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The Nexus Between Economic Growth and Environmental Degradation: Insights from High-Impact Asian Economies

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Abstract
This study investigates the relationship between green finance and carbon emissions in China and India, two of the world's largest carbon emitters. Using data from 2000-2020, the research applies the ADF unit root test, ARDL Bound test, and other diagnostic tests to explore how green finance impacts CO2 emissions, controlling for GDP, inflation, and the shadow economy. The findings reveal that in China, CO2 emissions are driven by past emissions and inflation, while economic growth reduces emissions. In India, inflation and land use changes contribute to emissions, while socio-economic factors mitigate them. The error correction term indicates that both countries are converging toward long-run equilibrium. The results emphasize the importance of green finance in reducing emissions, suggesting policymakers should prioritize sustainable investments and strategies that balance economic growth with environmental protection. These findings are particularly relevant for global efforts to combat climate change, offering insights for emerging economies aiming to achieve sustainability goals.
Keywords: Green finance, CO2 emissions, Shadow economy, Environmental Degradation, ARDL bound test

1. Introduction

As the population of the world increases, the energy consumption also increases, thus leading to more emission of carbon dioxide (CO2). In its 2019 edition, the Global Carbon Atlas indicates that the carbon dioxide emissions resulting from human energy use reached a new level of 33.1 gigatons in 2019 with China, United States, and India leading the list of polluters (Atlas, 2019). This is the most acute problem in China and India, which are the leading Asian countries that emit the most carbon. These countries are now finding it harder to tackle the environmental problems they face as they further develop their economies and modernize.

The IEA estimates that CO2 emissions from energy use in these countries make up over forty percent of the global total (IEA, 2022). The latest data from the World Bank shows that the global carbon intensity of GDP has been decreasing in the last few years, even though progress at the regional and country level remains uneven (World Bank, 2020; Ibrahim & Simian, 2023). However, most of these improvements have been realized in the developed countries while the developing countries have not done much to reduce their CO2 emissions (Audi & Ali, 2016; Wiafe, 2018; Khan & Hssan, 2019; Friedlingstein et al., 2020).

In recent years, there has been an increasing shift to utilize cleaner and renewable energy sources which are as a result of the necessity to deal with the effects caused by climate change (Kostruba & Pasko, 2019; Mustapha, 2022; Nut & Kumar, 2023). Hand in hand with these changes, the use of green finance and the creation of financial organizations that support the development of a sustainable future is also taking place. In the year 2021, an increase of 5.9% in worldwide economic activity was equivalent to a 6% increase in CO2 emissions. Since 2010, when global emissions rebounded 6.1% and economic output grew 5% as the globe emerged from the Global Financial Crisis, this is the strongest relationship between CO2 emissions and GDP growth (IEA,2022).

This is important to study because both China and India are among the highest CO2 emitting nations in the world and at the same time both nations are capable of sustainable development. Such countries with growing economy can put measures and policies that would lead to sustainable economic development but unlock the effects of climate change (IEA, 2021). The findings of this research may be helpful to these countries on how to establish policies for a sustainable development that are pro-active instruments to fight climate change and can enable these nations to achieve the climate goals and limit the emission of carbon. It is even more crucial since the climate goals that these countries pledged to meet are quite aggressive, for instance, China's commitment to attain net-zero emissions by 2060 (Gorus & Groenveld, 2018; Bakht, 2020; Stern & Xie, 2022; Zhao et al., 2022; Rossi, 2023).

The study hypothesizes that green financing, shadow economy, and inflation have a significant relationship with the CO2 emissions of China and India controlling GDP. This study is relatable to current global challenges collectively being faced by all countries. Regarding the effects of carbon emissions in Pakistan, it is also pertinent to note that they have become rather more profound and conspicuous lately. However, like other nations of the world, Pakistan also faces soaring carbon emissions resulting from Industrialization and growing population. Some of the challenges are air pollution which has greatly affected Lahore and Karachi and its effects ranges from respiratory problems among people to overall health complications (WorldBank,2022). Carbon emissions have also been on the rise, which has led to climate change issues such as erratic weather patterns, higher temperatures, and frequent instances of extreme weather, including floods and droughts. These events have affected agriculture, water resource and the general economy in the affected areas. Also, the glacial melting in the Himalayas, which can be linked to carbon emissions, is a future concern for water resources in Pakistan. Mitigating the impacts of carbon emissions is a fundamental concern for Pakistan, requiring effective measures for carbon cut down and climate change mitigation (GOP, 2021).

