Carbon emissions and trade interdependence between China and the US

Yaowu Dong[1,a], Denghui Duan[1,b], Ruoxi Hu[2,c,*]

[1] Guizhou University of Commerce，No.1, 26th Avenue, 550014 Guiyang, China

[a]dongyaowu@gzcc.edu.cn, [b]17212001@qq.com, [c]huruoxi1993@outlook.com

Abstract. China and the US were the world's top exporters and carbon emitters and the most crucial trading partners for each other at the same time. Trade interdependence between the two countries affect each country's carbon emissions, and linked to the world's total emissions. In order to research the effect of trade interdependence on carbon emissions of China and the US, we built a dynamic econometric model to distinguish long-term and short-term effects with datasets from 1992 to 2018 by means of the autoregressive- distributed- lag method. The results revealed that a 1% increase in trade interdependence was linked to a 0.038% decrease in China's carbon emissions and a 1.939% decrease in US emissions over the long-term. Moreover, trade interdependence produced a positive effect on China and US emissions in the short-term. In the short-term, trade interdependence decreased China's carbon emissions but increased US carbon emissions. By simulating a 1% of the counterfactual positive shock of trade interdependence, back-of- the- envelope estimations suggested a 0.220% reduction of carbon emissions for China and a 0.034% reduction for the US. At last, trade interdependence between China and the US, which reduced carbon emissions for each country in the long-term, so that policies on trade protectionism might not be necessary.

Keywords:trade interdependence, carbon emissions, the long-run effect, the short-run effect, time-series.

1. Introduction

Energy consumption contributed much to the expansion of the world economy in past decades, but it also generated large amounts of carbon emissions. Meanwhile, increasing carbon emissions caused severe environmental issues like global warming, abnormal weather, and the spread of pests and disease, for example. The International Committee of the World Meteorological Organization published theGreenhouse Gases Report (2019), which showed that global concentrations of carbon dioxide in the atmosphere reached 407.8 parts per million (ppm) in 2018. Moreover, the concentration increased by 1.87 ppm a year over the period 1978 -2018. Specifically, China and the US (The United States of America) were ranked as the world's two biggest carbon emitters in the past decade. From the data come out by the International Energy Agency (IEA), China and the US emitted 9.5 Gt and 4.9Gt carbon dioxide in 2018, respectively, and they accounted for 42.99% of the world's carbon emissions. Therefore, the world cannot achieve meaningful reductions in carbon emissions unless China and the US make substantial progress in this regard.

As it is concluded by Ehrlich and Holdren[1], environmental issues, like carbon emissions, are closely associated with human activity and economic growth. The US has remained the world's largest economy, and its gross domestic product (GDP) reached 20.58 trillion US dollars in 2018, which accounted for 23.83% of the world's GDP. In 2010, China overtook Japan in GDP and was ranked as the world's second-largest economy. In 2018, China's GDP was 13.89 trillion US dollars, which accounted for 16.08% of the world's GDP. In addition to economic development, international trade was one of the most critical influences on environmental issues [3]. China and the US also ranked as the world's top two countries in exports, and their export sales contributed to 21.38% to the world's total exports. Specifically, China and the U.S. were the most essential trading partners to each other. From the US Census, China was the third-largest market for goods and services of the US, and the US exported 118.9 billion dollars of goods to China in 2018. The US was also the second-largest importer of Chinese goods, and China exported 539 billion dollars in goods to the US. Thus, we are interested in the effect of trade interdependence between China and the US on their carbon emissions.

Many studies have discussed the carbon emissions that are reflected in international trade [4-5]. In the past decade, detailed research has concluded that about one-third of China's total carbon emissions was associated with the volume of exports [6-7]. Furthermore, some studies explored the causality between multinational trade and carbon emissions [8], and they concluded that it was significant relevant but heterogeneous across countries with different income levels [2,9-10]. In addition, few studies concentrate on the relevance between carbon emissions and trade interdependence among trading partners, which was our main focus.

