Peer-reviewed version available at *Sustainability* **2020**, *12*, 1060; doi:10.3390/su12031060

Article

Bootstrap ARDL Test on the Relationship among Trade, FDI and CO2 Emissions: Based on the Experience of BRICS Countries

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Abstract: We used the Bootstrap ARDL method to test the relationship among BRICS countries' trade, FDI and CO2 emissions. We found that Brazil's CO2 emissions and FDI have a cointegration relationship with the trade on the lag of one-period. Russia and India and CO2 emissions and trade have a cointegration relationship with FDI on the lag of one-period. In the long-term, Brazil's FDI has a long-term causal relationship with the trade on the lag of one-period. The trade between Russia and India has a long-term causal relationship with FDI on the lag of one-period. Among other BRICS variables, Russian trade and FDI on the lag of one-period of CO2 emissions and FDI and CO2 emissions are on the lag of one-period on trade which is McNown et al. mentioned the Degenerate Case #1 in their paper; while China's trade and FDI on the lag of one-period of CO2 emissions, is the country of Degeneration Case #2. When we examined short-term causality, we found that CO2 emissions showed a causal relationship with trade, while FDI and CO2 emissions were less pronounced. Trade has a positive causal relationship with FDI. These variables are different in different situations and in different countries. These results should be related to BRICS countries' FDI, international trade development and their different CO2 emission policies.

Keywords: global emission reduction; trade; FDI; BRICS countries; Bootstrap ARDL

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1. Introduction

Since the financial crisis in 2008, the global economic growth has slowed sharply, and the economic growth of major developed countries has been weak, but the BRICS countries are still the group with the greatest economic potential at present. They are in the process of economic development, and they have great commonalities in the process of industrialization, and each has its own characteristics. Emerging economies, represented by the BRICS countries, still maintain strong growth. In 2017, the total GDP of the BRICS countries (Brazil, Russia, India, China, and South Africa) was 188.76 billion U.S. dollars, accounting to 23.3% of the world total; The five countries' trade exports totaled 32.216 billion U.S. dollars, accounting to 18% of the world's total exports; The total net inflow of FDI in the five countries was 307.79 billion US dollars, accounting for 16.5% of the world's net FDI inflow. The rapid development of economic globalization has led to the rapid growth of international trade and has led to a sharp increase in global greenhouse gas emissions. According to the Intergovernmental Panel on Climate Change (IPCC), CO2 emissions account for about 60% of greenhouse CO2 emissions. The world has recognized the serious challenges of climate change. The United Nations has developed agreements such as the United Nations Framework Convention on Climate Change and the Kyoto Protocol to address greenhouse gas emissions in response to climate

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Peer-reviewed version available at Sustainability 2020, 12, 1060; doi:10.3390/su12031060

change. BRICS countries play an increasingly important role in the development of the world economy. At the same time that economic development has received global attention, the total energy consumption of the BRICS countries has also risen rapidly. The resulting pollution problems such as CO2 emissions have also become the focus of global research and attention. For the BRICS countries, FDI and export trade have injected strong momentum into economic growth, but with global warming, these emerging economies are experiencing increasing pressure on public opinion, under the open economy.

In the context of current globalization, trade between countries is becoming increasingly close, and capital breaks the limits of national borders and flows to industries and regions with higher returns. The increase in FDI provides utilities such as capital, skills, technology transfer, market access, and export incentives, and international trade and free capital flows exacerbate FDI in developing countries. Hoffman et al. [1] argue that in low-income countries, CO2 emissions affect FDI entry; in middle-income countries, FDI inflows lead to increased CO2 emissions; in high-income countries, no causal relationship between FDI and CO2 emissions is found. Aliyu [2] use the host country's annual total CO2 emissions, total known particulate emissions, rising temperatures, and total energy consumption to test “dirty” FDI, resulting in “dirty” FDI outflows. Environmental policies in 11 OECD countries are positively correlated, but FDI inflows do not significantly explain pollution levels and energy use in 14 non-OECD countries. Cole and Elliott [3] estimate the scale and technical effects of trade on SO2, NOx, CO2, and BOD, and conclude that trade technology effects are stronger than economies of scale for SO2 and BOD, while scale effects are stronger than NOx and CO2. The effect, that is, the increase in CO2 caused by the scale effect is greater than the decrease in CO2 emissions caused by the technical effect.

Empirical studies by more and more scholars have shown that FDI can improve the environmental conditions of host countries through technological spillover effects. Winkelman et al. [4] combined data from several countries and analyzed that FDI is conducive to reducing the carbon intensity of host countries and promoting the development of a low-carbon economy in host countries. Based on this kind of thinking, some scholars have carried out a classification test on the relationship between FDI and different investment environments. The research shows that when the investment location is different in terms of income level, population factor, opening up and geographical environment, FDI The impact on the environment is also significantly different. Therefore, the FDI campaign has promoted rapid economic growth in developing countries. However, while foreign direct investment has contributed to economic growth, its potential impact on environmental quality over the past decade is now being discussed (Baek, [5]). Foreign direct investment is moving towards countries where environmental regulations are relatively less stringent, with lower environmental taxes and lower standards (Seker et al., [6]). In this way, multi-ethnic countries are shifting their high-pollution industries to developing countries to avoid high environmental costs in their countries. This indicates that the impact of FDI on the host country's environment may have a threshold effect, that is, as the host country's economy and society continue to develop, the relationship between FDI and the environment also changes.

In some industrially developed countries, it has become a so-called development of developing countries by importing high-carbon products to replace domestic production or directly transferring high-carbon emissions industries to foreign countries through foreign direct investment in the country’s “pollution shelter”. The CO2 emissions of the BRICS countries accounted for the world's total carbon dioxide emissions, rising from 27.35% in 2001 to 37.78% in 2011. By 2016, the greenhouse gas emissions of the BRICS countries accounted for 41.3% of the world's total. This article examines the theme of exports, foreign direct investment, and CO2 emissions of the BRICS countries. It can be used to find out the reasons for this topic. From our research, we can explore whether developing countries represented by BRICS countries have become a “pollution paradise” for high-carbon industries in developed countries. We use the Bootstrap ARDL model to explore the impact of BRICS exports on CO2 emissions. From long-run cointegration relations and long-term short-run causality, the results are beneficial to BRICS countries seeking a balance between trade and CO2 emissions. From the perspective of trade and FDI, it is of great significance to study the CO2 emissions reduction

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problem of emerging economies and seek new emission reduction paths for the development of low-carbon economy and global emission reduction targets of BRICS countries. The BRICS countries have made some contribution to the formulation of relevant international trade policies and environmental policies. The first part of the structure of this paper is the introduction, the second part is the literature review, the third part is the method, the fourth part is the data period, the fifth part is the empirical results, and the sixth part is the conclusions.