The main goals of this paper are to identify the determinants of short-term and long-term CO2 emissions in China and India taking into account historical emissions, inflation rates, GDP and shadow economies. Thus, we will try to reveal the tendencies of carbon emissions in these two large economies considering these factors. In addition, we aim at exploring the effect of long-term strategies such as green finance in the reduction of CO2 emissions given China's pledge to cut down carbon intensity and increase the share of non-fossil energy. Furthermore, we will also try to highlight the issues associated with the low-carbon development in India such as infrastructure constraints, financing, and social equity.

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In conclusion, this paper seeks to provide important knowledge on the relationships between economic conditions, policy interventions, and environmental preservation in both countries. These findings can guide policy debates and actions that seek to reduce CO2 emissions while supporting economic development in China and India, and more broadly, around the world, where international collaboration is becoming ever more important in the fight against climate change. The core objective is to examine how GDP, inflation, shadow economy, and green finance can affect carbon emissions over time, and what policy-oriented solutions can be proposed in order to decrease emissions while taking into account economic factors.

2. Review of Literature

Climate change remains a universal issue that affects the global society and developing countries such as India and China being among the biggest economies in the world have the responsibility of navigating on how to strike the balance between economic development and environmental conservation (Emodi, 2019; Mahmood, 2019; Khan et al., 2021; Hussain & Khan, 2022; Zhang et al., 2022; Bhattacharya, 2020; Iqbal & Noor, 2023). Green finance was considered as such a possibility that let those organizations that are conscious about their responsibility to get the necessary funds. This paper gives a review of literature based on the findings of previous research works as regards the relationship between carbon emission of India and China with other variables like GDP, inflation and shadow economy.

Emissions of carbon dioxide and financing that is environmentally responsible: Referring to the arguments stated above, green finance comprise one or different facilities that support sustainable development in the long-run. A number of articles that have addressed the effect of green cash on carbon emission in India and China exist. Zhu and Jiang (2020) at the beginning of COVID-19 noted that green credit schemes that have been implemented in China have improved on the reduction of carbon emissions. Likewise, Bhanot et al. (2019) have established the fact that green bonds can assistance in lessen India's totality emissions of greenhouse gasses. Therefore, green finance can therefore be able to fund the reduction of carbon emissions in high impact economies support the evidence presented in this paper to Sharif et al (2022). The relationship between CO_2 emissions and inflation dynamics highlights the need for economic policies that balance environmental sustainability and price stability. Vision 2030's strategic alignment emphasizes reducing CO_2 emissions while managing labor force participation, foreign direct investment, and trade openness to sustain economic growth and control inflationary pressures (Bilal et al., 2024).

GDP is one of the key measures of economic growth but the same is linked with increased CO2 emissions. Both countries have therefore directed a lot of their energy in trying to ascertain a correlation between GDP and carbon emissions. Li et al. (2021) observed that China's GDP has contributed to the increase in carbon emissions has a positive slope, there is some evidence that the slope is reducing with time. This was done even though China's economic advancement has led to enhanced emission of carbon dioxide. Sahoo and Singh (2018) also confirm the existence of a positive relationship between GDP and carbon emission in India and further observe that through the use of renewable energy there was likelihood of decoupling economic growth from carbon emission.

Another factor that might also affect carbon emissions can be inflation whereby a rise in prices might cause an upsurge in carbon emissions in the economy. For instance, inflation causes increased price of electricity which as a result is used more intensively to cause emission of a huge amount of carbon. On the other hand, no such study has synthesized the effects of inflation on carbon emissions in economies of India and China (Chen et al., 2022).

The underground economy and carbon dioxide emissions: Shadow economy which is also referred to as the underground economy is referred to as the economic activities that are not taken into consideration in the official statistics (Schneider, 2022; Modibbo & Saidu, 2023; Wang & Li, 2024). Since the shadow economy is less efficient and that has high dependency on fossil energy, some researchers have observed that the shadow economy may cause carbon emission to increase. This is because the shadow economy consumes more fossil energy than the formal economy (Willy, 2018; Skhirtladze & Nurboja, 2019; Camara & M, 2022).