In this work, we focus on exploring the effects of trade interdependence on carbon emissions and used China and US datasets for 1992-2018. Our results showed that strengthening trade interdependence produced a long-term, negative effect on carbon emissions for China and the US. However, trade interdependence decreased China's emissions, but it increased US emissions in the short-term. In general, trade interdependence implied economic cooperation between trading partners that resulted in improving industrial specialization and resource allocation, which was linked to each country's carbon emissions in the long-term.

More critically, our work contributed to the literature on two fronts. First, despite trade openness or trade liberation, our work showed that trade interdependence also played an important role in carbon emissions. Second, we followed the conceptual framework of Ehrlich and Holdren [1] and built a dynamic econometric model, which allowed us to distinguish the long-term and short-term effects.

2. Methods

We began our study by specifying how carbon emissions were generated by human activity. Ehrlich and Holdren [1] considered that environmental issues were determined by population, affluence, and technology, and this conceptual framework was applied to the issue of carbon emissions[11]. Meanwhile, Grossman and Krueger[12] proposed the hypothesis of the Environmental Kuznets Curve and concluded that environmental issues correlated with economic development. Therefore, we modeled carbon emissions with equations (1) and (2):

$$\mathrm{Ln}(\mathrm{CC_t}) = \alpha + \beta_1 \mathrm{Ln}(\mathrm{CG_t}) + \beta_2 \mathrm{Ln}(\mathrm{CT_t}) + \beta_3 \mathrm{Ln}(\mathrm{CTD_t}) + \varepsilon_t \quad (1)$$

$$\mathrm{Ln}(\mathrm{UC_t}) = \alpha + \beta_1 \mathrm{Ln}(\mathrm{UG_t}) + \beta_2 \mathrm{Ln}(\mathrm{UT_t}) + \beta_3 \mathrm{Ln}(\mathrm{UTD_t}) + \varepsilon_t \quad (2)$$

Equation (1) specified the carbon emissions for China, and equation (2) modelled the same for the US. Following the suggestion of Dietz and Rosa[13], equations (1) and (2) took a log-linear form. CCit and UCit denote carbon emissions per capita for China and the US, respectively. CGt and UGt are the GDP per capita for China and the US, respectively, which represent their corresponding economic development. CTt and UTt denote the technology level of China and the US, respectively. CTDt is for China's trade interdependence with the US, while UTDt is for US trade interdependence with China. β3 in equations (1) and (2) denote the effects of trade interdependence on carbon emissions. εt denote the error term, which captured the time-invariant heterogeneous effects.

When the time series in equations (1) and (2) were stationary, the method of ordinary least square (OLS) was practicable to estimate how trade interdependence impacted carbon emissions. However, time-series always contain the unit-root process, so that the OLS might produce biased results. Thus, we represented equations (1) and (2) in a structural, autoregressive- distributed- lag (ARDL) form.

$$\begin{aligned}\mathrm{Ln}(\mathrm{CC_t}) = {} & \alpha + \theta_0 \mathrm{Ln}(\mathrm{CC_{t-1}}) + \beta_{1,1} \mathrm{Ln}(\mathrm{CG_t}) + \beta_{1,2} \mathrm{Ln}(\mathrm{CG_{t-1}}) + \beta_{2,1} \mathrm{Ln}(\mathrm{CT_t}) \\ & + \beta_{2,2} \mathrm{Ln}(\mathrm{CT_{t-1}}) + \beta_{3,1} \mathrm{Ln}(\mathrm{CTD_t}) + \beta_{3,2} \mathrm{Ln}(\mathrm{CTD_{t-1}}) + \varepsilon_t \quad (3)\end{aligned}$$

$$\mathrm{Ln}(\mathrm{UC_t}) = \alpha + \theta_0 \mathrm{Ln}(\mathrm{UC_{t-1}}) + \beta_{1,1}\mathrm{Ln}(\mathrm{UG_t}) + \beta_{1,2}\mathrm{Ln}(\mathrm{UG_{t-1}}) + \beta_{2,1}\mathrm{Ln}(\mathrm{UT_t}) + \beta_{2,2}\mathrm{Ln}(\mathrm{UT_{t-1}}) + \beta_{3,1}\mathrm{Ln}(\mathrm{UTD_t}) + \beta_{3,2}\mathrm{Ln}(\mathrm{UTD_{t-1}}) + \varepsilon_t \quad (4)$$

