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Does the Level of Absorptive Capacity Matter for Carbon Intensity? Evidence from the USA and China

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Abstract: Interest in the rapid growth of CO₂ emissions, together with the economic performance of various countries continues to attract researchers and practitioners' interest. Alongside, concerns regarding global warming and its effects on human and animal health, and thus sustainable development, escalate. The present study employs the nonlinear autoregressive distributed lag to identify short- and long-run dynamics and the asymmetric nexus between absorptive capacity, and CO₂ emissions intensity from 1970 to 2018 in the case of the USA and China. In the short-run, an increase in technology transfer based on human resources increases CO₂ emissions in China. Contrarily, the decrease in technology transfer based on infrastructure has an emissions-decreasing effect in China. In the long-run, the effects of an increase in absorptive capacity based on innovation and infrastructure developments provide positive and significant impetus to mitigate the carbon intensity in China and the USA. The results are robust using GHG intensity. Thus, policymakers and researchers have to consider the pivotal role of absorptive capacity in facilitating sustainable development.

Keywords: absorptive capacity; carbon intensity; sustainable economic growth; innovation; infrastructure developments

1. Background

The economic growth performances of countries have improved substantially in recent decades. This remarkable improvement comes at an immense cost; rapid climate change and environmental degradation [1–3]. In recent years, the link between economic growth and environmental pollution has continued to be one of the controversial topics in the stream of environment and sustainable economics. There is a comprehensive consensus among researchers that the problems of climate change and environmental problems have been caused by human activities [4]. Currently, global warming and its fallout are among severe threats to sustainable development and life itself [5].

Parallel to the quest for economic growth, the mechanisms of the global carbon equilibrium have altered [6]. With this, global warming is at the top of most burning environmental issues across the world, and the associated effects of carbon dioxide (CO₂) emissions are being closely scrutinized [7]. The greenhouse gas emissions produced by industry and power plants are the cause of climate change [8].

Researchers and stakeholders in different disciplines have recommended a plethora of emission reduction strategies to stymie the ensuing adverse impacts climate change brings about. The global environmental summit at Cancun, which brought a global consensus to reduce greenhouse gas (GHG) emissions is quintessential. The main target of the summit was to maintain a global average temperature increase to below 2 °C [9,10].

Similarly, the Paris environmental summit negotiated with 196 participant bodies to reduce global climate change to a level below 2 °C vis-à-vis pre-industrial levels. The agreement calls for zero net human-induced GHG emissions to be realized during the second half of the 21st century. The Paris Agreement was also focused on transforming the current economic system expeditiously. Specifically, it was agreed upon to mitigate the rising global temperature and make the planet fit for humans, flora, and fauna. This plan also envisions retooling entirely the world's energy production systems [11].

It is, therefore, necessary to hasten innovation and include them quickly into policies focused on reducing CO₂ emissions [12]. Currently, the relationship between the level of economic development and the intensity of CO₂ emissions (measured by CO₂ emissions/gross domestic product) has changed. According to the findings by Roberts and Grimes [13], the linear relationship between CO₂ intensity and economic growth in 1692 has changed to be a curvilinear one now. In addition, they projected the curvilinear relationship to deepen with continued economic growth. Similarly, Antweiler et al. [14] identified economic growth geared by capital intensity to have a tendency to increase environmental pollution.

Regarding the actions of the polluting country, a study made by Fang et al. [15] identified China's commitment to decrease the carbon intensity between 2005 and 2020 [16,17]; however, during the period 2002 to 2009 China experienced a 3% surge in carbon intensity, even though the trend varied significantly in its 30 provinces. The decomposition analysis of Guan et al. [17] finds that the sectoral gains in efficiency were offset by the provinces by the carbon-intensive economic structure of the country and by the increase in investments favoring sectors with high carbon intensity. Such drivers have made China exceed the USA in CO₂ emissions nearly a decade ago. Currently, China leads the world in CO₂ emissions and energy consumption, consequently facing international pressure to control its increasing CO₂ emissions [18,19].

Regarding the USA, a study examined the relationship between energy consumption and carbon intensity [20]. Results show that there was no Granger-causality between income and carbon emissions in the long term. Contrarily, the energy use of the country is found in Granger-causing carbon emissions. Hence, income growth may not by itself be the driver of environmental complications in these particular cases [20].

As to the practicality of the environmental Kuznets curve (EKC), i.e., whether CO₂ emission rises and then falls as countries attain higher levels of economic development, it has serious implications for policymaking and practice. If the evidence supports the "Kuznets curve", it may suggest that current developments are capable and are environmentally benign in the long term [21–24]. The challenge will then be to examine how best to fast-track those strategies and processes so that all economies could realize economic production with environmental sustainability. Thus, technology transfer (absorptive capacity) and innovation have a double-edged advantage of enhancing economic growth and transforming the production system to environmental sustainability.

In some developing countries, the internationalization of capital, particularly foreign direct investment [25], has improved radically in the past two decades. Consequently, it has become an important substitute source in the development process by providing innovation and ways to enhance absorptive capacity [26,27]. Studies ascribe many reasons for the importance of FDI inflows, including employment creation, technology transfer, and enhanced competitiveness [28]. With FDI, there is a swift technological transfer, particularly if the host country has the capacity to learn and adopt foreign knowledge, skills, and innovation (i.e., absorptive capacity).

Absorptive capacity (AC) has been defined as the receiving country's ability to access, learn, integrate, and implement innovative technologies from foreign sources with domestic capacities [29].

