From the perspective of research methods, scholars use diverse models and methods. Shahbaz et al. [8] selected time series data of France and used the ARDL bound test. They found that FD, especially financial stability, reduced CE. At the same time, the research conclusion also supported the pollution havens and environment Kuznets curve (EKC) hypothesis. Pata [21] selected Turkey's time series data and used the ARDL bound test to verify the EKC curve. The results supported the EKC hypothesis. It was found that FD promoted CE. Salahuddin et al. [22] used time series ARDL and found that FD led to a reduction in CE. Zhang and Zhang [23] used ARDL to study whether there was an EKC curve in China from 1982 to 2016. They indicated that the EKC curve existed and that service trade and exchange rates reduced CE. Abokyi et al. [24] found that FD increased CE in Ghana. Fang et al. [25] showed that financial scale promoted CE. Tariq et al. [26] used panel ARDL to study the impact of FD on CE. Results in Asia and the Americas showed that FD reduced CE by developing environmentally friendly technologies. Kwame et al. [27] used panel ARDL and found international trade reduced CE in developed countries, while FDI increased CE in developing countries.

Although there have been quite a lot of studies on the impact of FD on CE, no unified conclusion has been drawn. Some scholars found that FD reduced CE and improved the environment, while some scholars found that FD promoted CE. Some scholars proved that the impact of FD on CE had a threshold effect. In addition, some studies, such as Salahuddin et al. [10], concluded that there was no connection between the two.

3. Methodology

3.1. Model Specification

3.1.1. Time Series ARDL Model

Compared with other models, the ARDL model (Pesaran et al. [28]) has the following advantages: (1) the ARDL model is applicable whether the variables in the model are I (0) or I (1). This is what the traditional cointegration test cannot do. (2) The ARDL model allows variables to have different optimal lag orders. (3) The ARDL model can estimate long-term and short-term relationships between variables.

Firstly, we constructed an unrestricted error correction model (UECM):

$$\begin{aligned}\Delta lnCO_{2t} = {} & \beta_0 + \sum_{i=1}^{p} \beta_i \Delta lnCO_{2\,t-i} + \sum_{i=0}^{p} \beta_i \Delta lnFD_{t-i} + \sum_{i=0}^{p} \beta_i \Delta lnCI_{t-i} + \sum_{i=0}^{p} \beta_i \Delta lnIS_{t-i} \\ & + \sum_{i=0}^{p} \beta_i \Delta lnUR_{t-i} + \sum_{i=0}^{p} \beta_i \Delta lnTI_{t-i} + \beta 1 lnFD_{t-1} + \beta_2 lnCI_{t-1} + \beta_3 lnIS_{t-1} \\ & + \beta_4 lnUR_{t-1} + \beta_5 lnTI_{t-1} + \beta_6 lnCO_{2\,t-1} + \varepsilon_t\end{aligned} \quad (1)$$

where CO_2 is the dependent variable, representing China's carbon dioxide emissions; *FD*, *CI*, *IS*, *UR* and *TI* are independent variables; *FD* represents China's FD; *CI* represents China's carbon emission intensity; *IS* represents China's industrial structure; *UR* represents China's urbanization level; and *TI* represents China's technological innovation level.

If there is a cointegration relationship among variables, the coefficients of the long-term relationship between variables are estimated. Then, we construct an ECM to analyze the short-term dynamic relationships among variables. The ECM was constructed as follows:

$$\begin{aligned}\Delta lnCO_{2t} \;=\; & \varphi + \sum_{i=1}^{p-1} \varphi_i \Delta lnCO_{2\ t-i} + \sum_{i=0}^{p-1} \varphi_i \Delta lnFD_{t-i} + \sum_{i=0}^{p-1} \varphi_i \Delta lnCI_{t-i} \\ & + \sum_{i=0}^{p-1} \varphi_i \Delta lnIS_{t-i} + \sum_{i=0}^{p-1} \varphi_i \Delta lnUR_{t-i} + \sum_{i=0}^{p-1} \varphi_i \Delta lnTI_{t-i} + \xi ECM_{t-1} + \varepsilon_t\end{aligned} \tag{2}$$

where ECM_{t-1} is the error correction term. When the short-term change deviates from the long-term equilibrium, the error correction term can play a role of adjustment. The coefficient ξ reflects the adjustment speed. Generally, the coefficient is negative.

3.1.2. Panel ARDL Model

The panel ARDL model can overcome the bias and inconsistency caused by traditional OLS regression. Moreover, compared with the traditional panel model, the panel ARDL model has its advantages. First, the model weakens endogenous problems. The model limits that the long-term coefficients are homogeneous, but the coefficients and error variance of the models between different groups can be heterogeneous. The panel ARDL model can effectively improve the accuracy of the estimation results. Second, the model can be used to study both long-term and short-term relationships between variables.

The panel ARDL model was constructed as follows:

$$\begin{aligned}\Delta lnCO_{2\ it} \;=\; & \phi_i(lnCO_{2\ i,t-1} - \gamma_0 - \gamma_1 lnFD_{it} - \gamma_2 lnCI_{it} - \gamma_3 lnIS_{it} - \gamma_4 lnUR_{it} - \\ & \gamma_5 lnTI_{it} - \eta_1 \Delta lnFD_{it} - \eta_2 \Delta lnCI_{it} - \eta_3 \Delta lnIS_{it} - \eta_4 \Delta lnUR_{it} - \eta_5 \Delta lnTI_{it} + \varepsilon_{it})\end{aligned} \tag{3}$$

where CO_2 is the dependent variable, representing CE; *FD*, *CI*, *IS*, *UR* and *TI* are independent variables, representing FD level, carbon emission intensity, industrial structure, urbanization level and technological innovation level, respectively; $\varnothing_i$ is the error correction parameter, which represents the adjustment speed: if $\varnothing_i = 0$, there is no evidence that there is a long-term equilibrium between variables; if $\varnothing_i < 0$ and is statistically significant, it indicates that the variables will converge to long-term equilibrium under disturbance; ε_{it} is residual error; and ln is the form of the natural logarithm.

In model (3), $lnCO_{2\ i,t-1} - \gamma_0 - \gamma_1 lnFD_{it} - \gamma_2 lnCI_{it} - \gamma_3 lnIS_{it} - \gamma_4 lnUR_{it} - \gamma_5 lnTI_{it}$ is the long-term part. $\gamma_1, \gamma_2, \gamma_3, \gamma_4,\ \gamma_5$ represents the long-term coefficients of FD, carbon emission intensity, industry structure, urbanization and technological innovation on CE, respectively. $\eta_1, \eta_2, \eta_3, \eta_4, \eta_5$ represent the short-term coefficients of the above five variables on CE.