Furthermore, all variables might be stationary in their first-differences, and then carbon emissions would cointegrate with dependent variables in equations (3) and (4). Therefore, equations (3) and (4) could fit an error-correction form as follows:

$$\Delta\mathrm{Ln}(\mathrm{CC_t}) = \alpha + \varphi[\mathrm{Ln}(\mathrm{CC_{t-1}}) - \lambda_1\mathrm{Ln}(\mathrm{CG_{t-1}}) - \lambda_2\mathrm{Ln}(\mathrm{CT_{t-1}}) - \lambda_3\mathrm{Ln}(\mathrm{CTD_{t-1}})] + \phi_1\Delta\mathrm{Ln}(\mathrm{CG_t}) + \phi_2\Delta\mathrm{Ln}(\mathrm{CT_t}) + \phi_3\Delta\mathrm{Ln}(\mathrm{CTD_t}) + \varepsilon_t \quad (5)$$

$$\Delta\mathrm{Ln}(\mathrm{UC_t}) = \alpha + \varphi[\mathrm{Ln}(\mathrm{UC_{t-1}}) - \lambda_1\mathrm{Ln}(\mathrm{UG_{t-1}}) - \lambda_2\mathrm{Ln}(\mathrm{UT_{t-1}}) - \lambda_3\mathrm{Ln}(\mathrm{UTD_{t-1}})] + \phi_1\Delta\mathrm{Ln}(\mathrm{UG_t}) + \phi_2\Delta\mathrm{Ln}(\mathrm{UT_t}) + \phi_3\Delta\mathrm{Ln}(\mathrm{UTD_t}) + \varepsilon_t \quad (6)$$

where the coefficients of φ in equations (5) and (6) refer to the error-correcting speed of adjustment. In addition, the negative and significant φ indicate that the impact of carbon emissions for all explanatory variables are cointegrated. For the case in which all variables were cointegrated, the impact of long-term carbon emissions from trade interdependence is represented by estimates of $\lambda 3$, and $\phi 3$ captures the short-term impact.

Here, we gave the econometric steps for equations (5) and (6). First, we used the method of Dickey-Fuller[14] and Phillips-Perron [15] to investigate whether the time-series contained a unit-root process . And then, for the case that all variables were stationary in their first-difference, we used the system cointegration method [16-17] to test whether all variables were cointegrated. If cointegration occurred, we then estimated equations (5) and (6) and chose the lags of ARDL by the likelihood ratio. Furthermore, the impulse function was used to investigate the dynamic effects of trade interdependence on carbon emissions. Finally, to conduct the robustness analysis, we added the variable for US carbon emissions into equation (5) and the variable for China's carbon emissions into equation (6), and we re-estimated the two equations.

3. Data

In this work, we conducted datasets for China and the US. The datasets covered the period from 1992 to 2018. During this period, China tried to participate in the world market and joined the World Trade Organization in 2001. Moreover, China also matured into the world's largest exporter and the most important trading partner for the US. Meanwhile, global warming- that was related to carbon emissions had become more and more important in the international community. Many intergovernmental co-operations were established to address the environmental issues, such as the United Nations Framework Convention on Climate Change in 1992, the Kyoto Protocol in 1997, and the Paris Agreement in 2015. Fortunately, the dataset for the period 1992-2018 was available for computing the characteristics of carbon emissions and trade interdependence between China and the US and was suitable for investigating the relationship between carbon emissions and trade interdependence between the two countries.

In our work, we were interested in carbon emissions that were produced by energy consumption, and the data existed in the database of the World Bank. We used the index of bilateral trade intensity to calculate the variable of trade interdependence[18-19] and collected data from the database of the United Nations Comtrade. We measured economic development by GDP per capita at the constant price of 2000, and the data were collected from the database of the World Bank. The technology level was calculated as the proportion of expenditures for research and development to the GDP. We used the natural log of all variables (Table 1).