2. Literature review

With the continuous expansion of trade and the intensification of global warming, since the 1990s, the international community and academia have begun to pay attention to the impact of international trade on climate change. "Trade and carbon emissions" have become one of the important topics of the global climate change conference. The mechanism of international trade affecting climate change began when Grossman and Krueger [7] explored the impact of the North American Free Trade Area on greenhouse gas emissions, and they decomposed the environmental effects of trade into scale effects, structural effects, and technological effects, and emphasized these three effects are mutually influential, and the final total effect is not a simple superposition. The "three-different-effects" analysis helps to clarify the path and direction of the influence of international trade on climate change and becomes the basic analysis frame of the effects of international trade and climate change. Under the framework of the "three effects" analysis, many scholars have carried out empirical tests on the impact of international trade on climate change. The results of the test have two viewpoints: one is that the expansion of trade increases greenhouse gas emissions and exacerbates climate change (Copeland and Taylor [8]; Guo et al. [9]; Lin et al. [10]; Lin [11]).

Another view is that free trade reduces greenhouse gas emissions and slows climate change. For example, Antweiler et al. [12] found that the structural effects of free trade are very small and that a percentage point increase in the production scale will result in pollution concentration in sample countries. The degree is increased by 0.25 to 0.5 percentage points, and the technical effect can reduce the pollution concentration by 1.25 to 1.5 percentage points. The three effects will improve the environment as a whole. Peters et al. [13] study concluded that international trade is an important factor in explaining changes in CO2 emissions in many countries. In their study, they find that the stability of CO2 emissions in developed countries is partly due to increased imports from developing countries. Liddell [14] studied the nature of trade in national emissions and found that internal government policies affect CO2 emissions, especially China and India are countries that help reduce CO2 emissions. Hasanov et al. [15] examined the impact of exports and imports on CO2 emissions, the impact of long-run and short-run signs of exports and imports on consumption-based CO2 emissions, and the impact of trade on CO2 emissions changes will be fully within three years absorb. Regionally based CO2 emissions are not statistically significant for exports and imports. Different scholars have different indicators, data samples, and research methods when analyzing the impact of trade on greenhouse gas emissions, and the conclusions are not the same. As Managi et al. [16] believe the impact of trade openness on greenhouse gas emissions depends on pollutants and country choices. The results show that trade can reduce SO2 and CO2 emissions in OECD countries, but not in OECD. The national situation is the opposite. It can also be seen that the impact of trade on greenhouse gas emissions is a complex dynamic system process.

In studying the relationship between economic growth and greenhouse gas emissions, Knight and Shore [17] found that during this period there was some evidence that there was a decoupling between economic growth and regional emissions, but there was no evidence that consumption-based emissions were decoupled. Fernandez-Amador et al. [18] investigated the relationship between per capita real GDP and per capita CO2 emissions associated with production and consumption activities. They found that both of this income elasticity is dependent on policies, reflecting the small carbon efficiency gains brought about by economic development. The carbon footprint shows greater income elasticity, and national policy instruments for production can obviously be circumvented by carbon embodied in intermediate trade. There are three main viewpoints in the academic world about the impact of FDI on the environment: First, the "pollution paradise hypothesis". The core view is that in order to attract foreign capital inflows, countries will gradually lower their environmental standards and appear to "race to the bottom line". Because developed countries have higher environmental standards than developing countries, polluting industries will shift from developed to developing countries, and developing countries will become "pollution shelters" (Walter and Ugelow [19]), Asghari [20], Abdouli et al. [21]) confirmed that FDI caused a decline in the environmental quality of the host country.

The second view is the "polluting halo" effect. The core view is that FDI carrying advanced technology can spread greener and cleaner production technologies to the host country and improve the environmental protection level of its production, thus helping to reduce carbon emissions in the host country (Antweiler et al. [12]; Popp [22]; Poelhekke [23]). The third view is that the impact of FDI on the host country's environment is complex and multidimensional. The two opposite effects of FDI on carbon emissions are affected by the technology spillover effect, absorption capacity and capital accumulation effect of FDI. These effects are different based on different conditions (economic level, industrial structure, environmental policy, investment structure, etc.). The environmental effects are uncertain (Kim and Adilov [24]).

Most of the existing research is based on a single perspective of trade or FDI to study its relationship with the environment or carbon emissions. In recent years, some scholars have begun to consider the impact of greenhouse gas emissions under the entire open economy, and have included foreign trade and FDI in the scope of the investigation. Keho [25] studied the economic community of West African countries and found that the impact of FDI on carbon dioxide emissions depends on the degree of trade openness of the host country. With the increase of trade openness in Burkina Faso, Gambia and Nigeria, the emission reduction of FDI The effect is also more obvious; and with the reduction of foreign trade in Ghana, Mali and Togo, the emission reduction effect of FDI also declines; In Benin, Niger, Senegal, and Sierra Leone, the long-term impact of FDI on carbon emissions is not significant. Frutos-Bencze et al. [26] investigated the relationship between FDI, trade and industrial emissions from the Central American Free Trade Agreement (CAFTA-DR) from 1979 to 2010. Studies have shown that FDI and trade have a negative impact on selected pollutant emissions, including carbon dioxide, that is, increased emissions. Liu and Wang [27] divided emerging market countries into two sample groups according to the average level of per capita income from 1985 to 2007. The empirical results show that FDI inflows are alleviated to some extent, whether in countries with higher per capita income levels or lower countries. The pressure of CO_2 emissions; export trade dependence has a positive effect on CO_2 emission reduction in the more developed six countries. Only developed countries have significant linkages between FDI, export trade and carbon emissions. The existing research shows that different scholars have different indicators, samples, and research methods when analyzing the environmental effects of trade and FDI, and the conclusions are not the same. The relationship between the three is complex and multidimensional, and the environmental effects based on different conditions are not the same. It can also be seen that the evaluation of the environmental effects generated by trade and FDI is a complex dynamic system process. How to reduce the negative effects of the environment and improve the positive effects of the environment in the process of international economic cooperation is a common issue faced by all countries.

3. Methodology

Improving energy and environmental efficiency is an important means to ensure economic growth as well as to achieve energy saving and emission reduction. As an important source of technological progress, foreign trade is one of the key drivers of the improvement of energy-environment efficiency. Foreign trade makes domestic companies to have more opportunities to access and absorb international advanced technologies, and on the other hand have to face global competition, which is conducive to promoting the efficiency of the energy environment. In terms of global energy consumption and greenhouse gas emissions, China, the European Union, and the United States are the three countries with the world's largest greenhouse gas emissions, and their greenhouse gas emissions account for more than half of global emissions. The top 10 emitters account for nearly three-quarters of the world's total emissions; the last 100 emitters account for only 3.5% of global emissions. If these major emitters do not have significant actions to reduce greenhouse gas emissions, the world will not be able to successfully address the challenges of climate change, Olivier et al., [28]. In the past 10 years, the energy industry has remained the largest source of greenhouse gas emissions.