3. Data and Methodology

To achieve the objectives of the study, the research adopted different methods of analysis to establish the correlation between green finance, GDP, inflation, shadow economy, and carbon emission in India and China. While some of the papers examined the impacts of specific policies or investments through case analyses or questionnaires, others quantitatively assessed the relationships between numerous determinants and carbon emissions based on econometric models. This suggests that a combination of policies and investments, like green finance and renewable energies, might be needed to decrease carbon emissions in economies that have a high impact, for instance, India and China. This is the conclusion that can be drawn from the findings taken as a whole.

According to the findings of this evaluation of the relevant research, green finance has the potential to considerably cut carbon emissions in India and China. It is difficult to find studies on the relationship between inflation and carbon emissions in India and China, and there is still very limited knowledge on how shadow economy influences carbon emissions. High-impact economies need a mix of policies and investments to secure the future. Such policies and investments can also encompass green financing as well as economic development.

A regression methodology is employed to investigate the relationship between CO_2 emissions, green finance, shadow economy, inflation and gross domestic product in China and India. This analysis utilizes annual data spanning from 2000 to 2020, sourced from the World Development Indicators (WDI) and the International Renewable Energy Agency (IRENA). The predictive model for CPI elasticities incorporates the following independent variables in their natural logarithmic forms: CO_2 emissions, green finance, shadow economy, inflation and gross domestic product.

Utilizing the adjusted autoregressive distributed lag (ARDL) approach as outlined by Jordan and Phillips (2018), the study examines the actual changes in the dependent variable resulting from variations in the independent variables. Prior to conducting the ARDL analysis, tests are performed to assess the stationarity and variance of the data series, as well as to determine the integration order of the relevant variables. The presence of non-stationary variables can potentially lead to spurious regression outcomes; hence each variable is tested for stationarity at both level and first difference. A variable exhibiting a unit root at level but becoming stationary at first difference is considered integrated of order one, or I(1). The ARDL framework permits inclusion of variables that are stationary at I(0) or I(1), while excluding those integrated at order two, or I(2), in accordance with the common features criteria defined by Pesaran (2001).

To accurately discern whether a time series variable is stationary, some scholars suggest distinguishing between stochastic trends and difference-stationary processes. This study employs the Augmented Dickey-Fuller (ADF) test by Dickey and Fuller (1979) for unit root tests to detect the presence of linear stochastic trends within the series. The following functional structure for the model has been built so that it may effectively demonstrate the primary objective of our research:

$CO_2 = f\ (GF, SE, Inf, GDP)$ (i)

Building on the findings of previous research, particularly the studies by Balsalobre-Lorente et al. (2018) and Rahman & Kashem (2017), the linear econometric form of the model is defined as follows:

$CO_{2t} = \propto_0 + \propto_1 GF_t + \propto_2 SE_t + \propto_3 Inf_t + \propto_4 GDP_t + \varepsilon t$ (ii)

In the equation above, ∝0 represents the intercept, while ∝1, ∝2, ∝3, and ∝4 are the coefficients of the explanatory variables. The term ε denotes the error term, and the subscript t indicates the time period. By taking the natural logarithm of the variables on both sides, the equation transforms as follows:

$lnCO_{2t} = \propto_0 + \propto_1 lnGF_t + \propto_2 lnSE_t + \propto_3 lnInf_t + \propto_4 lnGDP_t + \varepsilon_t$ (iii)

3.1. ARDL Bound test

Co-integration testing and determination of short-run and long-run relationships between variables can be done using different methodologies that have been developed over time. This study will use the ARDL bounds testing approach which has several advantages over the traditional cointegration technique. These benefits include: The benefits of using VECM are: (a) better results if the data are cointegrated of I(0) or I(1); (b) ease of application when dealing with a single equation; (c) ability to handle small samples; (d) the use of various lag order for the variables; and (e) unbiased estimation of short-run relationships and long-run co-movement. From the analysis using the ECM in the context of the ARDL technique, it was revealed that the system will return to the long-run equilibrium position after a short-run disturbance. The ECM model involves both long and short-run coefficients, and the long-run Granger causality is confirmed by having a highly negative coefficient for the ECT, while other variables have high coefficients to signify the short-run causality (Kashem & Rahman, 2021; M. M. Rahman & Kashem, 2017). By the application of information criteria like AIC, SC, and HQ, the maximum lag lengths of up to 1, 2, and 3 can be ascertained. Pesaran (2001) gave crucial values of F-statistic concerning the bounds testing approach. To do this, they used this procedure to find the maximum and minimum values for key variables across different scenarios. When the calculated F-statistic is less than the lower bound, it means that there is no cointegration between the variables. This shows that they are independent of one another. On the other hand, if the value is above the upper threshold, this suggests a long-term relationship. If it falls between these two limits, the results of the test are ambiguous.