Table 1. Summary Statistics

		Mean	Median	Maximum	Minimum	Std. Dev.
For China	Carbon Emissions	-3.157	-3.156	-2.583	-3.774	0.454
	Trade Interdepende-nce	-0.312	-0.022	0.531	-2.334	0.840
	Economic Development	7.559	7.391	9.083	5.898	1.050
	Technology Level	0.151	0.232	0.763	-0.574	0.465
For the US.	Carbon Emissions	-1.663	-1.612	-1.570	-1.844	0.090
	Trade Interdepende-nce	-1.571	-1.330	0.797	-4.053	1.276
	Economic Development	10.618	10.671	10.997	10.146	0.259
	Technology Level	0.957	0.954	1.034	0.845	0.052

4. Results and Discussion

By using the methods of Phillips-Perron[15] and Elliott-Rothenberg-Stock [14], we reported the results of unit-root tests (Table 2). The estimations indicated that none of the variables for China and the US were stationary, but we rejected the hypothesis that the first-differenced terms of all variables did not contain the unit-root process. Then, we ran a system cointegration test[16-17], which implied that three cointegration vectors existed in the variables for China and the US.

Table 2. Econometric Tests

Unit-root Test		Phillips-Perron		Elliott-Rothenberg-Stock	
		Level	First-Difference	Level	First-Difference
For China	Carbon Emissions	-0.593	-1.723*	99.476	0.009***
	Trade Interdependence	-1.271	-5.570***	51.089	1.987**
	Economic Development	-0.706	-2.545**	364.105	2.256**
	Technology Level	-1.918*	-2.710***	136.912	1.007***
For the US.	Carbon Emissions	-1.161	-2.207**	2.165*	1.155***
	Trade Interdependence	-2.004**	-4.446***	6.079	1.391***
	Economic Development	-0.050	-2.880***	545.727	2.442**
	Technology Level	-0.784	-3.252***	11.168	1.033***

System Cointegration Test	For China		For the US.	
	Eigen value	Trace Statistic	Eigen value	Trace Statistic
None	0.797***	103.282***	0.924***	161.882***
At most 1	0.665***	65.041***	0.867***	102.650***
At most 2	0.533***	38.782***	0.775***	56.231***
At most 3	0.481***	20.527***	0.476***	21.895***

Notes: ***, **, * denoted a significance of 1%, 5%, and 10%, respectively.

We estimated equation (5) for China and equation (6) for the US (table 3). Based on the statistics of Log-Likelihood, the ARDL lag for both equations was 1. Meanwhile, all coefficients for the estimations were statistically significant and negative, which indicated that the variable of carbon emissions was cointegrated with trade interdependence, economic development, and technology level. In addition, we treated the carbon emissions of the trading partner as the exogenous variable in the two equations, which produced similar estimates, and then we concluded that the estimations for China and the US were robust.

Table 3. Estimations of the equation in the error-correction form

	For China				For the US.			
	Cointegrating Equation	Error Correction	Cointegrating Equation	Error Correction	Cointegrating Equation	Error Correction	Cointegrating Equation	Error Correction
Carbon Emissions		1.252*** (0.197)		1.184*** (0.108)		-0.055 (0.250)		0.051 (0.259)
Trade Interdependence	-0.038** (0.032)	-0.056*** (0.022)	-0.007*** (0.004)	-0.057** (0.022)	-1.939*** (0.263)	0.001*** (0.000)	-0.070*** (0.011)	0.007*** (0.002)
Economic Development	-0.541*** (0.120)	-0.205*** (0.112)	-0.551*** (0.133)	-0.225** (0.116)	-15.484*** (4.9333)	-1.243** (0.558)	-1.830*** (0.207)	-1.288** (0.554)
Technology Level	0.040*** (0.119)	-0.028 (0.105)	0.123*** (0.013)	-0.070 (0.136)	10.088*** (1.285)	-0.627*** (0.212)	3.819*** (0.518)	-0.738*** (0.223)
Constant	7.155 (6.259)	0.037*** (0.105)	7.170 (3.299)	0.035 (0.036)	6.374 (4.227)	0.067** (0.027)	3.577 (2.317)	-0.234*** (0.015)
Error Correction	-0.256*** (0.112)		-0.225*** (0.108)		-0.008*** (0.003)		-0.163*** (0.079)	
Carbon emissions of China							-0.077** (0.041)	
Carbon emissions of the US.			-0.057** (0.025)					
Log-Likelihood	148.783		152.620		202.098		207.182	