In this paper, we use the Bootstrap Autoregressive Distributed Lagged Model (ARDL) to examine the impact of China's trade, FDI and carbon emissions; Bootstrap ARDL has used the principle of self-regression and multiple loop calibrations to make the time series related data close to the expected result that needs to be verified. Before doing the Bootstrap Autoregressive Distribution Lagged model, it is necessary to know whether the collected data is for the fixed state, the general treatment method is the unit root test first. In the time series analysis, it is necessary to first check whether the data is stationary. The so-called steady-state means that the statistic statistics such as the mean and the variance do not change with time, that is, the self-covariance and the variance are fixed finite constant values can avoid false regressions. In the time series analysis, it is necessary to first check whether the data is stationary. The so-called steady-state means that the statistic statistics such as the mean and the variance do not change with time, that is, the self-covariance and the variance are fixed finite constant values can avoid false regressions. The purpose of a single test is to determine the integration level of time series variables to determine the nature of the time series. The method begins with Fuller-Fuller (referred to as DF test) proposed by Fuller [29] and Dickey and Fuller [30]. Augmented Dickey-Fuller unit root test (ADF), in addition to the more common unit root test, Phillips and Perron [31] proposed PP unit root test, because most time-series data are self-related characteristic.

3.1. Unit root test

The Augmented Dickey-Fuller (ADF) the unit root test method is based on the least-squares method for three basic regression equations, namely standard (no time-interval item with no intercept), intercept mode (with intercept, no trend). Estimated with intercept trend mode (with intercept and trend terms).

Model 1: No intercept & trend term (random walk):

$$\Delta y_t = \alpha_0 + \alpha_1 y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + \varepsilon_t \tag{1}$$

Model 2: Intercept item with no trend term (random walk with drift):

$$\Delta y_t = \alpha_0 + \alpha Y_{t-1} + \sum_{i=1}^{p} \beta_j \Delta Y_{t-i} + \varepsilon_t \tag{2}$$

Model 3: Intercept item & trend term (random walk with drift and trend):

$$\Delta y_t = \alpha_0 + \alpha Y_{t-1} + \alpha_2 t + \sum_{i=1}^{p} \beta_j \Delta Y_{t-i} + \varepsilon_t \tag{3}$$

Where Δ is the first-order difference, α_0 the variable to be discussed is the drift term, *t* is the trend term of the time trend term, and *p* is the maximum number of deferred periods, it is the error term.

As long as there is no sequence correlation in the AR (1) process in the DF test, the critical value of the DF test is the same as the threshold of the ADF test. The coefficients of the different terms $\Delta y_{t-i} (i = 1,2,\cdots, p-1)$ converge to the t-distribution, indicating that the joint significance test of these coefficients will converge to the F-distribution. Therefore, regardless of any value in the model, the coefficients of the different term can be inferred using traditional statistical checksum statistics.

The lag period selection of the AR model is very important for the results of the ADF test. In practice, there are usually many ways to choose a lag period, such as the information standard method or the lag method.

If the result of the above-mentioned ADF unit root test is to reject the null hypothesis H_0, it means that the data of this time series is fixed, there is no unit root phenomenon, also called $I(0)$ sequence; if the null hypothesis is not rejected H_0: $\alpha_1 = 0$, it means that the data has unit root , is a non-stationary time series. This test adds the self-deferred term of the interpreted variable to the right side of the regression so that the residual term is closer to the white noise process and the state change of the variable is controlled.

3.2. Optimum lag period test

After completing the unit root test, then the Akaike information criterion (AIC) is determined. Because the ADF method or the PP method needs to determine an optimal backward period, the self-related problem of the residual term is corrected to make the residual term is a white noise process. However, if they're too many lag periods are added, the ability to reject the null hypothesis will be reduced; but, if we add too few lag periods in the model will not be able to completely correct the shortcomings of the threshold increase caused by the moving average; how many lag periods are these necessary to add-in? As a time series fixed-state test analysis, it will be found that the selection of the time series of lag periods plays a very important role, and different lag periods often affect the results of the final analysis. Therefore, the selection of the number of lag periods is quite important. In this paper, we choose a widely used financial and economics industry to use the AIC criteria to judge and choose the smallest AIC to be the optimal lag period.

The Akaike Information Criterion (AIC) equation is shown in equation (4):

$$\mathrm{AIC} = \mathrm{n}ln\ (SSE) + 2P \tag{4}$$

Where P represents the number of parameter estimates; n represents the number of observations used; SSE is the sum of squared errors.

3.3. Vector Autoregression Model (VAR)

When the multivariate time series model is expressed by linear regression, it implies the assumption of causality between variables. However, due to the subtle operation of the economic system, it is sometimes impossible to distinguish between the variables in the model and the endogenous variables. It is an exogenous variable, so it creates difficulties in identification. Sims [32] proposed the Vector Autoregression Model (VAR) to solve the problem of structural model identification. Sims believes that the characteristics of economic activity will be completely reflected in the data over time, so the data itself can be analyzed directly. It is easy to understand the nature of economic activities, so you can make structural settings without knowing the exact relationship of these endogenous variables in economic theory. In the VAR model, all variables are treated as endogenous variables, so it is not necessary to distinguish between endogenous variables or exogenous variables, and a set of regression equations to explore the relationship between variables, and each regression equation Both the backward of the variables and the backward of other variables are used as explanatory variables. Therefore, the VAR model is more in line with the spirit of time series analysis; because the time series analysis considers that the backward terms of the variables cover all relevant information.

3.4. Bootstrap ARDL test

Using the Bootstrap Autoregressive Distributed Lag model (ARDL) test, we can better understand the cointegration state of the series in the model, and use the Monte Carlo simulation for the size and power characteristics of the endogenous problem frame. The asymptotic threshold of the simulation has only a small effect; if the re-sampling process is applied properly, the pilot-to-test ratio is determined, and the asymptotic test in the ARDL test based on the size and power characteristics

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is performed better and eliminated. Uncertain is the possibility of inference. It can also describe the extension of the validation framework in the case of alternative degradation, as well as the threshold generated by the Bootstrap ARDL. The Bootstrap ARDL test is based on the Granger Causality Test. The standard Granger causality test will determine the direction of the short-term causal relationship. If y is due to a variable, no agreement is found between y and x. The whole relationship, then the Granger causality test of $x \rightarrow y$ should only include the hysteresis difference of x, that is, we test whether $\delta > 0$, if there is cointegration relationship between the variables, then this means the relevant variables and independent variables form a fixed linear combination. The hysteresis term can be considered as $I(0)$, and the Granger causality test of $x \rightarrow y$ should include the hysteresis difference of x and the hysteresis level of x, that is, whether $\beta > 0$ and $\delta = 0$. The cointegration method proposed by Pesaran et al. [33] is that the Auto Regressive Extended Lag (ARL) can simultaneously process different time series variables with different integration orders. The ARDL is used the critical interval to detect whether there is a long-term equilibrium relationship, which not only solves the problem of sequence inequalities but also processes small sample data and processes time-series changes with different integration orders. The advantage of this model is that it includes both short-term adjustment and long-term equilibrium relationship, which can correctly describe the relationship between variables. The advantage of the ARDL approach is that other cointegration techniques require that all regressions be integrated with the same specification, but it can be applied regardless of their integration order under this constraint test. The cointegration test includes a comparison of the threshold and the F statistic. ARDL Bound test (Pesaran et al., [33]) has a time series of mixed integration sequences, which can be defined as:

$$\Delta y_t = c + \alpha y_{t-1} + \beta x_{t-1} + \sum_{i=1}^{p-1} \gamma \Delta y_{t-1} + \sum_{i=1}^{p-1} \delta \Delta x_{t-1} + \sum_{j=1}^{q} \psi D_{t,j} + \varepsilon_t \tag{5}$$