$$\Delta lnCO2_{it} = \propto_0 + \sum_{i=1}^{p} \propto_1 \Delta lnCO2_{it-i} + \sum_{i=1}^{p} \propto_2 \Delta lnGF_{it-i} + \sum_{i=1}^{p} \propto_3 \Delta lnGDP_{it-i} + \sum_{i=1}^{p} \Delta \mathrm{lnSE}_{it-i} + \sum_{i=1}^{p} \Delta lnINF_{it-i} + \beta_1 lnCO2_{it-1} + \beta_2 lnGF_{it-1} + \beta_3 lnGDP_{it-1} + \beta_4 lnSE_{it-1} + \beta_5 lnINF_{it-1} + \mu_t \quad \text{(iv)}$$

The terms with ∑ symbols represent the short-run error correction dynamics, while the terms with β indicate the long-run relationships among the variables (Queirós et al., 2017; Rahman & Kashem, 2017). The maximum lag lengths ρ, ρ1, ρ2, and ρ3 are determined using the Akaike Information Criterion (AIC), with t-i indicating the optimal lag selection according to this criterion. Pesaran (2001), provided the critical values concerning the F-statistic in the framework of bounds testing technique and constructed both, upper and lower bound standards for different circumstances. Their account indicates that if the F-statistic computed is lower than the lower bound, then the variables of interest are not cointegrated. Thus, it can be concluded that the relationship is long-term if the F-statistic is greater than the upper bound. If the F-statistic is located in the range of these bounds, the result of the test is said to be non-significant.

3.2. Diagnostic analysis

In conducting this research, we aimed to identify the model using best practice methodologies. The ARDL bounds testing approach is grounded in the fundamental assumption of homoscedasticity, where errors are assumed to be independently and uniformly distributed. To detect the presence of serial correlation, we employed the Breusch-Godfrey Serial Correlation LM test, while the Jarque-Bera test was used to assess the normality of errors within the model (Rois et al., 2012). To determine whether the model exhibits heteroscedasticity, we conducted the Breusch-Pagan-Godfrey and ARCH tests.

3.3. Stability test

Model stability is crucial, particularly for models with autoregressive components, which are often inherent. Following the approach of Pesaran (2001), the model's reliability will be evaluated using the recursive CUSUM and CUSUM of squares tests, with necessary modifications as appropriate (Brown et al., 1975).

Table 1 below presents a summary of the study variables, including their symbols, units of measurement, and data sources.

Table 1: Variables of the study and their descriptions

Variables	Symbol	Measurement	Source
CO2 emission	CO2	Metric tons	www.bp.com
Green finance	GF	Green finance in renewable energy projects (Bn US$)	www.irena.org
Shadow economy	SE	MIMIC	www.worldbank.org
Inflation	INF	Consumer price index	www.worldbank.org
Gross domestic product	GDP	Per capita (constant US$ 2015)	www.worldbank.org

4. Results and discussion

The descriptive statistics in Table 2 offer a comprehensive overview of key variables for China and India. For China, CO_2 emissions ($lnCO_2$) have the highest mean value at 8.9556, while inflation (lnInf) has the lowest mean at 0.7993. The skewness analysis shows CO_2 emissions and GDP are negatively skewed, while green finance (lnGF) is positively skewed. The kurtosis for GDP suggests a peaked distribution, hinting at potential outliers. In contrast, India's mean for green finance (lnGF) is higher at 6.3008 compared to China, whereas CO_2 emissions are lower at 7.4029. Skewness indicates a slight positive skew for inflation, while GDP remains negatively skewed. India's kurtosis for GDP implies a more normal distribution than China. The correlation matrix reveals that in China, CO_2 emissions have a strong negative correlation with sustainable energy (lnSE) and a weak positive correlation with green finance (lnGF). In India, the negative correlation between CO_2 emissions and sustainable energy is similarly strong, but green finance has a stronger positive correlation with CO_2 emissions than in China. Hamsal (2015) suggests that correlation testing among variables of interest allows researchers to identify potential high multicollinearity, which could lead to contradictory estimates in economic theory. However, multicollinearity is only a concern when the correlation coefficient exceeds 0.95. According to the results in Table 2, all Pearson correlation coefficients are below 0.95, which indicates that multicollinearity among the independent variables is not an issue.