The variables in the models are summarized in Table 1.

Table 1. List of variables.

Symbol	Variables	Measurement	Explanation
CO_2	Carbon emissions	Ton/person	Carbon emission amount per capita
FD	Financial development	%	It is constructed by the sum of deposit and loan balances of financial institutions/GDP (%), non-state sector credit/GDP (%), listed company market value/GDP (%) and stock trading volume/GDP (%).
CI	Carbon intensity	Ton/yuan	Carbon emissions/GDP

Table 1. *Cont.*

Symbol	Variables	Measurement	Explanation
IS	Industrial structure	%	Financial industry increase/GDP
UR	Urbanization	%	Urban population/Total population
TI	Technology innovation	piece	Number of patent applications authorized by a country or region.

3.2. Variables

3.2.1. Dependent Variable

Carbon emission amount per capita is selected as the dependent variable. We calculate CE using data obtained from the China Energy Statistical Yearbook. The calculation method in this paper is based on the 2006 IPCC report. The formula is as follows:

$$CO_2 = \sum_{i=1}^{n} Energy_i \times Cofficient_i \tag{4}$$

where i is the energy source; $Energy_i$ is the energy consumption of a certain energy; and $Coefficient_i$ is the carbon emission coefficient of the energy source, which can be obtained from IPCC.

3.2.2. Independent Variable

This paper selects FD (FD) as the main independent variable. On the basis of the existing literature and data, four indicators are selected to measure FD comprehensively, including: (1) the sum of deposit and loan balances of financial institutions/GDP which is used as an indicator to measure the scale of FD; (2) non-state sector credit/GDP which is used as an indicator to measure the efficiency of FD; and (3) listed company market value/GDP and stock trading volume/GDP which are used to measure the Chinese stock market's development.

This paper uses the entropy method (Liu et al. [29]; Abu et al. [30]) to construct the four indicators into a comprehensive indicator to measure FD. The entropy method is an objective weighting method, which calculates the weight according to the degree of dispersion. Compared with other methods, the entropy method is objective which can avoid the interference of other subjective factors. The entropy method is a robust method to offer a precise estimation of the weights of four FD indicators.

The process of using the entropy method to construct the FD indicator is as follows:

(1) Standardize the secondary indicators:

$$X'_{ij} = \left[X_{ij} - \min\left(X_j\right)\right] / \left[\max(X_j) - \min\left(X_j\right)\right] \tag{5}$$

where X'_{ij} is the standardized indicator; X_{ij} is the original indicator; $\min\left(X_j\right)$ is the minimum in the indicators; and $\max(X_j)$ is the maximum in the indicators.

(2) Calculate the proportion of the indicator value of index j in year i:

$$Y_{ij} = X'_{ij} / \sum_{i=1}^{m} X'_{ij} \tag{6}$$

where m is the number of statistical years.

(3) Calculate the entropy of the index j:

$$e_j = -k \sum_{i=1}^{m} Y_{ij}\left(lnY_{ij}\right) \tag{7}$$

where $k = 1/lnm, 0 \leq e_j \leq 1$.

(4) Calculate the otherness coefficient of index *j*:

$$f_j = 1 - f_j \tag{8}$$

The otherness coefficient can reflect the variability of the data. The larger the f_j, the greater the data variability, and the greater the weight of this indicator.

(5) Calculate the weight of index *j*:

$$w_j = f_j / \sum_{i=1}^{n} f_j \tag{9}$$

(6) Finally, calculate the primary indicator:

$$FD = \sum_{j=1}^{n} (w_j \times X'_{ij}) \tag{10}$$

After calculation, the weights of constructing the FD indicator are shown in Table 2.

Table 2. Construction of financial development indicator.

Primary Indicator	Secondary Indicator	W_1	W_2
FD (%)	The sum of deposit and loan balances of financial institutions/GDP (%)	0.133	0.095
	Non-state sector credit/GDP (%)	0.189	0.047
	Listed company market value/GDP (%)	0.279	0.528
	Stock trading volume/GDP (%)	0.399	0.330

Note: W_1 is the weight of variable *FD* required for time series analysis. W_2 is the weight of variable *FD* required for panel analysis.

3.2.3. Control Variables

Control variables in this paper include: (1) carbon intensity (*CI*): the ratio of CE to GDP; (2) industrial structure (*IS*): the ratio of the added value of the financial industry to GDP; (3) urbanization (*UR*): the ratio of urban population to total population; and (4) technology innovation (*TI*): the number of patent applications authorized by a country or region.

3.3. Data Source

The annual data of China and its 30 provinces (except Tibet, Hong Kong, Macao and Taiwan due to the availability of the data) from 1997 to 2016 used in this paper are obtained from the China Statistical Yearbook, China Energy Statistical Yearbook, China Financial Statistical Yearbook and Wind database.

4. Empirical Results and Discussions

4.1. Time Series ARDL

4.1.1. Descriptive Statistics of Time Series Data

The basic statistical characteristics of all variables are summarized in Table 3. Table 3 shows that the minimum of China's per capita CE from 1997 to 2016 after taking the logarithm is 0.376, and the maximum is 1.312, which shows a rapid growth. From 1997 to 2016, the minimum of China's FD after taking the logarithm is 0.907, and the maximum is 4.423, which also experienced a rapid development.

Table 3. Descriptive statistics of time series.

Variable	Obs	Mean	Std.Dev.	Min	Max
lnCO$_2$	20	0.908	0.363	0.376	1.312
lnFD	20	3.027	0.940	0.907	4.423
lnCI	20	0.296	0.404	−0.444	0.898
lnIS	20	1.714	0.221	1.383	2.128
lnUR	20	3.791	0.181	3.463	4.049
lnTI	20	12.742	1.146	10.839	14.377

4.1.2. Unit Root Tests and ARDL Bound Test

In this paper, we use the classical unit root tests (ADF, PP and KPSS) to test the stationarity of time series data. Table 4 provides the unit root test's results. Some variables are stable at I(0), while some variables are stable at I(1). Moreover, we perform a cointegration test using the ARDL bound test. The results are shown in Table 5. It shows that the null hypothesis is rejected. There is a cointegration relationship between variables.

Table 4. Unit root tests of time series.