In the case of exogenous weak regression, in the long run, these regression factors are not affected by the variables. The model does not exclude the existence of cointegration between regressions. It does not assume that the dependent variable to the regression does not exist (short-term) Granger Causality. The time series Bootstrap ADRL test method, McNown, Sam and Goh [34] proposed changes to the Pesaran et al. [33] ARDL test model.

The ARDL model is:

$$y_t = a + \sum_{i=1}^{k} \alpha_i y_{t-i} + \sum_{i=1}^{k} \beta_i x_{t-i} + \sum_{j=1}^{l} \psi_j D_{t,j} + \mu_t \tag{6}$$

i and j are the indicators of the lag period, $i = 1, 2,..., k$; $j = 1, 2,..., k$. t represents time $t = 1, 2, ..., T$. The y_t in the equation is the explanatory variable and x_t is the explanatory variable, there is a variable $D_{t,j}$, is a dummy variable. The parameters α_i, β_i are the coefficient values of the interpreted variable y_i and the explanatory variable x_i. The error term is μ_t, and equation (6) can be rewritten and expanded into the following equation:

$$\Delta y_t = \gamma_0 + \sum_{i=1}^{k-1} \gamma_1 \Delta y_{t-i} + \sum_{i=1}^{k-1} \gamma_2 \Delta x_{t-i} + \sum_{i=1}^{k-1} \gamma_3 \Delta z_{ti} + \sum_{j=1}^{l} \gamma_4 D_{t,j} + \theta_1 y_{t-1} + \theta_2 x_{t-1} + \theta_3 z_{t-1} \tag{7}$$

Where $\gamma = 1 - \sum_{i=0}^{k} \alpha_i$; $\theta = \sum_{i=0}^{k} \beta_i$; other parameters are the function values of the original parameters in equation (7).

McNown et al. [34] proposed to add the original ARDL model to a lag period for interpreting variables. The null hypothesis is H_0: $\theta = 0$. The conditions for testing the cointegration relationship by Pesaran et al. [33] will be more complete. The Bootstrap ARDL test is the cointegration relationship by relying on the following assumptions:

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$$H_0: \gamma = \theta = 0,\ H_0: \gamma = 0,\ H_0: \theta = 0$$

According to Pesaran et al. [33], the cointegration test needs to be F-test or *t*-test. The following assumptions are made:

$$H_0: \theta_1 = \theta_2 = \theta_3 = 0 \text{ or} H_0 = \theta_1.$$

However, McNown et al. [34] suggested adding three tests to distinguish between cointegration and non-cointegration. McNown et al. [34] require that cointegration must reject all three virtual hypotheses.

The null hypothesis error term F_1 is tested as H_0: $\theta_1 = \theta_2 = \theta_3 = 0$.

The *t*-test for the lag dependent variable is H_0: θ_1.

The F_2 test for the lag independent variable is H_0: $\theta_1 = \theta_2 = \theta_3 = 0$.

Based on three null hypotheses, McNown et al. [34] explain two degenerates of Pesaran et al. [33].

Only the critical value of case #2 is presented. The two degeneration cases are as follows:

- Degenerate case #1, the F_1 test and the *t*-test for the lag dependent variable are significant, but the F_2 test for the lag independent variable is not significant.
- Degenerate case #2, the F_1 test and the F_2 test for the lag dependent variable are significant, but the *t*-test for the lag dependent variable is not significant.

We found that Pesaran et al. [33] excluded degeneration case #1, and if they did not consider the integration order of the dependent variable, it must be $I(1)$. However, McNown et al. [34] used the Bootstrap ARDL test to solve this problem by an additional test of the lagging independent coefficient.

If there is a cointegration relationship between the dependent variable and the independent variable, the above three virtual hypotheses will be rejected at the same time, and the explanatory variable and the explanatory variable are stable linear coincidences. Granger causality test based on the bootstrap ARDL model, we can examine the short-term causal relationship between the three variables of export, FDI and carbon emissions.

After testing the long-term relationships, we found they have no cointegration relationship between y, x and z. We use the Granger causality test for x and z, which should include the difference in hysteresis on x or z. We test $\gamma_2 = 0$ or $\gamma_3 = 0$ in equation (8). However, if there is cointegration between the dependent variable and the independent variable; this means that they form a fixed linear combination. In this case, the short-term relationship test should include the hysteresis difference of x or z and the hysteresis level of x or z; that is, test γ_2 and θ_2 or γ_3 and θ_3.

4. Data period

In this paper, we use CO2 emissions, trade and FDI data for BRICS countries. Trade and FDI data have adjusted to prices in 1980, which means we used the 1980 deflator, while CO2 emissions are based on per capita CO2 emissions in BRICS countries. It is calculated by dividing the CO2 emissions by the metric tons per capita for the current year. Information on CO2 emissions, international trade (including imports and exports) by the percentage of GDP and FDI (Foreign direct investment, net inflows, by the percentage of GDP) data come from the International Monetary Fund. We have a note here that the data on IMF of CO2 emissions is only available in 2014, and the data from 2014 to 2018 comes from Global Energy & CO_2 Status Report 2017, 2018, 2019 published by International Energy Agency. Since the Bootstrap ARDL is performing operations, the variable must be a stable sequence of I (0) or I (1), otherwise false regression will occur. At the time of the unit root test, the data presents I (2), and we abandon the data and use the data of CO2 emissions. The BRICS data is not uniform, Brazil is from 1975 to 2018, Russia is from 1992 to 2018, India is from 1975 to 2017, China is from 1982 to 2018, and South Africa is from 1970 to 2018.