Thus, the interplay between FDI, innovation, and absorptive capacity is determinant for environmental sustainability and the future convergence of countries [30,31]. However, some studies are skeptical about whether technology and innovation can mitigate CO₂ emissions and improve energy efficiency, arguing that it might not deliver the ultimate solution to sustainable economic growth due to the rebound effect, in which the system of innovations and the processes thereof may not provide the expected benign environmental outcomes [12,32]. Nevertheless, recent literature identifies technological progress and innovation methods reducing environmental degradation [33]. Similarly, Agustin et al. [32] confirmed that the environmental sustainability process benefits immensely by energy-related innovation processes and renewable energy sources.

Several other studies also propose different mechanisms that affect economic growth and the wellbeing of the environment. Regarding this, technology and innovation can be critical for emissions reduction in the face of increasing income and economic growth [34]. On the one hand, increased levels of economic activity may lead to increased energy ingestion into the system that could increase emissions. On the other hand, systems or processes of innovation may decrease energy demands and consumption, thereby reducing overall pollution [35]. Consequently, economic growth buoyed by green technological advancement reduces environmental pollution. The endogenous growth theory indeed does predict such ameliorating effects, giving credence to improving production processes by increasing productive capacities or by substituting polluting inputs with environmentally friendly ones [36]. However, the model is based on a culture dedicated to the environment and a society that could invest more resources on environmental protection as its income increases.

Parallel to this, some studies have pointed out that innovation spillover may come from the collaboration between technologies intended at mitigating environmental effect, and other technologies that may be part of the combined dynamics between economic activities (motivated by yield expansions from innovation) and environmental efficiency (processes naturally measured in terms of the pollutant emission intensity of the value-added) [34,37]. Another study also points out the improvement in the absorptive capacity of enterprises with capacity building to enhance productivity through innovation and learning parallel with environmental efficiency [38]. The way innovation influences environmental pollution could, in fact, reflect the interaction that may exist between innovative activities, economies' absorptive capacity, and the spatial dispersion of production efficiency, which has appeared as a key issue in regional and national innovation studies.

The efficiency of innovation in reducing pollution depends on the integration between different kinds of innovations and absorptive capacities within a particular economic and sector framework [32,38]. Therefore, the false dichotomy between economic growth and the environment can be readily resolved by the collective effects of green technological innovations in the near future [39]. The share of annual global emissions, both in absolute and relative terms, produced by the USA has decreased between 1997 and 2015, as has its GDP during the same timeframe, whereas China's relative and absolute share of emissions and GDP have increased by leaps and bounds. Owing to these dramatic changes, the USA and China have pledged to national climate action with a joint declaration in 2014 [40].

The Sino-U.S. Joint Statement on the Climate Change Declaration saw the Chinese government commit to a peak in CO₂ emissions by 2030 and to reduce its CO₂ emissions by 60–65%. Above all, these show the synchronization and the significant attention for economic growth and environmental management in the countries. Therefore, vivid appraisal of the countries' innovation and absorptive capacity improvements effect on CO₂ intensity in China and the USA is a matter of serious concern. In addition to this, not only due to the economic power but also due to the political negotiating and bargaining power of the economies on the international environmental issues, the result of this study may provide paramount significance to unlock the future trajectories related to the issue.

Therefore, this study hypothesizes that with increasing absorptive capacity and innovation, CO₂ emissions in China and the USA may decrease without necessarily affecting economic growth. As per the theory of endogenous economic growth, R&D sectors create and enhance technological innovation

with prevailing human capital and knowledge endowments [41]. In relation to the theme of the current study, a question that arises is whether expenditures on R&D plays a central role in reducing emissions while producing less polluting economic development in the future. In recent years, there is a clear understanding that green or eco-friendly innovations and technological transformations will take us closer to sustainable economic development. Hence, there is a growing interest in green innovation and its promotion and implementation in most economies of the world [35,42–45].

Absorptive capacity act as a moderator between the internal social network and innovation [46]. Empirical studies have used the total aggregate level of R&D expenditure as a proxy for innovation due to various reasons. First, because of the availability of continuous data; second, they adopt and use an economy-wide modeling approach and has the objective of trying to find outcomes that can assist policy recommendations; and third, almost all these studies analyze the pollution and energy sectors using R&D expenditure as a proxy for innovation [35]. The current study follows a similar methodological approach. Consequently, absorptive capacity and innovation might facilitate the evolution of low-carbon economies and provide clean and affordable energy needed for sustainable economic development.

The main objective of the current study is therefore to show the long-run relationship between R&D and absorptive capacity with the CO₂ emission intensity of various countries. Thus, the study attempts to examine the ameliorating effects of the absorptive capacities on CO₂ emissions intensity in two of the largest emitting countries—USA and China, during the years 1970–2018 using a nonlinear autoregressive distributed lag (NARDL) model. The findings of the paper offer benefits to policymakers in formulating policies to facilitate long-run sustainable development.

2. Economic Implications of Carbon Intensity

Beginning in the mid-18th to early 19th century, the ever-increasing consumption of fossil fuels has brought about an upsurge in CO₂ emissions causing increased global temperatures and what we know are the negative effects of global warming. Climate change, especially increasing temperature, has had wide-ranging impacts on the environment, humans, agriculture, and animals. Extreme weather events (like over flooding, extreme droughts, and seasonal migrations), sea-level increase, defects in crop growth, and interrupted hydrological patterns have also increased in frequency and intensity [47]. Alongside this, most countries are engaged in increased unsustainable economic activities to lift their citizens out of poverty and/or attain a higher standard of living. Energy consumption and resource transformation continue unabated, exacerbating the surge in GHGs [48].