Variables	Intercept		Trend and Intercept	
	Level	1st Difference	Level	1st Difference
ADF	t-Statistic			
lnCO$_2$	−4.357386 ***	−2.865522 *	1.272015	−5.267663 ***
lnFD	−2.201536	−5.125743 ***	−3.327953 *	−5.208675 ***
lnCI	0.910973	−2.781330 *	−0.977180	−2.821867
lnIS	0.435973	−2.769204 *	−2.139744	−2.924774
lnUR	−10.66783 ***	−1.636309	−1.952534	−3.429871 *
lnTI	−1.085666	−3.961646 ***	−1.826953	−3.920970 **
P-P	Adj. t-Stat			
lnCO$_2$	−0.880041	−1.525264	−1.260415	−1.364377
lnFD	−2.925153 *	−6.028767 ***	−3.782997 **	−7.143777 ***
lnCI	0.729064	−2.814929 *	−1.247738	−2.821867
lnIS	0.045084	−2.769204 *	−1.790971	−2.924774
lnUR	−26.54165 ***	−1.614760	−4.466936 ***	−4.073116 **
lnTI	−1.119336	−3.938817 ***	−1.940240	−3.899645 **
KPSS	LM-Stat.			
lnCO$_2$	0.552359 *	0.178965 ***	0.122540 **	0.147049 *
lnFD	0.603365 *	0.354627 **	0.139222 **	0.500000
lnCI	0.608901 *	0.188855 ***	0.130176 **	0.073877 ***
lnIS	0.472750 *	0.307129 ***	0.144029 **	0.085126 ***
lnUR	0.613532 *	0.564636 *	0.171791 *	0.132873 **
lnTI	0.609775 *	0.150288 ***	0.082084 ***	0.100444 ***

Note: ***, ** and * refer to 1%, 5% and 10% level of statistical significance, respectively.

Table 5. ARDL bound test.

Optimal Lag Order	**(1,0,1,0,0,1)**			
Estimated Equation	**lnCO$_2$ = F(lnCO$_2$, lnCI, lnFD, lnIS, lnUR, lnTI)**			
Critical Bounds	**95% Lower Bound**	**95% Upper Bound**	**90% Lower Bound**	**90% Upper Bound**
F-statistic = 5.4765	3.7291	5.5030	2.9256	4.3879
W-statistic = 32.8587	22.3744	33.0177	17.5538	26.3275
Diagnostic Tests				
Test Statistics	LM Version		F Version	
A: Serial Correlation CHSQ(1)	=0.90071[0.343] F(1,9)		=0.44788[0.520]	
B: Functional Form CHSQ(1)	=1.0324[0.310] F(1,9)		=0.51711[0.490]	

Table 5. *Cont.*

Optimal Lag Order	(1,0,1,0,0,1)			
Estimated Equation	$lnCO_2$ = F($lnCO_2$, lnCI, lnFD, lnIS, lnUR, lnTI)			
Critical Bounds	95% Lower Bound	95% Upper Bound	90% Lower Bound	90% Upper Bound
C: Normality CHSQ(2)	=0.28868[0.866]		Not applicable	
D: Heteroscedasticity CHSQ(1)	=0.020448[0.886] F(1,17)		=0.018315[0.894]	

Note: A: Lagrange multiplier test of residual serial correlation. B: Ramsey's RESET test using the square of the fitted values. C: Based on a test of skewness and kurtosis of residuals. D: Based on the regression of squared residuals on squared fitted values.

4.1.3. Long-Term and Short-Term Coefficient Estimation

Table 6 shows the long-term coefficient estimation results. The coefficient of variable *lnFD* is −0.067, which is significant at the significance level of 5%. In addition, *lnCI*, *lnIS*, *lnUR* and *lnTI* are all significantly positive, which means that carbon intensity, industrial structure, urbanization and technology innovation promote carbon emissions in the long term. Carbon intensity and urbanization have larger coefficients, which are 2.081 and 4.191, respectively.

Table 6. Long-term coefficient estimation of time series ARDL (dependent variable: $lnCO_2$).

Variable	Coefficient	Standard Error	T-Ratio
lnFD	−0.067232 **	0.029662	−2.2666
lnCI	2.0805 ***	0.17431	11.9354
lnIS	0.78348 ***	0.13594	5.7636
lnUR	4.1914 ***	0.53291	7.8650
lnTI	0.28542 ***	0.083477	3.4191
Constant	−20.2939 ***	1.3113	−15.4762

Note: ***, ** and * refer to 1%, 5% and 10% level of statistical significance, respectively.

Table 7 shows the short-term coefficient estimation results. The coefficient of Δ*lnFD* is −0.064 and is significant at a significance level of 1%. In addition, the coefficients of Δ*lnCI*, Δ*lnIS* and Δ*lnUR* are all significant and positive, which shows that in the short term, carbon intensity, industrial structure and urbanization promote CE. Carbon intensity and urbanization have larger coefficients of 1.283 and 2.585, respectively.

Table 7. Short-term coefficient estimation of time series ARDL (dependent variable: $\Delta lnCO_2$).

Variable	Coefficient	Standard Error	T-Ratio
ECM	−0.61668 ***	0.10076	−6.1205
Δ*lnFD*	−0.064456 ***	0.015886	−4.0574
Δ*lnCI*	1.2830 ***	0.21455	5.9800
Δ*lnIS*	0.48316 ***	0.14157	3.4130
Δ*lnUR*	2.5848 ***	0.39813	6.4923
Δ*lnTI*	-0.1691×10^{-3}	0.052187	−0.0032395
Diagnostic Tests			
R^2	0.95771		
Adj. R^2	0.92389		
DW-statistic	2.1382		
F(6,12)	37.7483[0.000]		

Note: ***, ** and * refer to 1%, 5% and 10% level of statistical significance, respectively.

Comparing the long-term coefficient (−0.067) and short-term coefficient (−0.064) of FD in the time series ARDL model, it is found that the two coefficients are very close. This illustrates the consistency of estimation results of long-term and short-term models in time series analysis. In other words, the improvement of China's FD reduces CE, but its role is relatively weak. This may be due to the imperfect market mechanism of using financial instruments to guide carbon emissions reduction.

4.2. Panel ARDL

Section 4.1 analyzes time series data. Compared with time series data, panel data have two dimensions of cross-section and time, which can improve the effectiveness of model estimation. Therefore, Section 4.2 selects panel data for analysis.