5. Empirical results

Table 1 Description of statistics

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Economies	Brazil			Russia		
Variables	CO2	TRA	FDI	CO2	TRA	FDI
Mean	1.754673	0.210544	0.020079	11.57713	0.558724	0.017814
Median	1.749501	0.203944	0.015254	11.51359	0.517061	0.016893
Max	2.612934	0.296783	0.050341	13.97997	1.105771	0.045027
Min	1.275133	0.143909	0.001287	10.12730	0.461934	0.001746
Std. Dev	0.357300	0.046883	0.015048	0.918029	0.129364	0.012532
Skewness	0.647122	0.200940	0.458010	0.582980	2.965699	0.595385
Kurtosis	2.427507	1.686156	1.790895	3.020905	12.97000	2.382151
Variables	44	44	44	27	27	27

Economies	India			China		
Variables	CO2	TRA	FDI	CO2	TRA	FDI
Mean	0.940178	0.274436	0.007802	4.067414	0.382184	0.028084
Median	0.898163	0.226194	0.005950	2.820568	0.372102	0.030399
Max	1.961458	0.557937	0.036205	7.946870	0.644789	0.061869
Min	0.404751	0.122193	-0.000297	1.566740	0.179211	0.002097
Std. Dev	0.449012	0.148388	0.008933	2.253928	0.130330	0.016675
Skewness	0.760020	0.635443	1.156480	0.635025	0.335337	0.049052
Kurtosis	2.611596	1.899792	3.758870	1.771486	2.308199	1.981967
Variables	43	43	43	37	37	37

Economies	South Africa		
Variables	CO2	TRA	FDI
Mean	8.497800	0.526731	0.008309
Median	8.647141	0.523117	0.004790
Max	9.979458	0.728654	0.059789
Min	6.785930	0.374875	-0.008405
Std. Dev	0.930114	0.077086	0.011911
Skewness	-0.060876	0.084575	1.978112
Kurtosis	1.839234	2.672987	8.531169
Variables	49	49	49

Note: The descriptive statistics are based on the differences of each variable.

Table 2 Unit Root Test (Level)

Countries	Test	DF		ADF			PP		
	Variable	Intercept	Trend and Intercept	Intercept	Trend and Intercept	None	Intercept	Trend and Intercept	None
Brazil	CO2	-0.6329 (1)	-2.3934 (0)	-0.6265 (0)	-2.5547 (1)	0.8005 (1)	-0.7928 (2)	-2.3149 (2)	0.9759 (2)
	TRA	-1.2113 (0)	-2.5886 (0)	-1.2198 (0)	-2.3678 (2)	0.3810 (0)	-1.2699 (1)	-2.8640 (1)	0.4740 (3)
	FDI	-1.0126 (0)	-2.3973 (0)	-1.0956 (0)	-2.4737 (1)	-0.0221 (0)	-1.13876 (2)	-2.5625 (2)	0.0010 (1)

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Russia	CO2	-1.6946*	-2.6186	-2.8511*	-4.3426**	-0.6771	-2.8808**	-4.8080***	-0.6410
		(0)	(0)	(0)	(0)	(0)	(2)	(2)	(1)
	TRA	-0.9969	-2.5975	-2.6537	-3.4774*	-0.2570	-6.4353***	-6.3301***	-2.0606**
		(1)	(1)	(1)	(1)	(1)	(2)	(2)	(1)
	FDI	-1.7647*	-1.8077	-1.9507	-1.5379	-0.9990	-1.8485	-1.3257	-0.8689
		(0)	(0)	(0)	(0)	(0)	(3)	(3)	(3)
India	CO2	-0.1660	-2.4747	0.8472	-1.8302	-1.0962	0.8014	-1.9884	-1.2414
		(3)	(3)	(0)	(1)	(3)	(3)	(3)	(3)
	TRA	-0.2129	-1.3726	--0.7201	-2.0240	0.9629	-0.8285	-1.7466	0.6866
		(0)	(0)	(0)	(2)	(0)	(3)	(3)	(3)
	FDI	-1.3729	-2.9294*	-1.5809	-2.9687	-0.8247	-1.5124	-2.9688	-0.7603
		(0)	(0)	(0)	(0)	(0)	(1)	(0)	(2)
China	CO2	-0.0298	-1.6977	0.0203	-1.8699	1.4095	0.6820	-1.5150	3.2573
		(1)	(1)	(1)	(1)	(1)	(3)	(3)	(3)
	TRA	-1.3465	-1.7590	-1.8972	-1.4719	-0.0037	-1.5780	-1.0660	0.0803
		(1)	(1)	(1)	(1)	(1)	(2)	(2)	(2)
	FDI	-1.3937	-1.8836	-2.2193	-1.8492	-0.6685	-1.9454	-1.4165	-0.7318
		(0)	(1)	(1)	(1)	(0)	(1)	(3)	(2)
South Africa	CO2	-1.3971	-1.4843	-1.8347	-1.6389	-0.0819	-2.2456	-1.7301	-0.0898
		(0)	(0)	(1)	(0)	(0)	(3)	(2)	(2)
	TRA	-1.8026*	-2.3211	-2.0346	-2.2730	0.1631	-2.0786	-2.3501	0.1999
		(0)	(0)	(0)	(0)	(0)	(2)	(2)	(2)
	FDI	-1.3244	-1.5904	-1.5027	-2.1591	-1.0221	-4.9309***	-5.7532***	-3.6719***
		(3)	(3)	(0)	(3)	(3)	(0)	(0)	(1)

Note: The asterisks ***, ** and * indicate the 1%, 5% and 10% levels. The numbers in parentheses represent the lag period.

Table 1 shows the statistical descriptions of the three variables of CO2 emissions; trade and foreign direct investment in the BRICS countries applied the Augmented Dickey-Fuller (ADF) unit root test to verify the stationary of each time series. Table 2 is the unit root test result of the level term, and Table 3 is the unit root test result of the first-order difference term. We cannot reject the null hypothesis that all series have a unit root of 5% significance level when using the ADF test. On the other hand, when using the Zivot-Andrew (ZA) test to consider structural breaks, we found that some series are static at the level. Since the Pesaran boundary ARDL test (Pesaran et al, [33]) allows modeling variables with different integration orders, we continue to estimate models for all economies. If the dependent variable is static, the new bootstrap ARDL test for Degenerate Case #1 also prevents incorrect inference and therefore does not cointegrate with the other two series. Table 4 reports the estimation and testing of equation (6) using Bootstrap ARDL. Each ARDL equation passes all diagnostic tests for autocorrelation, non-normality, and heteroscedasticity. These lag lengths were determined using the Akaike Information Criterion (AIC). Diagnostic tests, such as Jarque Bera test, LM test, and ARCH test, are performed in the post-estimation to check the normality, autocorrelation, and heteroscedasticity of the residuals. Each ARDL equation passes all diagnostic tests for autocorrelation, non-normality, and heteroscedasticity. F_1^*, F_2^* and t^* refer to a critical value of 0.05 significance level, generated by the Bootstrap ARDL procedure proposed by McNown et al. [34].