Retrospectively, what explains the differences between nations in the levels of CO₂ emissions when their carbon-based economies grow at similar rates? This controversial reality is partially elucidated by the variations in the intensity of CO₂ emission by different nations. For instance, if we begin in 1750 and calculate the amount of CO₂ each country has produced to date, the UK comes out at the top of the list of the industrial-scale emitter of CO₂. Following this, the rest of the European economies and North America produce industrial-scale CO₂. Other regions, such as Latin America, Asia, and Africa, started to contribute to the total CO₂ emissions more recently, largely towards the end of the 20th century. When it comes to the total accumulation of CO₂, the US and Europe dominate; however, China's economic growth and in emissions towards the end of the 20th-century place it second in the cumulative polluter table but still contributing less than 50% of the US cumulative [47] (see Figures 1 and 2).

Therefore, in this study CO₂ intensity is measured by the quantity of CO₂ released per unit of GDP (kgCO₂ per total GDP 2010 constant \$) and, according to Ritchie and Roser [47], this is affected by energy efficiency, which is directly related to the levels of technology and technological transfer, infrastructure, and carbon efficiency of a country. Studies define energy efficiency as the quantity of energy required for one unit of GDP. This relationship is generally influenced by technological efficiency and the level of productivity. It is also associated with the type of economic sector and activity the underpin the output. Thus, if a nation transforms from primarily manufacturing to service-oriented, it ends up using lower amounts of energy per unit of GDP generated.

According to Dones, “carbon efficiency is the quantity of CO₂ emitted per unit energy (grams of CO₂ emitted per kilowatt-hour)” [49]. Carbon efficiency has mainly associated the type of energy the country uses. An economy that utilizes coal energy will release more CO₂ per unit of energy than one that relies more on renewable energy. Thus, countries that will increase their use of renewable energy will see gains in efficiency as the quantity of CO₂ produced per unit of energy declines [47,50].

Prior to this volatility being addressed, it is vital that two variables that seemingly are separate but are often related, are given a closer look; these being CO₂ emissions and GDP. Carbon intensity tells us the relative variation between CO₂ and GDP. If a country’s GDP temporarily falls, it is possible to see an increase in intensity, even if CO₂ emissions remain the same. This is because GDP has dropped relative to CO₂ [51].

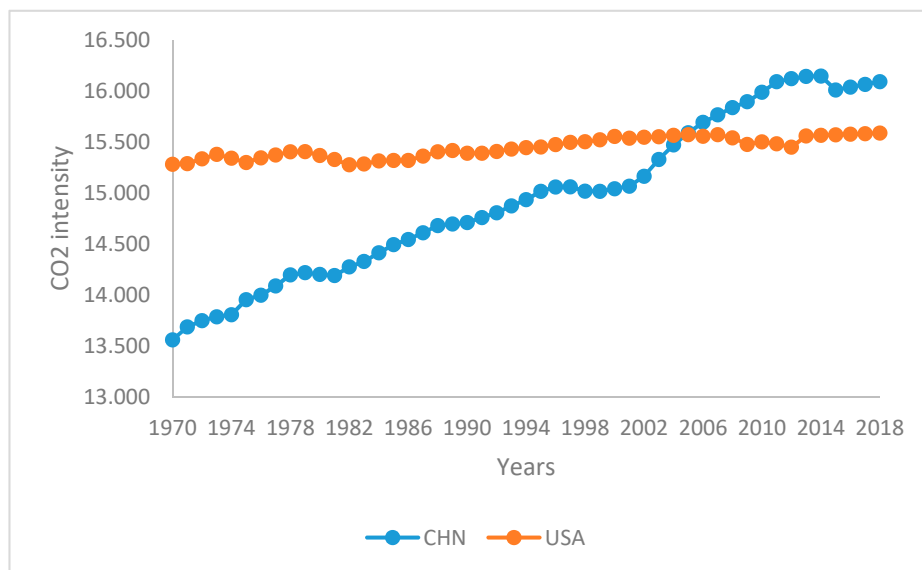


Figure 1. The CO₂ emission intensity of China and the USA.

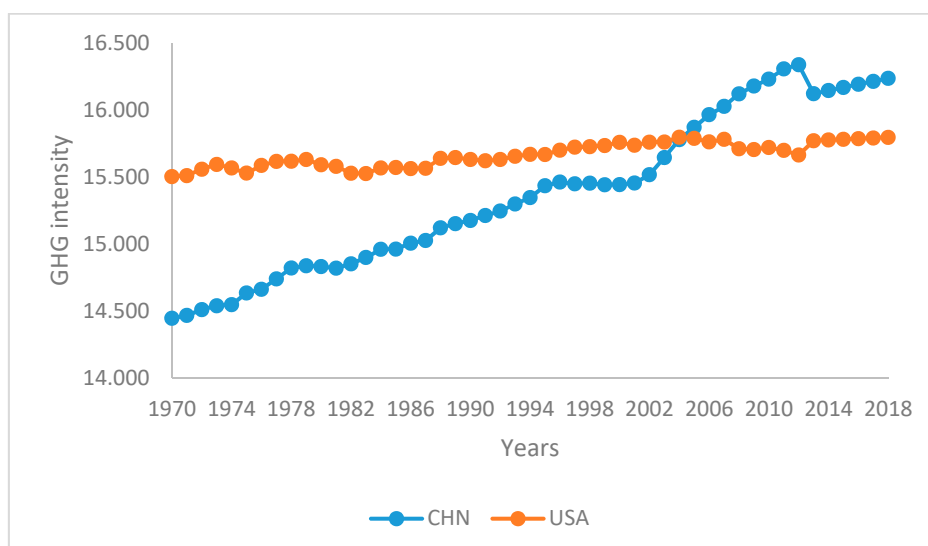


Figure 2. The GHG emission intensity of China and the USA.