Table 2: Descriptive Statistics and Correlation Matrix

Variables	China					India				
	CO2	GF	SE	Inf	GDP	CO2	GF	SE	INF	GDP
Mean	8.9556	5.4163	2.4727	0.7993	2.0939	7.4029	6.3008	3.0473	1.7425	1.8612
Median	9.1026	5.2842	2.4638	0.7298	2.0930	7.4312	6.2586	3.0512	1.6172	2.0194
Std. Dev.	0.3010	0.5682	0.0377	0.5692	0.3893	0.3243	0.8074	0.0459	0.4142	0.3086
Skewness	-1.3343	1.2112	0.6922	-0.0196	-1.7668	--0.2204	0.1219	0.0328	0.4388	-1.116
Kurtosis	3.8727	5.4023	3.0551	2.4776	7.4669	1.6852	1.9196	1.9465	1.7687	3.0125
Correlation Matrix										
CO2	1					1				
GF	0.2056	1				0.7791	1			
SE	-0.9181	-0.2306	1			-0.9453	-0.7718	1		
Inf	0.2846	-0.2335	-0.2196	1		0.1112	0.0096	0.0703	1	
GDP	-0.4458	-0.4534	0.3856	0.1349	1	0.1198	0.0195	-0.1991	0.0250	1

4.1. Unit Root

To assess the stationarity properties of the time series data for China and India, the Augmented Dickey-Fuller (ADF) test was employed. This test determines whether a time series is stationary or contains a unit root. Table 3 shows the results of unit root test, which indicate that some variables for both countries are stationary at their original level I(0), meaning they fluctuate around a constant mean over time. Other variables required first differencing I(1) to achieve stationarity, suggesting that their differences from period to period are stationary.

Importantly, none of the variables exhibited a unit root at the second difference I(2), a condition necessary for applying the ARDL model. Thus, the data meets the preconditions for using the ARDL methodology in this study.

Table 3: Unit Root Results

Variables	ADF (CHINA)			ADF (INDIA)		
	At I(0)	At I(1)	Decision	At I(0)	At I(1)	Decision
lnCO2	-6.67776*** (0.0000)	---	I(0)	-1.984095 (0.2906)	-4.379572** (0.0032)	I(1)
lnNF	-2.6358 (0.1026)	-4.6001** (0.0020)	I(1)	-5.3929** (0.0006)	---	I(0)
lnGDP	-0.081870 (0.9383)	-6.517791** (0.0000)	I(1)	-3.543433** (0.0188)	----	I(0)
lnGF	-3.767119** (0.0109)	---	I(0)	-2.210207 (0.2089)	-4.923214** (0.0013)	I(1)
lnSE	-2.514632 (0.1270)	-3.902701** (0.0086)	I(1)	-1.269692 (0.6223)	-5.383852** (0.0005)	I(1)

Note: *,**&*** refers to rejection of null hypothesis at 10%, 5% and 1% respectively.

4.2. Estimation of ARDL Model

The order of the lag selection of variables is crucial in specifying the model in accordance with the ARDL method.

Table 4: VAR lag selection criteria

	China			India		
Lag	AIC	SC	HQ	AIC	SC	HQ
0	-1.9821	-1.7335	-1.9400	-2.5397	-2.2912	-2.4977
1	-6.9994	-5.5082	-6.7470	-7.7776	-6.2864	-7.5252
2	-8.3449*	-5.6110*	-7.8823*	-9.1646*	-6.4307*	-8.701*

To determine the optimal structure of the Vector Autoregression (VAR) model for China and India, the lag length of the dependent variables was assessed using information criteria. This involves testing different numbers of past values of the dependent variables to find the best fit for the model. By comparing the Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), and Hannan-Quinn Information Criterion (HQ) for various lag lengths, as shown in Table 4, it was determined that a lag length of 2 is optimal for both countries. This selection balances the model's complexity with its ability to accurately represent the data.

4.3. Diagnostic Test of the Model

The models developed for China and India demonstrate strong predictive power, with R-squared values of 0.9727 and 0.9590, respectively, indicating that a substantial portion of the variation in the dependent variable is explained by the included independent variables. Diagnostic tests were conducted for normality, serial correlation, and heteroscedasticity to assess the model's reliability. Table 5 presents the results of these tests, which generally support the model's assumptions, suggesting that the models are well-specified and suitable for further analysis.