Table 3 Unit Root Test (1st difference)

Countries	Test	DF		ADF			PP		
	Variable	Intercept	Trend and Intercept	Intercept	Trend and Intercept	None	Intercept	Trend and Intercept	None
Brazil	CO2	-5.0336***	-5.0768***	-3.6905***	-3.6428**	-4.9210***	-5.0201***	-4.9538***	-4.9319***
		(0)	(0)	(1)	(1)	(0)	(1)	(1)	(2)
	TRA	-5.3430***	-3.2128**	-5.0928***	-5.0320***	-6.0212***	-5.9957***	-5.9336***	-5.9790***
		(0)	(2)	(1)	(1)	(0)	(3)	(3)	(3)
	FDI	-2.8456***	-6.3611***	-4.2871***	-4.2869***	-4.2443***	-6.3308***	-6.3021***	-6.3146***
		(3)	(0)	(1)	(1)	(1)	(1)	(1)	(1)
	CO2	-3.5899***	-4.4551***	-4.0413***	-4.3871***	-4.1583***	-3.9863***	-4.3657***	-4.1267***
		(0)	(0)	(0)	(0)	(0)	(2)	(1)	(2)

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Russia	TRA	-2.2641** (0)	-3.6403** (0)	-6.0093*** (1)	-6.3020*** (0)	-6.2013*** (1)	-6.8559*** (0)	-6.3020*** (0)	-7.2557*** (0)
	FDI	-4.4046*** (1)	-4.9660*** (1)	-4.4654*** (1)	-4.8319*** (1)	-4.5613*** (1)	-5.3454*** (2)	-5.6396*** (2)	-5.4813*** (2)
India	CO2	-2.4580** (2)	-2.8021 (2)	-2.8501* (2)	-2.7638 (2)	-0.8202 (2)	-6.0063*** (3)	-6.0452*** (3)	-2.7427*** (3)
	TRA	-5.5535*** (0)	-5.5584*** (0)	-5.4869*** (0)	-5.4206*** (0)	-5.3058*** (0)	-5.5228*** (2)	-5.4584*** (2)	-5.4017*** (3)
	FDI	-7.2646*** (0)	-7.2868*** (0)	-7.2694*** (0)	-7.1686*** (0)	-7.2934*** (0)	-7.3006*** (3)	-7.1962*** (3)	-7.3091*** (3)
China	CO2	-2.5805** (0)	-2.8038 (0)	-2.6334* (0)	-2.7061 (0)	-1.8443* (0)	-2.6334* (0)	-2.7061 (0)	-1.7443* (2)
	TRA	-4.1256*** (0)	-4.3638*** (0)	-4.2114*** (0)	-4.4000*** (0)	-4.2076*** (0)	-4.2114*** (0)	-4.3660*** (2)	-4.2076*** (0)
	FDI	-4.7446*** (0)	-5.0024*** (1)	-4.6760*** (0)	-4.9273*** (1)	-4.7391*** (0)	-4.5900*** (3)	-4.7548*** (3)	-4.6601*** (3)
South Africa	CO2	-2.1699** (0)	-6.5316*** (0)	-6.5824*** (0)	-6.7470*** (0)	-6.6576*** (0)	-6.5830*** (2)	-6.7472*** (1)	-6.6579 (2)
	TRA	-6.8214*** (0)	-6.8469*** (0)	-6.7791*** (0)	-5.2783*** (0)	-6.8269*** (1)	-6.8483*** (3)	-6.7594*** (3)	-6.8980*** (3)
	FDI	-3.7053*** (3)	-3.8300*** (3)	-4.4338*** (3)	-4.3831*** (0)	-7.7339*** (0)	-4.4338*** (1)	-4.3831*** (3)	-4.4900*** (3)

Note: The asterisks ***, ** and * indicate the 1%, 5% and 10% levels. The numbers in parentheses represent the lag period.

This paper examines the foreign direct investment (FDI) of the BRICS countries, whether there is a long-term (cointegration) relationship economy between trade and CO2. Many believe that an outward-looking strategy to promote trade and/or encourage FDI contributes to the reduction of CO2 emissions in the BRICS. If these outward-looking strategies result in long-term reductions in actual CO2 emissions, then there should be a long-term cointegration relationship between these variables. In addition, this long-term relationship must exist in a case where CO2 is a dependent variable. The study used a newly developed cointegration test, the Bootstrap ARDL, to study the long-term relationship between FDI in the BRICS economies, trade and CO2.

Table 4 Cointegration Analysis

Countries	Period	Dependent Variable| independent variable	Lag Specification	F_1	F_1^*	t	t^*	F_2	F_2^*	Dummy Variables	Cointegration Status
Brazil	1975-2018	(CO2|TRA|FDI)	(1, 2, 0)	0.877	3.173	-1.416	-2.076	0.566	3.096	D97, D10	No-cointegration
	1975-2018	(TRA|FDI|CO2)	(1, 0, 0)	6.134	4.276	-3.716	-1.903	8.501	5.282	D00	**Cointegration**
	1975-2018	(FDI|CO2|EXP)	(1, 0, 0)	2.308	3.311	-1.483	-2.168	3.307	3.134	D97	No-cointegration
Russia	1992-2015	(CO2|TRA|FDI)	(1, 0, 0)	4.455	4.152	-3.249	-2.581	2.911	4.512	No	**Degenerate case #1**
	1992-2018	(TRA|FDI|CO2)	(1, 0, 1)	5.276	5.189	-3.917	-3.397	4.018	7.021	D96	**Degenerate case #1**
	1992-2018	(FDI|CO2|EXP)	(1, 0, 0)	5.221	3.714	-7.890	-2.753	13.750	3.102	D03, D14	**Cointegration**
India	1975-2017	(CO2|TRA|FDI)	(1, 0, 0)	7.108	3.234	-1.998	-2.006	9.689	3.652	D86, D95, D08	No-cointegration
	1975-2017	(TRA|FDI|CO2)	(1, 2, 0)	0.232	3.870	-0.737	-0.824	0.339	2.923	D93, D04	No-cointegration
	1975-2017	(FDI|CO2|EXP)	(1, 0, 0)	5.469	4.007	-3.638	-2.740	8.202	4.615	D95, 06, D12	**Cointegration**
China	1982-2018	(CO2|TRA|FDI)	(1, 0, 0)	9.756	4.673	-2.699	-3.277	13.713	6.048	D95, D06, D11	**Degenerate case #2**
	1982-2018	(TRA|FDI|CO2)	(1, 0, 0)	0.954	3.923	-1.512	-2.145	0.455	4.420	D92, D00, D14	No-cointegration
	1982-2018	(FDI|CO2|EXP)	(1, 0, 0)	1.382	5.212	-1.810	-3.426	0.469	5.826	D92, D12	No-cointegration

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South Africa	1970-2018	(CO2|TRA|FDI)	(1, 0, 0)	2.351	3.959	-1.665	-2.830	1.951	4.849	D81, D90, D04, D12	No-cointegration
	1970-2018	(TRA|FDI|CO2)	(1, 0, 0)	1.650	13.979	-2.064	-1.322	0.753	14.623	D06,	No-cointegration
	1970-2018	(FDI|CO2|EXP)	(0, 0, 0)	8.981	11.363	-5.170	-9.546	1.119	3.106	D97	No-cointegration

Note: F_1 is the F statistic for the coefficients of $y(-1)$, $x_1(-1)$ and $x_2(-1)$; F_2 is the F statistic for the coefficients of $x_1(-1)$ and $x_2(-1)$; t denotes the t statistic for the coefficient of $y(-1)$. D## refers to the dummy of that year. Notations with an asterisk, *, indicate significance at 10% level based on critical values generated from the bootstrap method suggested by McNown et al. (2016).