4.2.1. Full-Sample Panel Data and Sub-Sample Panel Data

In this paper, we first estimate the full sample panel data of China, and observe how the estimation results differ from time series data analysis. Then, in order to explore how FD affects CE in different regions with different characteristics, we refer to Yan et al. [31], Pan et al. [32], Zhen et al. [33] and Cai et al. [34] and divide four sub-panels from two dimensions of CE and FD. We calculate the average CE and FD of each province in China from 1997 to 2016. The coordinate map is divided into four quadrants according the average CE and FD of each province, which is shown in Figure 1. The provinces distributed in each quadrant are listed in Table 8.

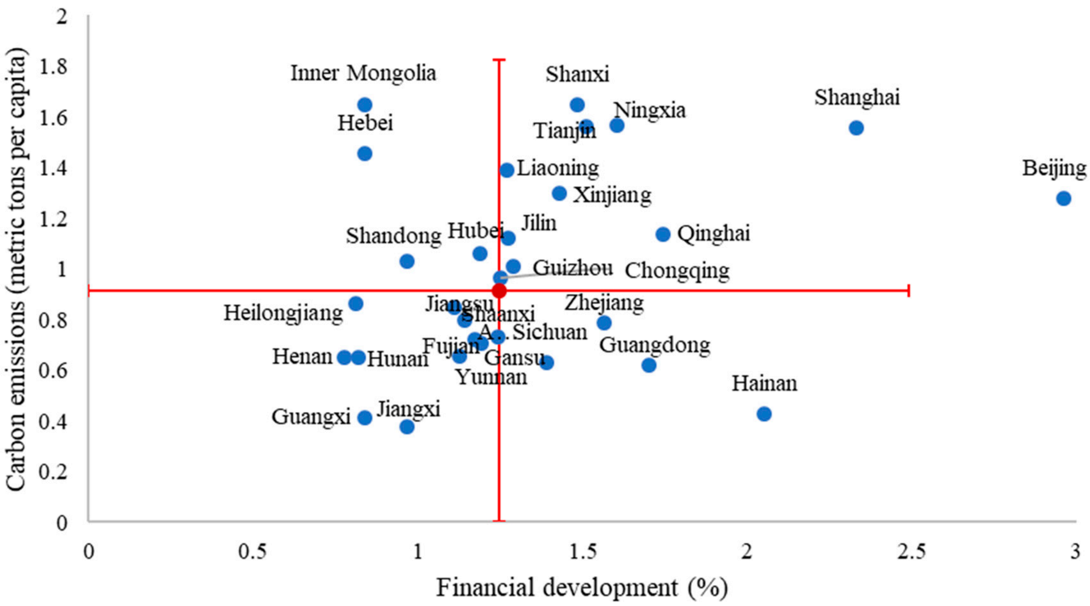

Figure 1. Panel data grouping.

Table 8. Panels grouping.

Panels	Group	Provinces
panel 1	High level of both financial development and carbon emissions	Beijing, Shanghai, Shanxi, Ningxia, Tianjin, Liaoning, Xinjiang, Jilin, Qinghai, Guizhou, Chongqing
panel 2	Low level of financial development and high level of carbon emissions	Inner Mongolia, Hebei, Shandong, Hubei
panel 3	Low level of both financial development and carbon emissions	Heilongjiang, Jiangsu, Shaanxi, Anhui, Fujian, Gansu, Yunnan, Henan, Hunan, Guangxi, Jiangxi
panel 4	High level of financial development and low level of carbon emissions	Zhejiang, Sichuan, Guangdong, Hainan

4.2.2. Descriptive Statistics of Panel Data

Table 9 provides the descriptive statistics of the full-sample panel data and sub-sample panel data. The average value of the FD in the full panel is 1.329, which indicates that the average FD level in China is not high. The standard deviation is 0.653, which indicates that the FD of each province is unbalanced. The descriptive statistics of FD variables in panels 1–4 also support the previous conclusions. In addition, there are differences among the selected variables.

Table 9. Descriptive statistics of panel data.

Panels.	Variable	Obs	Mean	Std.Dev.	Min	Max
whole panel	$lnCO_2$	600	0.987	0.548	−0.337	2.299
	$lnFD$	600	1.329	0.653	−0.645	4.267
	$lnCI$	600	0.410	0.643	−1.421	2.350
	$lnIS$	600	1.422	0.532	−0.454	2.837
	$lnUR$	600	3.751	0.387	2.631	4.495
	$lnTI$	600	8.404	1.688	4.025	12.506
panel 1	$lnCO_2$	220	1.321	0.408	−0.028	2.227
	$lnFD$	220	1.650	0.693	0.396	4.267
	$lnCI$	220	0.604	0.727	−1.421	2.350
	$lnIS$	220	1.739	0.509	0.675	2.837
	$lnUR$	220	3.876	0.407	2.631	4.495
	$lnTI$	220	7.954	1.687	4.025	11.519
panel 2	$lnCO_2$	80	1.299	0.543	0.223	2.299
	$lnFD$	80	0.957	0.386	0.182	1.924
	$lnCI$	80	0.648	0.505	−0.607	1.631
	$lnIS$	80	1.163	0.306	0.609	1.960
	$lnUR$	80	3.731	0.291	2.903	4.114
	$lnTI$	80	8.666	1.392	5.919	11.494
panel 3	$lnCO_2$	220	0.674	0.444	−0.201	1.422
	$lnFD$	220	1.018	0.489	−0.645	2.324
	$lnCI$	220	0.308	0.505	−0.925	1.547
	$lnIS$	220	1.197	0.476	−0.454	2.050
	$lnUR$	220	3.637	0.359	2.664	4.365
	$lnTI$	220	8.477	1.441	5.687	12.506
panel 4	$lnCO_2$	80	0.617	0.394	−0.337	1.154
	$lnFD$	80	1.678	0.524	0.551	2.891
	$lnCI$	80	−0.077	0.522	−1.117	1.139
	$lnIS$	80	1.426	0.465	0.344	2.134
	$lnUR$	80	3.743	0.392	2.844	4.237
	$lnTI$	80	9.178	2.181	5.118	12.465

4.2.3. Unit Root Tests and Panel Cointegration Test

Table 10 shows that all variables reject the null hypothesis after the first-order difference. That is, all panels are first-order-integrated. This paper uses the Kao test (Kao [35]) and Pederoni test (Pedroni [36,37]) to perform the panel cointegration test. Kao test's results shown in Table 11 indicate that there is a long-term equilibrium relationship between variables in the whole panel and sub-panels 1–4. Compared with the Kao test, the Pedroni test takes the heterogeneity of cross-sectional series into account. Pedroni test's results shown in Table 12 also indicate that there is a cointegration relationship between the variables in the whole panel and sub-panels 1–4.