Table 5: Diagnostic test

Test	China	India
	F-Statistics (Probability)	F-Statistics (Probability)
Breusch-Godfrey Serial Correlation LM Test	0.1468	0.3277
Breusch-Pagan-Godfrey Heteroskedasticity Test	0.1831	0.6396
Jarque-Bera test	0.9789	0.8121
	China	India
R^2	0.972718	0.794698
Adjusted R^2	0.959076	0.692047

The models developed for China and India exhibit strong explanatory power, with R-squared values indicating that a substantial portion of the variation in CO2 emissions is explained by the included variables. The Chinese model explains approximately 97% of the variation, while the Indian model accounts for about 59%. Diagnostic tests confirm the reliability of both models, suggesting that issues such as autocorrelation, heteroscedasticity, and normality are not significant concerns.

An ARDL bound test assessed the long-term relationship between the variables. Table 6 provides evidence of cointegration for both China and India, suggesting that the variables move together in the long run. This finding is supported by the calculated F-statistics, which exceed the critical values at conventional significance levels.

Table 6: Bound test for cointegration

Test Statistics	China		India	
F Statistics	9.7169		8.5572	
Number of Independent variables-k	4		4	
Critical Values (%)	Lower bound	Upper bound	Lower bound	Upper bound
1	3.29	4.37	3.29	4.37
5	2.56	3.49	2.56	3.49
10	2.2	3.09	2.2	3.09

4.4. Long Run Dynamics

We have calculated the long-run equilibrium relationship between the variables applying the ARDL (2,2,2,1,0) for China and ARDL (1,1,1,2,2) for India.

Table 7: Long-run estimates of ARDL

Dependent Variable: CO2 emissions					
China			India		
Variable	Coefficient	P-value	Variable	Coefficient	P-value
lnINF	0.2534	0.0068	lnINF	0.1334	0.0098
lnGDP	-0.4923	0.0101	lnGDP	0.0775	0.4472
lnGF	0.0590	0.3430	lnGF	0.1080	0.0284
lnSE	-0.7270	0.6221	lnSE	-4.9638	0.0001
C	11.4276	0.0122	C	21.5699	0.0000

Table 7 shows the long-term relationships between CO2 emissions and the examined variables vary across China and India. Inflation positively influences emissions in both countries. While GDP negatively impacts emissions in China, its effect is insignificant in India. Green finance benefits emissions in India but has no impact in China, and the shadow economy negatively affects emissions only in India. Both nations exhibit positive constant terms in their CO2 emissions models. Short-term analyses reveal dynamic relationships between the variables in both countries, supported by the presence of significant lagged error correction terms, as shown in Table 8. The impact of the current period, as well as different lag periods of the investigated variables are mixed.

The short-run estimation results from the Error Correction Model (ECM) indicate dynamic relationships among the investigated variables in both China and India, similar to the long-run relationships. The error correction term (ECT) is negative and significant for both countries, confirming the presence of long-term associations between CO2 emissions and the independent variables. In China, with an ECT coefficient of -0.2325, approximately 23.25% of disequilibrium is corrected each period, suggesting a moderate speed of adjustment. Past CO2 emissions, current inflation, and lagged GDP significantly and positively influence CO2 emissions, highlighting the role of economic growth and inflation in driving emissions. Conversely, in India, the ECT coefficient is -0.5930, indicating a faster adjustment to equilibrium with 59.3% of disequilibrium corrected each period. Inflation negatively impacts emissions, while green finance and the shadow economy have positive effects, suggesting that financial development and informal economic activities are key drivers of emissions in the short run. These results emphasize the differing factors influencing CO2 emissions in the short run across these two economies, reflecting their unique economic dynamics and environmental challenges.