We conducted Bootstrap ARDL empirical tests on CO2 emissions, trade and foreign direct investment in the BRICS countries. From Table 4 we find that Russia's trade and FDI on CO2 emissions as well as foreign direct investment and CO2 emissions to trade are degenerate case #1; China's FDI and lag CO2 emissions and exports are degenerate case #2. This may indicate that FDI has a long-term development relationship with China's economic development, because China is mainly an export-oriented economy, and FDI affects CO2 emissions. The long-term relationship between CO2 emissions and trade is a reasonable phenomenon, and empirical results can explain this phenomenon; Brazil's FDI and CO2 emissions have a cointegration relationship with the lag one period of trade, Russia and India's trade and CO2 emissions. There is a cointegration relationship with the lag one period of FDI. Among the BRICS countries, South Africa's economic data is: South Africa ranks lowest in the tangible food supply, and the labor force fell by more than 3% in 2008. It is the only country in the BRICS. Below this, India's workforce has grown by nearly 3%. South Africa's manual labor costs are higher than in India, and China. Workers in South Africa are paid more than Brazil, China, and India. South African workers are more productive than Russia, Brazil, China, and India.

In Table 5, we show that Russia and India have significant long-term causality in trade and FDI, and both have positive causality; Brazilian FDI and trade also have significant long-term causality. We find that although these variables have a cointegration relationship, there is no long-term causal relationship in the case of CO2 emissions and trade in Brazil. In Russia and India, CO2 emissions and FDI have no long-term causal relationship in the lag of one-period. Countries with higher per capita income levels are still in countries with lower per capita income levels. The inflow of FDI has reduced the pressure on CO2 emissions to a certain extent; trade dependence has positively reduced the CO2 emissions of the heavier BRICS countries. Impact, only FDI in developed countries, there is a significant relative between trade and CO2 emissions. One way to use the motivational guidance method behind it is to generate a data set for key-value use that is valid and suitable for a particular ARDL test.

Table 5 Causality Test (Long-run)

Countries		CO2	TRA	FDI
		F- statistics (P value)(sign)	F- statistics (P value)(sign)	F- statistics (P value)(sign)
Brazil	TRA	0.006403/[0.9368](+)	/	8.949400***/[0.0055](+)
Russia	FDI	0.029751/[0.8648](+)	27.11592***/[0.0000](+)	/
India	FDI	1.652010/[0.2096](+)	12.41976***/[0.0015](+)	/

Note: The asterisks ***, ** and * indicate the 1%, 5% and 10% levels, (+), (–) the positive and negative signs respectively. [.] is the characterization factor of the p value. No-cointergration and its causality test only involve lag variables.

In Table 6, we show the test of short-term causality for the BRICS countries. Brazil's trade has a positive causal relationship with the backward FDI (2.631094), indicating that Brazil's trade growth has a positive impact in the short-term. The Brazilian government's "import substitution strategy" is to first establish a joint venture factory by attracting foreign investment, and then subsidize the middle class to buy domestic industrial manufactured goods, thereby promoting economic growth. This is due to the fact that foreign investment in Brazil is mainly concentrated in technology-intensive sectors such as the automotive, electromechanical equipment and appliance industries. In order to attract capital, the Brazilian government raised the minimum wage standard by only 50% when the accumulated inflation rose by more than 100% in a few years. This has resulted in more than one-third of the Brazilian workforce that can only receive the minimum wage so that purchasing power is declining. In 1980, 57% of Brazil's exports were industrial products, compared with 20% in 1968 and 30% in 1973. The rapid development of the Brazilian economy is the result of the massive borrowing of foreign debt. In 1979, the external debt was 50 billion US dollars.

Table 6 Causality Test

Countries		CO2	TRA	FDI
		F- statistics (P value)(sign)	F- statistics (P value)(sign)	F- statistics (P value)(sign)
Brazil	CO2	/	0.636901/[0.5983](–)	0.358891/[0.7832](+)
	TRA	1.800154/[0.1886](–)	/	0.025480/[0.8741](+)
	FDI	2.412634/[0.1068](–)	2.631094*/[0.0885](+)	/
Russia	CO2	/	0.528510/[0.6727](–)	7.650304***/[0.0060](–)
	TRA	1.231427/[0.3238](+)	/	2.744058/[0.1014](+)
	FDI	0.812713/[0.3851](+)	8.617539**/[0.0125](+)	/
India	CO2	/	2.606520**/[0.0761](–)	2.02648***/[0.0001](–)
	TRA	2.019237/[0.1516](–)	/	8.173146***/[0.0016](+)
	FDI	0.157213/[0.8553](–)	2.072647/[0.1454](–)	/
China	CO2	/	1.781738/[0.1888](–)	0.485598/[0.6968](+)
	TRA	2.461789*/[0.0977](+)	/	1.070561/[0.3878](–)
	FDI	0.496611/[0.6892](+)	0.225741/[0.8772](–)	/
South Africa	CO2	/	3.159647*/[0.0839](+)	0.001429/[0.9701](+)
	TRA	0.019913/[0.9803](+)	/	3.831021**/[0.0313](+)
	FDI	0.818108/[0.4938](–)	1.054974/[0.3823](+)	

Note: The asterisks ***, ** and * indicate the 1%, 5% and 10% levels, (+), (–) the positive and negative signs respectively. [.] is the characterization factor of the p value. No-cointergration and its causality test only involve lag VAR.

In 1981, it exceeded 60 billion US dollars. In 1982, it was close to 70 billion US dollars. It's more than $80 billion in 1983, more than $90 billion in 1984, and $100 billion in 1986. Brazil has become the world's largest debtor In the short-term causal relationship, Russia, FDI has a negatively significant (7.650304) causal relationship to the lag of one-period CO2 emissions, indicating that FDI contributes to the reduction of CO2 emissions; in terms of trade and FDI, Russia Like Brazil mention above, it is a causal relationship that is positive significant (8.617539). In the short-term, India's trade and FDI have a negatively causal relationship with CO2 respectively (2.606520, 2.02648) and FDI has a positively causal relationship to trade (8.173146). China's short-term CO2 emissions are significant positively in the lag of one-period of FDI (2.461789). The IEA report shows that global CO2 emissions have reached record highs for two consecutive years, increasing by 1.4% in 2017 and expanding to 1.7% in 2018, the highest growth rate since 2013, after a lapse of five years. Among them, the power generation sector accounts for about 2/3 of the increase in emissions. The IEA analysis is one of the reasons for the expansion of the use of coal-fired power generation in developing countries with carbon dioxide increase in Asia. It's one-third of the increased CO2 emissions since 2017 using coal. China accounted for nearly 30% of the total emissions, reaching 9.481 billion tons, an increase of 2.5%. In the short term, South Africa's trade has a significant positive effect on in lag of one-period of CO2 emissions (3.159647) and FDI have a significant positively correlated effect in the lag of one- Period of trade (3.831021).