Table 10. Unit root tests of panel data.

Panels	Variables	Individual Intercept		Individual Trend and Intercept	
		Level	1st Difference	Level	1st Difference
whole panel		Levin–Lin–Chu (LLC) test			
	$lnCO_2$	−2.23486 **	−13.0369 ***	3.39601	−11.4997 ***
	lnFD	−6.01654 ***	−27.0577 ***	−11.3845 ***	−23.6179 ***
	lnCI	0.06042	−19.6076 ***	−3.37389 ***	−16.4966 ***
	lnIS	2.43896	−8.10056 ***	−2.22666 **	−9.16139 ***
	lnUR	−23.8465 ***	−19.9394 ***	−14.0169 ***	−14.1382 ***
	lnTI	1.34337	−16.8325 ***	−1.02256	−14.4141 ***
		Im–Pesaran–Shin (IPS) test			
	$lnCO_2$	2.33993	−11.9507 ***	1.54913	−8.35327 ***
	lnFD	−1.79760 **	−23.5228 ***	−6.70854 ***	−19.7569 ***
	lnCI	6.86228	−16.4419 ***	−1.51707 *	−13.1895 ***
	lnIS	4.63722	−6.65362 ***	2.64790	−8.01958 ***
	lnUR	−16.2589 ***	−15.7177 ***	−7.24206 ***	−14.5689 ***
	lnTI	8.03224	−13.8008 ***	−0.04589	−10.9546 ***
panel 1		Levin–Lin–Chu (LLC) test			
	$lnCO_2$	−1.21257	−10.1177 ***	0.99600	−7.10926 ***
	lnFD	−4.43222 ***	−16.6771 ***	−6.01021 ***	−14.4840 ***
	lnCI	−1.15513	−11.8051 ***	−3.97362 ***	−9.90243 ***
	lnIS	2.32505	−4.76349 ***	−1.07709	−3.77739 ***
	lnUR	−26.4956 ***	−11.3105 ***	−7.33463 ***	−9.72759 ***
	lnTI	−0.31471	−11.3533 ***	−1.37066 *	−9.28099 ***
		Im–Pesaran–Shin (IPS) test			
	$lnCO_2$	0.60908	−9.83961 ***	−0.95297	−7.18310 ***
	lnFD	−2.51326 ***	−13.8443 ***	−3.79291 ***	−11.5371 ***
	lnCI	2.51003	−10.7429 ***	−3.34719 ***	−8.44606 ***
	lnIS	2.74586	−3.61741 ***	3.13429	−4.65712 ***
	lnUR	−18.1867 ***	−7.85664 ***	−3.44626 ***	−7.93828 ***
	lnTI	3.55241	−10.2310 ***	−0.68843	−8.06366 ***
panel 2		Levin–Lin–Chu (LLC) test			
	$lnCO_2$	−2.08760 **	−1.42750 *	3.03213	−2.69631 ***
	lnFD	−0.00514	−5.15180 ***	−2.12701 **	−4.02629 ***
	lnCI	2.54676	−2.87410 ***	0.90337	−2.04303 **
	lnIS	1.99861	−1.56886 *	−1.08694	−3.06487 ***
	lnUR	−3.73744 ***	−2.54159 ***	−2.11716 **	−3.20287 ***
	lnTI	0.95176	−4.89564 ***	1.37911	−5.31215 ***
		Im–Pesaran–Shin (IPS) test			
	$lnCO_2$	0.93172	−3.48470 ***	3.51314	−2.63007 ***
	lnFD	−0.58830	−9.53196 ***	−2.51711 ***	−8.27311 ***
	lnCI	3.81865	−6.22278 ***	1.45815	−5.47194 ***
	lnIS	2.32563	−0.95708	2.05593	−3.85323 ***
	lnUR	−5.24736 ***	−3.69828 ***	1.39667	−4.45390 ***
	lnTI	2.72474	−5.32647 ***	1.47467	−4.24441 ***
panel 3		Levin–Lin–Chu (LLC) test			
	$lnCO_2$	−1.42617 *	−6.08283 ***	1.43613	−6.42742 ***
	lnFD	−3.03604 ***	−16.3426 ***	−6.66501 ***	−14.5018 ***
	lnCI	−0.54414	−11.1216 ***	−1.21993	−9.24861 ***
	lnIS	0.10547	−5.06591 ***	−1.94857 **	−5.96446 ***
	lnUR	−6.43367 ***	−14.0219 ***	−13.6667 ***	−8.28548 ***
	lnTI	3.74944	−8.04090 ***	−0.53999	−8.32029 ***

Table 10. *Cont.*

Panels	Variables	Individual Intercept		Individual Trend and Intercept	
		Level	1st Difference	Level	1st Difference
panel 3	Im–Pesaran–Shin (IPS) test				
	$lnCO_2$	2.15476	−5.33909 ***	0.56820	−3.27490 ***
	lnFD	−0.14152	−13.9802 ***	−3.92887 ***	−11.6619 ***
	lnCI	3.88500	−8.67074 ***	0.32491	−6.57570 ***
	lnIS	1.81746	−5.03488 ***	−0.16298	−4.96832 ***
	lnUR	−5.97704 ***	−11.7109 ***	−9.77424 ***	−10.5274 ***
	lnTI	7.30778	−6.02199 ***	0.56389	−5.84886 ***
panel 4	Levin–Lin–Chu (LLC) test				
	$lnCO_2$	−0.88701	−4.35149 ***	1.96381	−4.11421 ***
	lnFD	−1.52159 *	−7.13924 ***	−5.45718 ***	−5.68384 ***
	lnCI	2.68299	−8.35047 ***	−1.37027 *	−6.77852 ***
	lnIS	0.83093	−3.67584 ***	0.15629	−3.69360 ***
	lnUR	1.22465	−8.58321 ***	−0.40576	−5.65122 ***
	lnTI	−1.87893 **	−6.83780 ***	−1.23870	−4.44144 ***
	Im–Pesaran–Shin (IPS) test				
	$lnCO_2$	0.92925	−4.03024 ***	1.66549	−2.70913 ***
	lnFD	0.03911	−8.74457 ***	−3.04986 ***	−7.36066 ***
	lnCI	4.32623	−6.60770 ***	−0.60071	−5.70952 ***
	lnIS	2.86350	−2.92380 ***	0.40582	−2.13362 **
	lnUR	0.83843	−6.78990 ***	0.90314	−4.78594 ***
	lnTI	1.24577	−5.57234 ***	−1.30463 *	−2.70869 ***

Note: ***, ** and * refer to 1%, 5% and 10% level of statistical significance, respectively.