Figures 1 and 2 illustrate the comparative glimpse of CO₂ and GHG emission intensity for China and the USA. Historically, CO₂ intensity for the USA has been much higher than China, the latter overtaking the former only in the 21st century. It is also worth noting that there has been an exponential increase in China’s CO₂ intensity in the timeframe displayed herein. This escalation can be directly

associated with increased carbon-based economic activities and the subsequent modification of energy utilization, a move to coal departing from old-style biomass. If one takes a long-run perspective, the increasing trend of CO₂ intensity in China has been consistent with other countries. However, in relative terms, the USA CO₂ intensity trend shows a very minimal increase [52]. The GHG intensity trend is very similar to the CO₂ intensity trend for both countries.

3. Materials and Methods

Annual data were obtained from WDI, WGI, and IMF for the two highest CO₂ emitting countries—China and the USA—from 1970 to 2018. In Table 1 a summary of the variables is presented along with sources of raw data. Before running the econometrics estimation, the data were transformed into natural logarithm forms to allow elasticity.

Table 1. Variables of the study.

Variables	Abbreviation	Descriptions	Data Sources	Measurement Reference
Carbon Emissions	CO2	CO ₂ emissions (kt)	WDI	[7,53]
Green House Gases	GHG	Total greenhouse gas emissions (kt of CO ₂ equivalent)	WDI	
Absorptive capacity	AC1	FDI ^{1,*} R&D ²	WDI	[54,55]
	AC2	FD I* HU.C ³	WDI	
	AC3	FDI * INFR ⁴	WDI	
Gross Fixed Capital Formations	GFC	Gross fixed capital formation (% of GDP)	WDI	[56]
Financial Development	FD	Composite of Efficiency, Access & Financial depth	IMF	[57]
Term of Trade	TOT	Term of Trade	IMF	[56]
Institutional Quality	IQ	The average value of the rule of law, government effectiveness, regulatory quality, corruption	WGI	[57,58]
GDP per capita	GDP_PC	GDP per capita (constant 2010 US\$)	WDI	[56,57,59,60]

¹ Foreign direct investment measured by net inflow to the economies. ² Research and development expenditure measured in ratio of total GDP. ³ Human capital measured by school enrollment; a tertiary ratio of the gross enrollment.

⁴ Gross fixed capital formation ratio of the total GDP. * symbol indicates the interaction of respective variables.

Following Tang [54,61,62] and the intuitive definition of absorptive capacity, it is proxied by the interaction of FDI with the determinants human capital measured by the tertiary education ratio of the gross school enrollment; tertiary ratio of the gross (HU.C), research, and development expenditure; ratio of total GDP (R&D) and gross fixed capital formation; and the ratio of total GDP (INFR). Despite the substantial pieces of evidence on the importance of absorptive capacity based on R&D expenditure, human resources, and infrastructure development, the idea has received scant empirical considerations [45]. The capacity to innovate and adapt units that are efficient in reducing emission is the focus here, and such capacities emanate in a variety of ways.

Regarding this, current attempts to understand, examine, and use knowledge are directly related to the existence and extent of prevailing knowledge. At the very minimum, the prevailing knowledge and existing human, infrastructure, and technical capacities assure the capability to factor in the worth of new information, systems, and technologies, and its adoption and application to different uses. Collectively these abilities of the new knowledge are referred to as “absorptive capacity [63]”. Indeed, research has demonstrated that firms engaged in R&D are better off vis-à-vis those obtaining information from external sources. One can surmise from this that investments in R&D are a precursor to absorptive capacity.

Other work also points to the growth of absorptive capacity to be a result of a firm's manufacturing operations. In [63] it was also noted that a firm can quickly and simply capture and gain from new information related to a product through direct involvement in manufacturing. Similarly, firms improve the quality of human capital by providing technical training to their employees so as to enhance their absorptive capacity. In support of this, a study on absorptive capacity in 69 industrialized countries found that there is higher productivity of inputs when the host country has a minimum threshold of absorptive capacity based on the stock of human capital [64].

According to Tang [54] a country's capacity to realize benefits from external sources is proxied by the government policy, human resource quality, R&D, and infrastructures. Corresponding to this, studies associate increasing absorptive capacities with the transfer of innovation and technology that can enhance productivity and diminish harmful pollution through replacing outdated productive factors and increasing the efficiency as well as alternatives of production systems. The other variables used are supported by empirical literature; however, the CO₂ intensity variable requires further explanations.

4. Empirical Approach

The asymmetry between economy-wide variables and incidences has long been documented in the economic literature. Keynes [65], in his popular remarks, noted: "The substitution of a downward for an upward tendency often takes place suddenly and violently". Asymmetry refers to both positive and negative changes in the variables. Schorderet [66] used this basic notion to define and structure the nonlinearity concept. Nonlinearity emerged as a phenomenal extension to linear analysis, allowing relationships to be established between variables "hidden" in the linear version. This indicates that changes in explanatory variables reflect the different effects of independent variables.