6. Conclusions

The BRICS countries have different natural resource conditions and industrial structures, and their development models are different. They have certain complementarities and huge development space in economic and trade cooperation. Among the five member states, China is able to provide a large number of high-quality, low-cost industrial products. India can provide information software services and ore raw materials. Russia, Brazil, and South Africa have the capacity to provide abundant energy and mineral resources. By signing bilateral and multilateral trade agreements, the BRICS countries encourage international trade among member states, improve the level of economic and trade cooperation between the parties, and achieve the common rise of the BRICS countries.According to UN climate statistics, the world's top five greenhouse gas emissions are the United States, China, Russia, India, and Japan, while Brazil is also ranked eighth. Due to the relatively low level of production technology in the BRICS countries, the energy structure is mainly based on coal. Economic growth still depends mainly on resource inputs. In some developed countries, companies will avoid high pollution and high consumption to avoid strict supervision. The shift of the energy industry to developing countries has led to a rapid increase in CO2 emissions in these countries. Developed and developing countries should implement the principle of common but differentiated responsibilities for carbon reduction. Developed countries should provide carbon emission reduction funds and technologies to developing countries. Russia is through the framework of CO2 emissions through climate legislation. For example, CO2 emissions trading permits systems and companies can reduce or capture tax credits for their CO2 emissions. Russia is currently developing a policy plan that includes CO2 pricing to achieve the goal of reducing greenhouse gases by 2020, which is 25% lower than the 1990 level by 2030 and 25-30% lower than the 1990 level.

According to the International Energy Agency's (IEA) Global Energy & CO2 Status Report, 2018 global CO2 emissions hit a record high, and almost all countries have an increasing trend. In terms of CO2 emissions policy, Brazil is expected to reduce 600 million tons of CO2 emissions in the atmosphere by 2028, equivalent to the sum of emissions from the country's two-year fuel mix. At the same time, the Ministry of Mines and Energy of Brazil encouraged the share of biofuels to increase from 20% to 28.6%. India's CO2 emissions in 2018 reached 2.299 billion tons, up 4.8% from the previous year. China's CO2 emissions are in the same period increased by 3.5%. India and the United States and China account for nearly 70% of global energy demand growth. The government of India is committed to 40% of its energy from renewable sources by 2030, based on the intensity of CO2 emissions from economic development. The Chinese government has made a commitment to the expected goals: by 2020, China plans to reduce carbon intensity by 40% to 45% from 2005 levels and 60% to 65% by 2030. The South African "Carbon Tax Act" is the first African country to implement a carbon tax. The South African Ministry of Finance said that climate change is one of the biggest challenges facing humanity, and the main goal of the carbon tax is to reduce greenhouse gas emissions in a sustainable, cost-effective and affordable way. The structure will include 34 GW of coal (45%); nuclear power 1.9 GW (3%); 4.7 GW of hydropower (6%); 2.9 GW of pumping water (4%); 7.9 GW of solar photovoltaic (10%); 4GW wind (15%); 11.9GW natural gas (16%) and 0.6GW concentrated solar energy (1%). South Africa's current energy consumption depends on fossil fuels, so the carbon tax levy will inevitably affect the relevant industries and the economy. The BRICS countries have tried to reduce CO2 emissions without affecting economic growth. On the policy viewpoint, they comply with the Paris Climate Agreement and adopt the concept of "carbon neutrality" to implement tree planting, forest restoration and avoiding CO2 emissions such as foresting, planting trees on the farm to obtain wood, making biodiesel or using for other commercial purposes. Renewable energy compensators typically include the use of wind, solar and biomass fuels. While developing the economy, the BRICS countries are also committed to promoting the development of zero-carbon Buildings, smart infrastructure and ways to reduce CO2 emissions.

The Bootstrap ARDL simulation accommodates the bias of the narrow statistical environment used by McNown et al. [34]. In particular, the Bootstrap ARDL test allows for endogenous and feedback in the presence of variables. In addition, Pesaran et al. [33] provide a degenerate case #1 or #2 only in the key-value ARDL test framework to test one of two possibilities. Therefore, an empirical study using this method does not allow for two degenerate situations, and it can be concluded that there is cointegration when it does not exist. The BRICS countries are the most important emerging market countries in the world, accounting for 26% of the world's total area, and the population accounts for 42% of the world's total population. After 2015, affected by the global economy, the economic development of these five countries of the difference has become bigger. We use the

Peer-reviewed version available at Sustainability 2020, 12, 1060; doi:10.3390/su12031060

Bootstrap ARDL model to explore whether the three variables of CO2 emissions, trade and FDI in the five countries have a long-term cointegration relationship. As our results, we find that CO2 emissions from Brazil and FDI have a cointegration relationship with trade that lag of one period. Russia and India the CO2 emissions and trade have a cointegration relationship with FDI that lags behind a period. In the long-term, Brazilian FDI has a long-term causal relationship with trade that lag of one period of time. The trade between Russia and India has a long-term causal relationship with FDI that lag one period. In the short-term causality test, its more complexes which the results are presented in the empirical results described above. We use the Bootstrap ARDL model, and the biggest limitation is on the variables. So far this program from McNown et al. [34] can only use up to three variables. So it seems to be more than other models in explaining the causal relationship of variables. Of course, this may also be the direction that this model can be improved in the future.

Acknowledgments: We are grateful to the following funds in China for providing financial support for this paper: Key Project of Humanities and Social Sciences of Anhui Provincial Education Department (SK2018A0524); Anhui Provincial Social Science Association Innovation and Development Project (2018CX043); The Ministry of Education of China collaborates with the Innovation Project (201802170022). We also thank you Goh, S.K. for providing us with the Bootstrap ARDL program to complete this paper.

Author contributions: All authors contributed to the development of the Bootstrap ARDL test on the relationship between export trade, FDI and carbon emissions manuscript. Min Li and Xueping Li conceived the study, analyzed the data and wrote a manuscript. Fumei He and Fangjhy Li provided suggestions for the simulation. Fumei also guided the research direction and proposed an analytical framework. Ke-Chiun Chang contributed to the revision process of the manuscript and the overall quality of the manuscript. All authors have revised and approved the final manuscript.

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