Notes: ***, **, * denoted a significance of 1%, 5%, and 10%, respectively.

We first focused on estimations without the trading partner's carbon emissions (table 3). The long-term coefficients of trade interdependence were -0.038 for China and -1.939 for the US, with a significance level >5%. We then concluded that a 1% increase in trade interdependence between China and the US would lead to a 0.038% decrease in China's carbon emissions and a 1.939 decrease in US carbon emissions. In the error-correction estimations, trade interdependence produced a significant and negative effect on China's emissions, but a significant and positive effect on US emissions in the short-term. On the contrary, Ertugrul ound that trade scale was linked to a significant and positive effect on carbon emissions in China, Turkey, India, Indonesia, and Korea. For China, Andersson concluded that freedom to engage in international trade caused a significant and positive effect on carbon emissions in China's mineral industry, but it had no significant effect on other industries[8]. Our findings did not confirm these results. In general, trade interdependence involved cooperation between the economies of the trading partners, but trade openness or trade liberalization only linked to the hosting country, and then their impacts on carbon emissions diverged. In particular, China and the US were important trading partners in their respective, and the long-standing trading ties practicably improved industrial division and resource configuration, which resulted in a reduction in carbon emissions for both countries.

Because the estimations of the ARDL-form equation might have "hidden interpretations"[20], we followed the method of Phillips[21] to simulate a counterfactual positive shock of trade interdependence with all else being equal. We then calculated the responses of carbon emissions for China and the US (Fig. 1). For China, a positive-negative shock in trade interdependence yielded an increasing and negative effect on carbon emissions over the 2-5 period, but the effect showed a diminishing trend over the period 6-10. Similarly, the marginal impact on US carbon emissions also was negative and "U" shaped. Over the period 2-10, the accumulated response of China's carbon emissions was -0.2204, while that of the US was -0.0339. However, trade interdependence did more to reduce China's carbon emissions than it did for the US, which might be closely associated with the two countries' energy use structure. In addition, the production process contributed a great deal to energy use in China, but energy-related to consumption comprised most of the energy use in the US. Trade interdependence focused on the cooperation of the two countries in the production process and then produced different effects on each other's reduction of carbon emissions.