This study assesses the EKC hypothesis and the implications of the asymmetric impacts of GDP_PC absorptive capacity on CO₂ emissions in the USA and China using the nonlinear autoregressive distributed lag (NARDL) model which is prominent in recent studies [67,68]. Considering the factors' nature and economic growth, and global policies towards the CO₂ emissions–environment policy nexus, the study adopts a nonlinear framework. Therefore, the NARDL approach of Shin et al. [69], used to assess the dynamic association between absorptive capacity, and per capita, CO₂ emissions and GDP in the USA and China is followed herein. The NARDL model provides superior advantages to eliminate serial correlation and endogeneity effects and is competently able to identify the short- and long-term relationships of the nexus between the factors [59,70,71]; thus, one can adopt the NARDL, since it is the non-linear extension of the linear ARDL model [72].

Therefore, in this study, we examine the hypothesis that there is an improvement in environmental sustainability with improvements in absorptive capacity (technology transfer and adoptions) and that a country's intensity of emissions is expected to be appropriately reduced to enhance environmental quality as the economy grows in the model. Thus, following Griffith et al. [45], the following model is used in this study:

$$CO_2 = \beta_0 + \beta_1 GDP_PC_t + \beta_2 AC_t + \beta_3 IQ_t + \beta_3 GFC_t + \beta_4 FD_t + \beta_5 TOT_t + D_t + \varepsilon_t \quad (1)$$

where β_0 explains the fixed country effects, CO₂ is the logarithm of the level of per capita CO₂ emissions, GDP_PC is GDP per capita, and ε_t is the disturbance term. Factors are expressed in natural logarithm forms and in the long-run, the model assumes the elasticity of the explanatory variables represented.

The relationship between the variables presented in Equation (1) follows continuous developments to reach long-term equilibrium. Thus, representing Equation (1) under the ARDL representation it becomes the following:

$$\begin{aligned} \Delta CO_2 = \alpha_0 &+ \sum_{i=1}^1 \alpha_{1i} \Delta CO_{2t-1} + \sum_{i=0}^q \alpha_{2i} GDP_{PCt-1} + \sum_{i=0}^r \alpha_{3i} IQ_{t-1} \\ &+ \sum_{i=0}^s \alpha_{4i} GFC_{t-1} + \sum_{i=0}^t \alpha_{5i} FD_{t-1} + \sum_{i=0}^u \alpha_{6i} + AC_{t-1} \\ &+ \sum_{i=0}^v \alpha_{7i} + TOT_{t-1} + \alpha_7 CO_{2t-1} + \alpha_8 GDPP_{t-1} + \alpha_9 AC_{t-1} \\ &+ \alpha_{10} IQ_{t-1} + \alpha_{11} GCF_{t-1} + \alpha_{12} FD_{t-1} + \alpha_{13} TOT_{t-1} + D_t \end{aligned} \quad (2)$$

where Δ indicates the first difference, α_0 is a constant of the equation, $\alpha_{t,i}$ ($i = 1, 2, 3, 4, 5$) are the short-run coefficients, α_j ($j = 5, 6, 7, 8, 9, 10, 11, 12$) represents the long-run coefficients, and ε_t represents an error term. The ARDL procedure, as described by [70], allows us to identify the long-term nexus between the factors. A joint test of significance of the coefficients in a level or a lagged period [73]. To decide the appropriate lag order and identify the long-term association of the series ($q, r, s, t, u,$ and v), the study chooses the lag order selection test based on the Schwarz information criterion (SIC) and the Akaike information criterion (AIC) (see Appendix A Table A4).

Furthermore, to deal with nonlinear effects and accommodate the asymmetric effects, the study deploys the NARDL model developed by [69]. Unlike the linear ARDL model, the NARDL model lends itself to identify both the short- and long-term effects of the factors. Considering such relations between the variables represented in the ARDL model specification in Equation (2), the study proceeds to specify the NARDL model based on the purpose of the study, as follows:

$$\begin{aligned} \Delta CO_2 = \alpha_0 &+ \sum_{i=1}^1 \alpha_{1i} \Delta CO_{2t-1} + \sum_{i=0}^q \alpha_{2i} GDP_{PCt-1} + \sum_{i=0}^r \alpha_{3i} IQ_{t-1} \\ &+ \sum_{i=0}^s \alpha_{4i} TOT_{t-1} + \sum_{i=0}^t \alpha_{5i} FD_{t-1} + \sum_{i=0}^t \alpha_{6i} AC_{t-1} \\ &+ \sum_{i=0}^{u1} \alpha_{7i}^+ AC_{t-1}^+ + \sum_{i=0}^{u2} \alpha_{8i}^- AC_{t-1}^- + \alpha_9 CO_{2t-1} + \alpha_{10} GDP_{PCt-1} \\ &+ \alpha_{11} IQ_{t-1} + \alpha_{12} TOT_{t-1} + \alpha_{13} FD_{t-1} + \sum_{i=0}^{u1} \alpha_{14i}^+ + AC_{t-1}^+ \\ &+ \sum_{i=0}^{u1} \alpha_{15i}^+ + AC_{t-1}^- + D_t + \varepsilon_t. \end{aligned} \quad (3)$$

Based on the nonlinear model [69] that decomposes the exogenous factor into two partial sums, a positive partial sum AC_{t-1}^+ , which is expected to seize the positive variations of AC, and a negative partial sum AC_{t-1}^- , the negative deviations are accompanied in such a way that

$$\begin{aligned} AC_t^+ &= \sum_{i=1}^t \Delta AC_i^+ = \sum_{i=1}^t \max(\Delta AC_i, 0) \text{ and } AC_t^- = \sum_{i=1}^t \Delta AC_i^- \\ &= \sum_{i=1}^t \min(\Delta AC_i, 0). \end{aligned} \quad (4)$$

The long-run nonlinear effects are captured by α_{7i}^+ and α_{8i}^- , whereas the short-run nonlinear effects in the model are identified by α_{14i}^+ and α_{15i}^- .