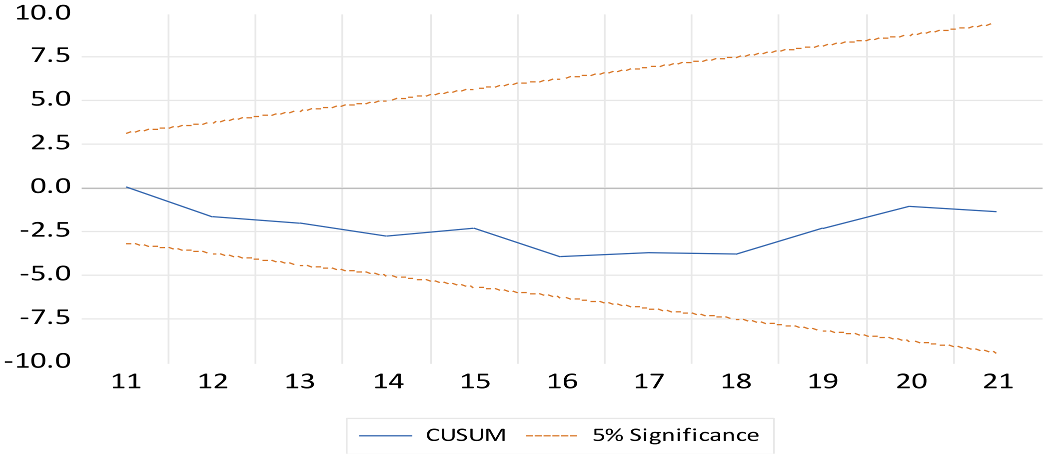
Table 8: Short-run estimates of ARDL

Dependent Variable: CO2 emissions					
China (2,2,2,1,0)			India (1,1,1,2,2)		
Variable	Coefficient	P-value	Variable	Coefficient	P-value
D(lnINF)	0.0315	0.0011	D(lnINF)	-0.0687	0.0194
D(lnINF(-1))	-0.0217	0.0081	D(lnGDP)	-0.0019	0.9164
D(lnGDP)	0.0153	0.1084	D(lnGF)	0.0260	0.0320
D(lnGF)	0.0038	0.3365	D(lnGF(-1))	-0.0188	0.1237
D(lnGDP(-1))	0.0837	0.0033	D(lnSE)	-0.6480	0.1357
CointEq(-1)	-0.2325	0.0000	D(lnSE(-1))	2.5126	0.0055
			CointEq(-1)	-0.5930	0.0000

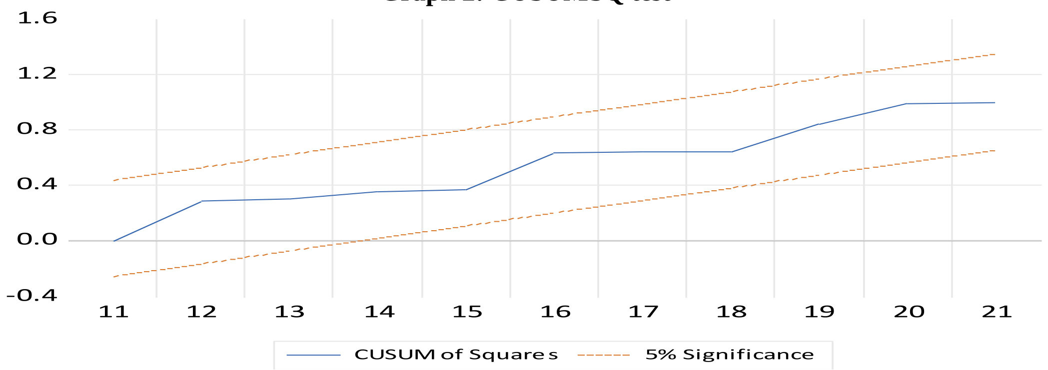
4.5. Stability of the Model

The study used CUSUM and CUSUMSQ tests to assess the stability of the model's parameters for China and India. The results, visualized in Graphs 1 to 4, indicate that both CUSUM and CUSUMSQ plots remain within the 5% critical bounds for both countries. This suggests that the model's parameters are stable over time and the model accurately captures both long-term and short-term dynamics for China and India.

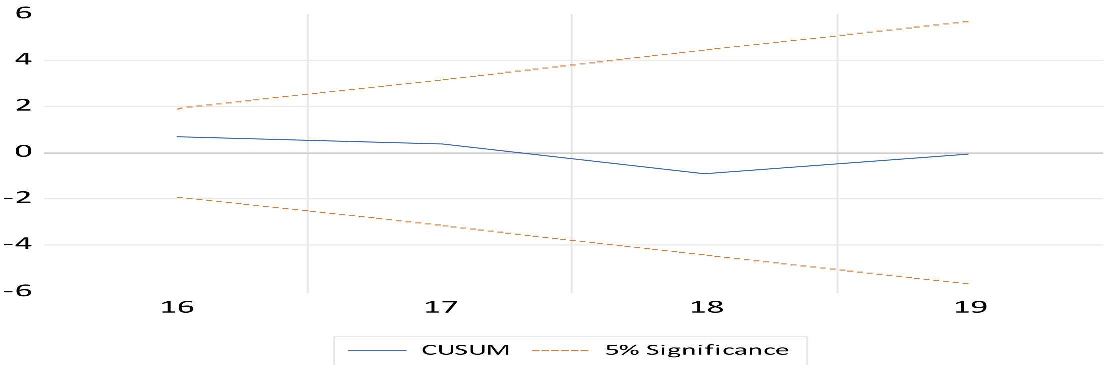
Stability tests for China:
Graph 1: CUSUM test