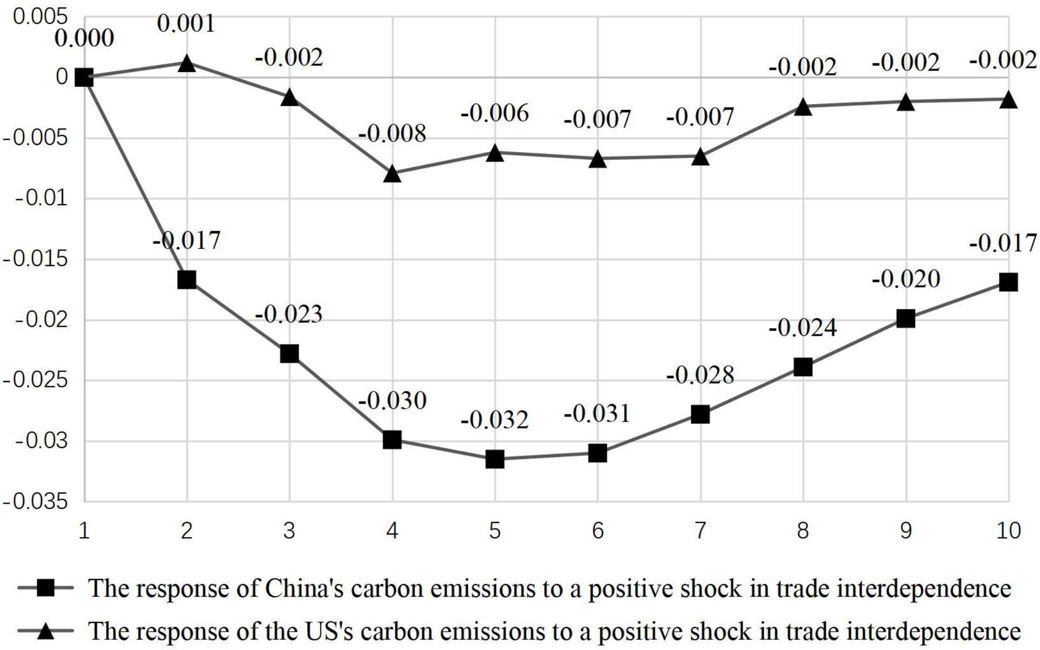

Fig.1 Responses of carbon emissions to a positive shock in trade interdependence between China and the US.

5. Concluding Remarks

Previous studies find total trade volume was a signifianct factor of the growth of China's embodied carbon emissions, and there is a correlation between carbon emissions and import and export[23-24]. Research also find that production structure reversals reveals an inverse relationship with the growth of embodied emission and suggested China to optimize its trade structure[25]. In addition, few studies find a specific relationship between carbon emissions and trade interdependence among trading partners. In our work, we investigated the effect of trade interdependence between China and the US on each country's carbon emissions during 1992-2018. Despite the many studies that focused on evaluating the relationship between international trade and carbon emissions, the evidence remained mixed within the socioeconomic context. Few studies paid close attention to trade interdependence, which emphasized the industrial specialization and resource allocation among trading partners. Thus, trade interdependence might produce an important and different effect on carbon emissions. Moreover, China and the US were not only the world's largest exporters and carbon emitters, but also the most crucial trading partners for each other. Trade interdependence between the two countries did not only affect each country's carbon emissions, but it was linked to the world's total emissions.

Our results indicated that carbon emissions were cointegrated with trade interdependence and other control variables for China and the US. In detail, a 1% increase in trade interdependence would leadto a 0.038% decrease in China's carbon emissions and a 1.939% decrease in US carbon emissions in the long-term. In the short-term, trade interdependence decreased China's carbon emissions while increasing US carbon emissions. By simulating a 1% of the counterfactual positive shock of trade interdependence, back- of- the- envelope estimations suggested a 0.220% reduction of carbon emissions for China and a 0.034% reduction for the US.

Furthermore, trade protectionism emerged in recent years, and increasing trade conflicts occurred among the world's major economies, especially for China and the US. Trade protectionism aimed to reduce trade interdependence among major countries and to reshape the spatial distribution of economic development. As our work suggested, each trading partner's carbon emissions decreased with an increase in trade interdependence in the long-term. However, the primary countries emphasized short-term trade imbalance excessively and established policies related to trade protectionism, which was unreasonable.

References

[1] Ehrlich, P. R., & Holdren, J. P. (1971) "Impact of population growth." Science 171.3977 (1971): 1212-1217.

[2] Heil, M. T., & Selden, T. M. (2001) "International trade intensity and carbon emissions: a cross-country econometric analysis." The Journal of Environment & Development 10.1 (2001): 35-49.

[3] Wyckoff, A. W., & Roop, J. M. (1994) "The embodiment of carbon in imports of manufactured products: implications for international agreements on greenhouse gas emissions." Energy Policy 22.3 (1994):187.

[4] Long, R., Li, J., Chen, H., Zhang, L., & Li, Q. (2018) "Embodied carbon dioxide flow in international trade: A comparative analysis based on China and Japan." Journal of environmental management 209 (2018): 371-381.