Prior to running these econometric procedures, the study assessed the properties of the series by running structural break examinations and unit root tests. For the standard deviation, we examined whether there are great deviations in the series. The correlation matrix followed to test the multicollinearity and skewness of the series (see Appendix A Tables A1 and A2). Furthermore, we ran the variance inflation factor (VIF) to identify the multicollinearity effects of the data (see Appendix A Table A3).

5. Empirical Results and Discussion

To examine the long-term association between absorptive capacity and CO₂ emission intensity, the study employed the NARDL model developed by Shin et al. [69].

Table 2 documents the descriptive statistics pertaining to all the underlying variables for China and the USA. The statistics represent the acronym of each variable, the number of observations, the mean, standard deviation, and the range, respectively. The overall properties are satisfactory for further estimation.

The study assessed the stationarity of the test using the augmented Dickey and Fuller [74,75] and Phillips–Perron (PP) [76] tests. Due to the inefficiency and misleading results a unit root test may yield when there are structural breaks, a Zivot [77,78] test was used. In Table 3 the results of the test are presented; augmented Dickey–Fuller (ADF) [75], PP, and Zivot–Andrews (ZA) tests. The upper half of the table reports the results for China, while the lower half considers the USA.

Table 2. Descriptive statistics (China).

Variable	Obs	Mean	Std. Dev.	Min	Max
GHG	47	15.372	0.591	14.444	16.338
CO ₂	47	14.943	0.787	13.556	16.147
AC1	47	292.877	370.319	2.693	1318.451
AC2	47	12.828	18.916	0.055	78.158
AC3	47	20.398	18.968	1.886	61.626
GFC	47	3.512	0.202	3.176	3.856
FD	47	4.437	0.408	3.734	5.116
TOT	47	4.661	0.412	3.67	7.019
IQ	47	4.191	0.091	3.994	4.325
GDP_PC	47	7.049	1.142	5.431	8.9
Descriptive statistics (USA)					
GHG	47	15.664	0.091	15.502	15.796
CO ₂	47	15.442	0.101	15.276	15.587
AC1	47	1832.377	537.33	973.744	2702.633
AC2	47	73.059	7.103	62.966	85
AC3	47	60.154	9.935	42.744	75.041
GFC	47	3.062	0.075	2.889	3.194
FD	47	4.888	0.308	4.471	5.329
TOT	47	4.615	0.043	4.543	4.683
IQ	47	4.041	0.233	3.676	4.317
GDP_PC	47	10.534	0.261	10.057	10.918

Table 3. Unit-root test.

Variable	Augmented Dickey-Fuller		Phillips-Perron		Zivot-Andrews			
	Level	First	Level	First	Level	Break	First	Break
China								
GHG	-2.606	-3.235 **	-9.17 ***	-	-2.469	2011	-5.34 ***	2007
CO ₂	-3.077	-3.415 **	-8.943 ***	-	-2.602	1978	-4.553 **	2009
AC1	-3.404	-6.798 ***	-6.167 ***	-	-6.434 ***	2001	-	-
AC2	-2.342	-5.762 ***	-7.462 ***	-	-2.941	2008	-5.319 ***	2007
AC3	-0.919	-4.045 **	-0.529	-7.739 ***	-3.935	1995	-5.853 ***	2010
GFC	-2.844	-5.204 ***	-6.392 ***	-	-5.28 ***	1991	-	-
FD	-2.17	-3.989 **	-6.433 ***	-	-3.054	1991	-6.275 ***	2008
TOT	-3.965 **	-5.151 ***	-8.319 ***	-	-6.652 ***	1989	-	-
IQ	-2.127	-3.063 **	-9.739 ***	-	-3.385	2010	-5.897 ***	2004
GDP_PC	-2.963	-3.524 **	-8.715 ***	-	-2.674	2011	-4.663 **	2009
USA								
GHG	-0.667	-4.494 ***	-2.834	-7.097 ***	-2.898	2003	-7.104 ***	1981
CO ₂	-2.764	-4.113 **	-2.509	-5.889 ***	-3.098	1983	-5.973 ***	1981
AC1	-2.407	-3.807 **	-3.012	-8.124 ***	-3.964	2007	-8.056 ***	2011
AC2	-3.862 **	-5.423 ***	-4.026 ***	-	-4.12 *	2011	-7.642 ***	2004
AC3	-4.222 **	-4.802 ***	-3.191	-5.832 ***	-4.737 **	2001	-5.775 ***	2008
GFC	-2.346	-4.066 **	-2.595	-3.996 **	-4.432 **	2005	-4.945 ***	2010
FD	-2.46	-4.928 ***	-1.819	-6.704 ***	-2.461	2007	-7.287 ***	1998
TOT	-2.596	-3.483 **	-2.206	-5.92 ***	-3.114	1984	-5.887 ***	1982
IQ	-0.592	-3.821 **	-0.67	-6.259 ***	-3.242	1999	-6.762 ***	1989
GDP_PC	-1.283	-4.141 **	-1.771	-5.052 ***	-4.56 **	2005	-5.155 ***	2011

***, **, and * indicate the level of significance at 1%, 5%, and 10%, respectively.

In the case of China as per ADF, the result shows that only TOT is stationary at level, and all the variables are stationary when transformed to the first difference. The PP results show that all other variables are stationary at level expect AC3. ZA considers the structural break in time series, and shows that AC1, GFC, and TOT are free from unit-root at level; however, all other variables are transformed to the first difference to fulfill the stationarity condition. In the case of the USA, AC1 and AC2 are stationary at the level as per ADF, and AC2 contains no unit-root pursuant PP test.