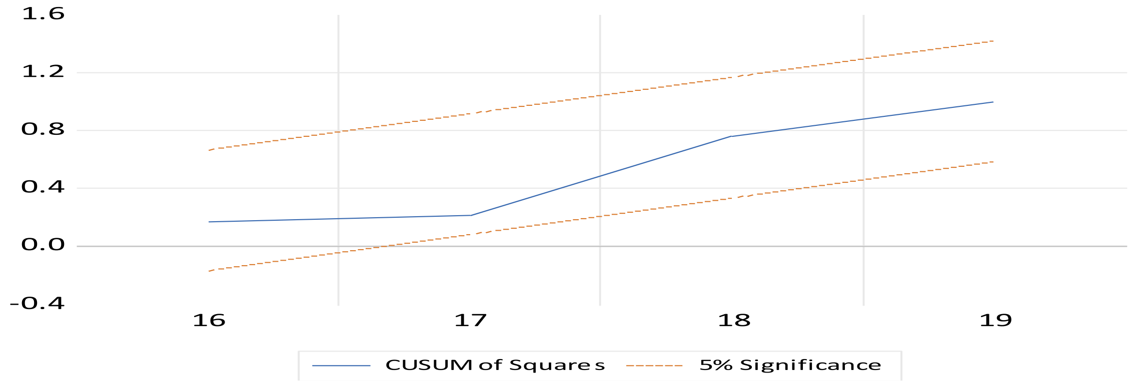
Graph 2: CUSUMSQ test



Stability tests for India
Graph 3: CUSUM test



Graph 4: CUSUMSQ test



5. Conclusion, Policy implications, and Future research

The findings indicate that the long-run and short-run characteristics of CO2 emissions for China and India as the leading oil importers such as the one providing oil to Canada are also divergent. In the long run, only inflation raises emissions in both countries; and only a decrease in GDP reduces emissions in China but it remains unchanged in India. Green finance has a positive effect on emissions in India while its effect is insignificant in China; the shadow economy has a negative effect on emissions in India and has no effect in China. In the short run the coefficient of past CO2 emission, current inflation rate, and lagged real GDP are positive to the CO2 emission in China, meaning that economic growth and inflation are major determinants of CO2 emission. Inflation, however, has a negative co-relation with emissions in India and green finance and shadow economy have positive co-relation depicted with financial development and informal economy respectively. This raises conscious awareness of such factors as drivers of emission in China and India and how they change at varying time horizons. China has the ability to mitigate emissions through green finance and policies that support low-carbon technologies, whereas India has constraints such as inadequate infrastructure, poverty, and inequality. Each country requires its own specific approach to how economic development can be achieved simultaneously with reducing emissions.

According to the Global Competitiveness Report of 2017-2018, there are many countries that can innovate but they need to take certain actions in order to harness the benefits. Some of the major developing and emerging economies such as China and India are shifting their focus and becoming hubs of innovation as they strive to compete with the developed economies. In increasing the preparedness of their people and industries to adapt to the new technology, both the countries will be benefited with the accelerated development. Therefore, it is important for both the countries to understand the potential of innovation for the economic progress and benefits of the country (Schwab). The study emphasizes the importance of integrated policies that leverage green finance, promote renewable energy, and address inflation to effectively reduce carbon emissions in China and India. The following policies should be adopted to support sustainable economic growth: promotion of green investments, legalization of the shadow economy, and measures that weaken the link between economic growth and environmental pollution. Thus, by implementing the approach discussed above, both countries can contribute to the attainment of their climate objectives and promote economic stability and sustainability. Future research should target emission sources, policies that encourage renewable energy and energy efficiency, and social and economic factors affecting emissions. International cooperation is an important tool to address climate change.

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