[5] Lin, B., & Sun, C. (2010) "Evaluating carbon dioxide emissions in international trade of China." Energy policy 38.1 (2010): 613-621.

[6] Arce, G., López, L. A., & Guan, D. (2016). "Carbon emissions embodied in international trade: The post-China era." Applied energy 184 (2016): 1063-1072.

[7] Weber, C. L., Peters, G. P., Guan, D., & Hubacek, K. (2008). "The contribution of Chinese exports to climate change." Energy Policy 36.9(2008): 3572-3577.

[8] Andersson, F. N. (2018). "International trade and carbon emissions: The role of Chinese institutional and policy reforms." Journal of environmental management 205 (2018): 29-39.

[9] Fernández-Amador, O., Francois, J. F., & Tomberger, P. (2016). "Carbon dioxide emissions and international trade at the turn of the millennium." Ecological economics 125 (2016): 14-26.

[10] Hasanov, F. J., Liddle, B., & Mikayilov, J. I. (2018). "The impact of international trade on CO2 emissions in oil exporting countries: Territory vs consumption emissions accounting." Energy Economics 74 (2018): 343-350.

[11] Sheng, P., & Guo, X. (2016). "The long-run and short-run impacts of urbanization on carbon dioxide emissions." Economic Modelling 53 (2016): 208-215.

[12] Grossman, G. M., & Krueger, A. B. (1995). "Economic growth and the environment." The quarterly journal of economics 110.2 (1995): 353-377.

[13] Dietz, T., & Rosa, E. A. (1997). "Effects of population and affluence on CO2 emissions." Proceedings of the National Academy of Sciences of the United States of America 94.1 (1997): 175-179.

[14] Elliott, G., T. J. Rothenberg, and J. H. Stock. (1996). "Efficient tests for an autoregressive unit root." Econometrica 64 (1996): 813-836.

[15] Phillips, P. C., & Perron, P. (1988). "Testing for a unit root in time series regression." Biometrika, 75.2 (1988), 335-346.

[16] Johansen, S. (1988). "Statistical analysis of cointegration vectors." Journal of economic dynamics and control 12.2-3 (1988): 231-254.

[17] Juselius, K. (1992). "Testing structural hypotheses in a multivariate cointegration analysis of the PPP and the UIP for UK." Journal of econometrics 53.1-3 (1992): 211-244.

[18] Deardorff, A.V. (1998). "Determinants of bilateral trade: does gravity work in a neoclassical world?", In: Frankel, J.A. (Ed.), The Regionalization of the World Economy. University of Chicago Press, Chicago

[19] Wei, S. J. (1996). "Intra-National Versus International Trade: How Stubborn are Nations in Global Integration?." NBER Working Paper, (w5531).

[20] Breunig, C., & Busemeyer, M. R. (2012). "Fiscal austerity and the trade-off between public investment and social spending." Journal of European Public Policy 19.6 (2012): 921-938.

[21] Philips, A. Q. (2018). "Have your cake and eat it too? Cointegration and dynamic inference from autoregressive distributed lag models." American Journal of Political Science 62.1 (2018): 230-244.

[22] Lantz, V., & Feng, Q. (2006). "Assessing income, population, and technology impacts on CO2 emissions in Canada: where's the EKC?." Ecological Economics 57.2 (2006): 229-238.

[23] Zhang Jijian, Angelina Kissiwaa Twum, Andrew Osei Agyemang, Bless Kofi Edziah, Emmanuel Caesar Ayamba (2021). "Empirical study on the impact of international trade and foreign direct investment on carbon emission for belt and road countries." Energy Reports, 7(2021):7591-7600.

[24] Zhengning PU, Shujing YUE, Peng GAO. (2020) "The driving factors of China's embodied carbon emissions: A study from the perspectives of inter-provincial trade and international trade." Technological Forecasting and Social Change 153(2020).

[25] Shuhong Wang, Xiaoqing Wang, Yun Tang. (2020) "Drivers of carbon emission transfer in China—An analysis of international trade from 2004 to 2011." Science of The Total Environment 709(2020)