The remaining variables are significant when transformed to the first difference. Similarly, ZA reveals that AC3, GFC, and GDP_PC are free from unit-root at level, and the transformation of the rest

of the indicators is stationary at the first difference. Further, the test results show a strong explanation for the use of a cointegration setting, such as the NARDL model, given that all variables are at the 1(1) and 1(0) level, and none is found to be 1(2).

Implementation of the NARDL estimation requires that we test the occurrence of long-run asymmetric association among the factors. Similarly, the table provides the results of the bound test F-statistics for China and the USA, describing long-term cointegration among the variables. Therefore, there is sufficient evidence to proceed with the NARDL model estimation.

In Table 4 the findings of the asymmetric impact of AC on CO₂ are presented. Panel-A represents the asymmetries translated by the different measures of AC on CO₂ in the case of China, whereas panel-B estimates the relevant models for the USA. The analysis is broken down into three categories; the first part shows the short-run dynamics under the positive and negative impact of the respective variables on CO₂ for both China and the USA.

In the first part, the results show that in China only an AC3-related increase in CO₂ emissions and a decrease in AC2-related emissions exist. The result suggests that in China and in the short-term, an increase in technology transfer based on human resources increases CO₂ emissions and a decrease in technology transfer based on infrastructure decreases emissions. The result indicates that a decrease in affluence diminishes the CO₂ intensity of China. The result supports the finding of van Vuuren and Riahi [52] and Zhang et al. [16] that indicate the effect of increasing affluence and that predominantly resulted in a shift to coal away from traditional biomass, and brought an increase in carbon intensity. All the other controls show a mix of asymmetric impacts on CO₂ emissions in both economies.

In the second part, results of long-run dynamics are presented in panel A. A positive change in AC1 and AC2 decreases CO₂ emissions in China, and a negative change is followed by a mixed effect; specifically, AC1 and AC2 increase the CO₂ the emissions level of China, while AC3 reduces it. The scenario of the USA is even more interesting, as AC1 drives CO₂ emissions, and it is surprising that both positive and negative changes in AC1 bring an increase in CO₂ emissions. However, a positive change in AC2 has a negative effect on CO₂ emissions. All other controls show a mix of asymmetric impacts on CO₂ emissions in both economies. This implies that a scheme similar to the Korean government's emissions trading system needs to be strict in order to control high emissions [48].

The results of the study indicate that absorptive capacity based on innovation and infrastructure development reduces the effects of CO₂ emissions in both China and the USA, indicating the crucial role of a technology transfer in combating climate change and enhancing sustainability in the long term. Therefore, the study cements the pivotal role of innovation and affluence technology transfer for the sustainable economic growth and environmental stewardship of China and the USA [35,79].

Consequently, one can say that in the long-term there is strong evidence that innovation (R&D) expenditures and raising the standards of affluence can decrease CO₂ emissions supporting the finding of [52]. Therefore, it is imperative to transform current carbon-based economic activities so as to attain sustainable development while reducing global CO₂ leaving standards of living unaffected in the long-run [80].

The third part consists of diagnostic statistics with respect to all settings. Overall results show that all the estimators satisfy the diagnostic properties, such as serial correlation, heteroscedasticity, normality, and stability. The cointegration test (t_BBM) carries a significant and negative coefficient, which justifies the long-run associations, and likewise, the significant F_PSS test ratifies this association. These two tests are vital to acknowledge the presence of a long-run relationship between the factors examined herein.

The NARDL is specifically designed to capture the asymmetries translated by various measures of AC, it witnesses the long-run asymmetries in the case of China, while only AC1 has an asymmetric long-run impact on CO₂ emissions in the USA. The findings imply that depending solely on linear modeling may not provide reliable policy inputs in every context; the presence of asymmetries calls for the policy agenda to be framed considering the asymmetric dynamics.

Table 4. Results of asymmetric impact absorptive capacity on CO₂.