Table 11. Kao panel cointegration test.

	Whole Panel	Panel 1	Panel 2	Panel 3	Panel 4
	t-Statistic	t-Statistic	t-Statistic	t-Statistic	t-Statistic
ADF	−8.107 ***	−2.237 **	−1.789 **	−6.684 ***	−3.502 ***

Note: *** and ** refer to 1% and 5% level of statistical significance, respectively.

Table 12. Pedroni panel cointegration test.

Whole Panel		Panel 1	Panel 2	Panel 3	Panel 4
Alternative hypothesis: common AR coefs. (within-dimensions)					
Panel v-Statistic	−3.974	−0.687	2.701 ***	4.525 ***	7.213 ***
Panel rho-Statistic	3.281	0.406	2.019	3.697	2.020
Panel PP-Statistic	−0.430	−4.056 ***	0.744	2.192	−1.535 *
Panel ADF-Statistic	−2.299 **	−4.683 ***	0.847	1.963	−2.683 ***
Panel v-Statistic (weighted)	−4.562	−0.841	2.062 **	3.816 ***	4.166 ***
Panel rho-Statistic (weighted)	3.514	0.601	1.515	3.307	1.691
Panel PP-Statistic (weighted)	0.352	−3.241 ***	−0.875	0.858	−3.504 ***
Panel ADF-Statistic (weighted)	−0.992	−4.082 ***	−0.870	0.575	−3.542 ***
Alternative hypothesis: individual AR coefs. (between-dimensions)					
Group rho-Statistic	4.683	1.799	2.292	4.597	2.870
Group PP-Statistic	−2.129 **	−3.957 ***	−0.229	0.530	−1.450 *
Group ADF-Statistic	−4.318 ***	−5.063 ***	−0.142	0.696	−2.523 ***

Note: ***, ** and * refer to 1%, 5% and 10% level of statistical significance, respectively.

4.2.4. Long-Term and Short-Term Coefficient Estimation

Table 13 shows the long-term coefficient estimation results. The coefficients of *lnFD* of all panels are all significantly negative at a significance level of 1%, which indicates that FD inhibits CE in the long run. The elasticity coefficients of *lnFD* of panels 1–4 are −0.182, −0.936, −0.222 and −0.416, respectively.

Table 13. Long-term coefficient estimation of the panel ARDL (dependent variable: $lnCO_2$).

Variable	Whole Panel	Panel 1	Panel 2	Panel 3	Panel 4
lnFD	−0.235 ***	−0.182 ***	−0.936 ***	−0.222 ***	−0.416 ***
	(0.048)	(0.061)	(0.255)	(0.064)	(0.124)
lnCI	0.177 *	0.317 **	0.198	0.614 ***	0.094
	(0.105)	(0.143)	(0.483)	(0.137)	(0.322)
lnIS	0.751 ***	0.979 ***	2.952 ***	0.409 ***	0.444 ***
	(0.089)	(0.129)	(0.920)	(0.083)	(0.144)
lnUR	−0.820 ***	−0.925 ***	1.191 *	0.022	−0.729 ***
	(0.141)	(0.245)	(0.719)	(0.127)	(0.277)
lnTI	0.540 ***	0.509 ***	0.323	0.592 ***	0.528 ***
	(0.048)	(0.069)	(0.230)	(0.054)	(0.105)
Obs.	570	209	76	209	76

Note: ① ***, ** and * refer to 1%, 5% and 10% level of statistical significance, respectively. ② Standard errors are in parenthesis.

Table 14 shows the short-term coefficient estimation results. The coefficients of ECM of the whole panel and panels 1–4 are all significantly negative, which indicates that the model is statistically valid. When the variables deviate from the long-term equilibrium, they are corrected at a rate of 10.4%, 11.8%, 6.5%, 14.6% and 14.7% per year, respectively. The coefficients of *lnFD* of all panels are all significantly negative at a significance level of 5%, which indicates that FD inhibits CE in the short run of all panels. This is consistent with the long-term results of the panel ARDL. The elasticity coefficients of FD of the whole panel and panels 1–4 are −0.037, −0.029, −0.073, −0.051 and −0.032, which means that for every 1% increase in FD, CE is reduced by 0.037%, 0.029%, 0.073%, 0.051% and 0.032%, respectively.

Table 14. Short-term coefficient estimation of the panel ARDL (dependent variable: $D.lnCO_2$).

Variable	Whole Panel	Panel 1	Panel 2	Panel 3	Panel 4
ECM	−0.104 ***	−0.118 ***	−0.065 **	−0.146 ***	−0.147 ***
	(0.014)	(0.028)	(0.026)	(0.023)	(0.028)
D.lnFD	−0.037 ***	−0.029 **	−0.073 ***	−0.051 ***	−0.032 ***
	(0.007)	(0.014)	(0.008)	(0.013)	(0.009)
D.lnCI	0.814 ***	0.819 ***	0.907 ***	0.851 ***	0.814 ***
	(0.035)	(0.049)	(0.052)	(0.084)	(0.087)
D.lnIS	−0.040	−0.091 *	0.053	0.023	−0.026
	(0.030)	(0.050)	(0.066)	(0.030)	(0.031)
D.lnUR	0.071 **	0.094	0.059	0.085 **	0.034
	(0.032)	(0.067)	(0.065)	(0.038)	(0.108)
D.lnTI	0.021 *	0.028	−0.012	0.043 *	0.004
	(0.012)	(0.019)	(0.021)	(0.024)	(0.027)
cons	0.221 ***	0.165 ***	0.661 ***	0.801 ***	0.316 ***
	(0.021)	(0.026)	(0.205)	(0.115)	(0.088)
Obs.	570	209	76	209	76

Note: ① ***, ** and * refer to 1%, 5% and 10% level of statistical significance, respectively. ② Standard errors are in parenthesis.

4.3. Discussions

From the estimation results of the time series ARDL, in the long term, there is a significant negative impact of China's FD on CE. Our conclusions are consistent with Shahbaz et al. [8], Salahuddin et al. [22] and Zhang and Zhang [23]. However, the value of the coefficient is small, which means the emission reduction effect of FD is insignificant. Moreover, in the short term, there is a significant negative impact of China's FD on CE. However, the role of FD in reducing CE is not particularly great. Causes of this phenomenon may be various. First, FD's negative effect offsets its positive effect. Besides, China's carbon financial market is immature, and the market mechanism for using financial instruments to guide carbon emissions reduction is also immature. Comparing the long-term coefficient (−0.067) and short-term coefficient (−0.064) of the time series ARDL, it is found that the two coefficients are very close. This shows that in the time series analysis, the estimation results of long-term and short-term models are consistent, that is, the improvement of China's FD reduces CE, but the carbon emissions reduction effect of finance is relatively weak. This may be due to the imperfect market mechanism of using financial instruments to guide carbon emissions reduction.

From the estimation results of the panel ARDL, in the long term, FD inhibits the CE of all panels. Our conclusions are consistent with Tariq et al. [26] and Kwame et al. [27]. The elasticity coefficients of FD of panels 1–4 are −0.182, −0.936, −0.222 and −0.416, which means that for every 1% increase in FD, CE can be reduced by 0.182%, 0.936%, 0.222% and 0.416%, respectively. The reason for carbon emissions reduction may be that FD promotes the development of clean energy, thus inhibiting CE. Moreover, in the short term, FD also inhibits the CE of all panels. Through a comparison of different panels, it can be found that the impacts of FD on CE in different regions are different.

In general, FD inhibits CE in China both in the long term and in the short term from the estimation results of the time series ARDL and panel ARDL. FD plays a positive role in the low-carbon economy of China. FD broadens the financing channels of the enterprises, which helps the enterprises to obtain more funds in developing energy-efficient and low-emission technologies. By providing sufficient funds for technological innovation, FD accelerates the transformation of technological achievements and makes contributions to carbon emissions reduction. Meanwhile, FD may exert an indirect effect on a low-carbon economy through updating industrial structure. In addition, the absolute value of the long-term coefficient of FD is significantly greater than that of the short-term coefficient. To a certain extent, it can be confirmed that the impact of FD on carbon emissions reduction has a lag effect. In the short term, the guidance of FD on emissions cuts (e.g., investment and development of green technology, the upgrading of energy-saving equipment, etc.) needs time to be achieved. On the other hand, the initial financial market is unperfect, which has both positive and negative effects on energy consumption. It not only provides funds for environment-friendly enterprises, but also provides funds for some non-environment-friendly enterprises. Over time, the financial market will become gradually mature and perfect, and the positive role of FD in carbon emissions reduction will become increasingly prominent.

5. Conclusions

This paper explores the impact of FD on CE in China and 30 provinces (excluding Tibet, Hong Kong, Macao and Taiwan due to the availability of the data) during 1997–2016, using both time series ARDL and panel ARDL. This paper uses the entropy method to construct a synthetical index to measure FD. Meanwhile, a two-dimensional panel framework is introduced to group provinces in the panel analysis. The paper makes the following conclusions. Firstly, the estimation results of the time series ARDL show that for China, there is a weak emissions reduction effect in FD, whether it is a long-term effect or a short-term effect. Secondly, the estimation results of the panel ARDL show that the coefficients of FD in the five panels are negative. They also support that FD inhibits CE both in the short run and in the long run. Finally, although FD inhibits CE both in the short run and in the long run, the absolute value of the long-term coefficient of FD is significantly greater than that of the short-term coefficient.

This paper is meaningful for promoting a low-carbon economy in China. However, it is needed to study the mechanism of FD's impacts on CE in depth in future research. In addition, other robust financial indicators should be taken into account to measure FD, such as financial indicators about green finance. Moreover, we only use the entropy method to determine the weights of financial indicators in this paper. In future research, further robustness with alternate measures of the weights of financial indicators is expected. Finally, this paper does not consider the non-linear relationship between FD and CE. In future research, panel data models that incorporate non-linear relationships between FD and CE should be considered.

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References

1. Wang, Z.; Yang, Z.; Zhang, Y.; Yin, J. Energy technology patents–CO_2 emissions nexus: An empirical analysis from China. *Energy Policy* **2012**, *42*, 248–260. [CrossRef]
2. Chang, S.C. Effects of financial developments and income on energy consumption. *Int. Rev. Econ. Financ.* **2015**, *35*, 28–44. [CrossRef]
3. Ziaei, S.M. Effects of financial development indicators on energy consumption and CO_2, emission of European, East Asian and Oceania countries. *Renew. Sustain. Energy Rev.* **2015**, *42*, 752–759. [CrossRef]
4. Nasreen, S.; Anwar, S.; Ozturk, I. Financial stability, energy consumption and environmental quality: Evidence from South Asian economies. *Renew. Sustain. Energy Rev.* **2017**, *67*, 1105–1122. [CrossRef]
5. Dogan, E.; Seker, F. The influence of real output, renewable and non-renewable energy, trade and financial development on carbon emissions in the top renewable energy countries. *Renew. Sustain. Energy Rev.* **2016**, *60*, 1074–1085. [CrossRef]
6. Riti, J.S.; Song, D.; Shu, Y.; Kamah, M. The contribution of energy use and financial development by source in climate change mitigation process: A global empirical perspective. *J. Clean. Prod.* **2017**, *148*, 882–894. [CrossRef]
7. Bekhet, H.A.; Matar, A.; Yasmin, T. CO_2, emissions, energy consumption, economic growth, and financial development in GCC countries: Dynamic simultaneous equation models. *Renew. Sustain. Energy Rev.* **2017**, *70*, 117–132. [CrossRef]
8. Shahbaz, M.; Nasir, M.A.; Roubaud, D. Environmental degradation in France: The effects of FDI, financial development, and energy innovations. *Energy Econ.* **2018**, *74*, 843–857. [CrossRef]
9. Shahzad, S.J.H.; Kumar, R.R.; Zakaria, M.; Hurr, M. Carbon emission, energy consumption, trade openness and financial development in Pakistan: A revisit. *Renew. Sustain. Energy Rev.* **2017**, *70*, 185–192. [CrossRef]
10. Salahuddin, M.; Gow, J.; Ozturk, I. Is the long-run relationship between economic growth, electricity consumption, carbon dioxide emissions and financial development in Gulf Cooperation Council Countries robust? *Renew. Sustain. Energy Rev.* **2015**, *51*, 317–326. [CrossRef]
11. Adams, S.; Klobodu, E.K.M. Financial development and environmental degradation: Does political regime matter? *J. Clean. Prod.* **2018**, *197*, 1472–1479. [CrossRef]
12. Anees, S.; Zaidi, H.; Wasif, M.; Shahbaz, M.; Hou, F. Dynamic linkages between globalization, financial development and carbon emissions: Evidence from Asia Pacific Economic Cooperation countries. *J. Clean. Prod.* **2019**, *228*, 533–543. [CrossRef]
13. Charfeddine, L.; Kahia, M. Impact of renewable energy consumption and fi nancial development on CO_2 emissions and economic growth in the MENA region: A panel vector autoregressive (PVAR) analysis. *Renew. Energy.* **2019**, *139*, 198–213. [CrossRef]
14. Kayani, G.M.; Ashfaq, S.; Siddique, A. Assessment of financial development on environmental effect. *J. Clean. Prod.* **2020**. [CrossRef]
15. Nguyen, T.T.; Anh, T.; Pham, T.; Thi, H.; Tram, X. Role of information and communication technologies and innovation in driving carbon emissions and economic growth in selected G-20 countries. *J. Environ. Manag.* **2020**, *261*, 110162. [CrossRef] [PubMed]
16. Xiong, L.; Tu, Z.; Ju, L. Reconciling regional differences in financial development and carbon emissions: A dynamic panel data approach. *Energy Procedia* **2017**, *105*, 2989–2995. [CrossRef]

17. Huang, L.; Zhao, X. Impact of financial development on trade-embodied carbon dioxide emissions: Evidence from 30 provinces in China. *J. Clean. Prod.* **2018**, *198*, 721–736. [CrossRef]
18. Reddy, S.; Alam, S.; Apergis, N. The role of stock markets on environmental degradation: A comparative study of developed and emerging market economies across the globe. *Emerg. Mark. Rev.* **2017**, *35*, 19–30. [CrossRef]
19. Liu, H.; Song, Y. Science of the Total Environment Financial development and carbon emissions in China since the recent world financial crisis: Evidence from a spatial-temporal analysis and a spatial Durbin model. *Sci. Total Environ.* **2020**, *715*, 136771. [CrossRef]
20. Wasif, M.; Anees, S.; Zaidi, H.; Sinha, A.; Gedikli, A.; Hou, F. The role of stock market and banking sector development, and renewable energy consumption in carbon emissions: Insights from G-7 and N-11 countries. *Resour. Policy.* **2020**, *62*, 427–436. [CrossRef]
21. Pata, U.K. The influence of coal and noncarbohydrate energy consumption on CO_2 emissions: Revisiting the environmental Kuznets curve hypothesis for Turkey. *Energy* **2018**, *160*, 1115–1123. [CrossRef]
22. Salahuddin, M.; Alam, K.; Ozturk, I.; Sohag, K. The effects of electricity consumption, economic growth, financial development and foreign direct investment on CO_2 emissions in Kuwait. Renew. *Sustain. Energy Rev.* **2017**, *81*, 2002–2010. [CrossRef]
23. Zhang, Y.; Zhang, S. The impacts of GDP, trade structure, exchange rate and FDI in flows on China' s carbon emissions. *Energy Policy* **2018**, *120*, 347–353. [CrossRef]
24. Abokyi, E.; Appiah-Konadu, P.; Abokyi, F.; Oteng-Abayie, E.F. Industrial growth and emissions of CO_2 in Ghana: The role of financial development and fossil fuel consumption. *Energy Rep.* **2019**, *5*, 1339–1353. [CrossRef]
25. Fang, Z.; Gao, X.; Sun, C. Do financial development, urbanization and trade affect environmental quality? Evidence from China. *J. Clean. Prod.* **2020**, *259*, 120892. [CrossRef]
26. Tariq, M.; Khan, I.; Rizwan, M.; Ali, Q. Nexus between financial development, tourism, renewable energy, and greenhouse gas emission in high-income countries: A continent- wise analysis. *Energy Econ.* **2019**, *83*, 293–310. [CrossRef]
27. Kwame, E.O.; Islam, M.; Kakinaka, M. Linking international trade and foreign direct investment to CO_2 emissions: Any differences between developed and developing countries? *Sci. Total Environ.* **2020**, *712*, 136437. [CrossRef]
28. Pesaran, H.; Smith, R.; Shin, Y. Bound testing approaches to the analysis of level relationship. *J. Appl. Econom.* **2001**, *16*, 289–326. [CrossRef]
29. Liu, X.; Zhou, X.; Zhu, B.; He, P.; Wang, K. Measuring the maturity of carbon market in China: An entropy-based TOPSIS approach. *J. Clean. Prod.* **2019**, *229*, 94–103. [CrossRef]
30. Reza, A.; Islam, T.; Mamun, A.A.; Rahman, M.; Zahid, A. Simultaneous comparison of modified-integrated water quality and entropy weighted indices: Implication for safe drinking water in the coastal region of Bangladesh. *Ecol. Indic.* **2020**, *113*, 106229. [CrossRef]
31. Yan, D.; Lei, Y.; Li, L.; Song, W. Carbon emission efficiency and spatial clustering analyses in China' s thermal power industry: Evidence from the provincial level. *J. Clean. Prod. J.* **2017**, *156*, 518–527. [CrossRef]
32. Pan, W.; Li, K.; Teng, Y. Rethinking system boundaries of the life cycle carbon emissions of buildings. *Renew. Sustain. Energy Rev.* **2018**, *90*, 379–390. [CrossRef]
33. Zhen, W.; Zhong, Z.; Wang, Y.; Miao, L.; Qin, Q.; Wei, Y. Evolution of urban household indirect carbon emission responsibility from an inter-sectoral perspective: A case study of Guangdong, China. *Energy Econ.* **2019**, *83*, 197–207. [CrossRef]
34. Cai, B.; Guo, H.; Ma, Z.; Wang, Z.; Dhakal, S.; Cao, L. Benchmarking carbon emissions efficiency in Chinese cities: A comparative study based on high-resolution gridded data. *Appl. Energy* **2019**, *242*, 994–1009. [CrossRef]
35. Kao, C. Spurious regression and residual-based tests for cointegration in panel data. *J. Econom.* **1999**, *90*, 1–44. [CrossRef]
36. Pedroni, P. Critical values for cointegration tests in heterogeneous panels with multiple regressors. *Oxf. Bull. Econ. Stat.* **1999**, *61*, 653–670. [CrossRef]
37. Pedroni, P. Panel cointegration: Asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. *Econom. Theory* **2004**, *20*, 597–625. [CrossRef]