Dependent Variable: CO ₂						
Panel-A (China)			Panel-B (USA)			
VARIABLES	(1)	(2)	(3)	(4)	(5)	[74]
	AC1	AC2	AC3	AC1	AC2	AC3
Short-Run Dynamics						
ECM _{t-1}	-0.915 **	-0.750 ***	-0.830 ***	-1.315 **	-1.621 ***	-0.975 *
ΔAC ⁺ _{t-1}	0.000	0.006	0.015 *	0.000	-0.001	0.017
ΔAC ⁻ _{t-1}	0.197	-0.085 ***		-0.000	-0.006	-0.004
ΔGFC ⁺ _{t-1}	-1.207 *	2.826 ***	0.885 *	-0.126	0.159	-0.099
ΔGFC ⁻ _{t-1}	-2.516 *	-0.935	-1.060 *	-0.275	0.491	0.787
ΔFD ⁺ _{t-1}	1.306	0.078	0.701	0.357 **	0.173	-0.114
ΔFD ⁻ _{t-1}	-3.836 *	-1.578 *	-2.482 *	0.680	0.842	-0.010
ΔTOT ⁺ _{t-1}	-1.654 **	0.230	-0.672 *	-1.004	-0.514	-1.030
ΔTOT ⁻ _{t-1}	-1.890 **	-0.072	-0.695 **	2.077 *	1.350	0.703
ΔIQ ⁺ _{t-1}	1.023	-2.547 **	-2.132 **	0.164	0.373	0.387
ΔIQ ⁻ _{t-1}	0.939	2.477 **	2.051 **	-0.969 **	-1.545 **	-1.086 **
ΔGDP_PC ⁺ _{t-1}	-0.888	-0.792 *	-0.330	0.018	0.033	0.017
ΔGDP_PC ⁻ _{t-1}	-2.713	5.486 **	0.630	0.015	0.022	0.017
ΔD ⁺ _{t-1}	0.307 **	0.176	-0.060	-0.097	-0.208	-0.000
ΔCO _{2,t-1}	0.387	0.002	0.348	0.325	0.341	-0.056
Long-Run Dynamics						
AC ⁺	-0.443 **	-0.008 ***	0.018 **	-0.002 **	-0.001 **	0.017
AC ⁻	0.001 ***	0.113 ***	-0.12 ***	0.003 *	0.004	0.005
GFC ⁺	2.595	3.769 ***	1.066 ***	-0.096	0.098	-0.102
GFC ⁻	5.828	1.247 **	1.276 ***	0.209	-0.303	-0.807
FD ⁺	-0.611	0.104	0.844	0.272 ***	0.107	-0.117
FD ⁻	1.98	2.105	2.99	-0.517	-0.52	0.01
TOT ⁺	-1.798	0.307	-0.809 ***	-0.763 **	-0.317	-1.056
TOT ⁻	2.345 *	0.096	0.837 **	-1.579 ***	-0.833 ***	-0.721
IQ ⁺	-4.524	-3.398 ***	-2.568 ***	0.125	0.23 ***	0.397
IQ ⁻	-0.888	-3.305 ***	-2.471 ***	0.737 ***	0.953 ***	1.114 ***
GDP_PC ⁺	-0.588	-1.057 ***	-0.398	0.014 *	0.02 ***	0.018 ***
GDP_PC ⁻	-10.559	-7.318 ***	-0.759	-0.012	-0.013 ***	-0.018
D1	-0.694	0.235	-0.073	-0.074 *	-0.128 ***	0.230
Constant	12.392 **	10.526 ***	11.379 ***	20.105 **	24.698 ***	14.891 *
Diagnostic Statistics						
Adj. R ²	0.837	0.858	0.716	0.890	0.867	0.760
F	16.77 ***	17.94 ***	14.13 ***	10.07 ***	18.29 ***	14.54 ***
T BDM	-2.93 ***	-6.91 ***	-4.45 ***	-3.98 ***	-4.89 ***	-2.38 ***
F_PSS	6.54 ***	8.59 ***	4.22 ***	5.40 ***	6.50 ***	2.75 ***
Serial	0.022	0.053	0.451	0.245	0.077	0.027
Het	0.927	0.939	0.423	0.923	0.422	0.155
Normal	0.410	0.013	0.894	0.986	0.948	0.168
RESET	0.214	0.142	0.094	0.392	0.036	0.104
LR Asymmetry	3.75 ***	23.2 ***	5.27 ***	2.57 ***	0.32	0.51
SR Asymmetry	0.31	0.59	0.41	0.96	0.15	0.25

Note: For brevity *t*-statistics is not reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. AC: absorptive capacity, Het: Heteroskedasticity, LR: long-run, SR: short-run, D1: dummy variable representing a structural break in CO₂, the +/- signs indicate positive/negative change in the dependent variable.

Table 5 incorporates the robustness captured with the alternative measure of dependent variables, e.g., GHG. Under the same settings, we replaced CO₂ with GHG and found the short- and long-run influence of AC on GHG in China and the USA. We also found a comparable short-run asymmetric association between AC and CO₂ emissions in the reference economies. Like Table 4, the long-run positive and negative changes in AC bring asymmetric changes in GHG in both economies. Absorptive capacity based on innovation shows significant GHG emissions effects in China.

Table 5. Robustness with an alternative measure (GHG).

Dependent Variable: GHG						
China						
USA						
VARIABLES	(1)	(2)	(3)	(4)	(5)	[74]
	AC1	AC2	AC3	AC1	AC2	AC3
Short-Run Dynamics						
ECM _{t-1}	-0.873 *	-1.927 ***	-1.272 **	-1.003 ***	-1.138 ***	-0.891 *
ΔAC ⁺ _{t-1}	-0.000 **	0.011	0.024 **	-0.000	-0.006 **	-0.003
ΔAC ⁻ _{t-1}	0.102	-0.075 ***	0.000	0.000 **	-0.007 *	0.004
ΔGFC ⁺ _{t-1}	-0.982	1.812 **	0.460	0.233	0.232 **	0.349
ΔGFC ⁻ _{t-1}	-1.035	-2.761 ***	-0.937	0.415	0.052	0.261
ΔFD ⁺ _{t-1}	0.890	2.034 **	1.531	0.196	0.211	0.213
ΔFD ⁻ _{t-1}	-3.809 *	-7.330 ***	-4.794 **	-0.751	-0.241	0.043
ΔTOT ⁺ _{t-1}	-0.781	-0.493	-0.262	-0.964	-1.178 ***	-0.976 ***
ΔTOT ⁻ _{t-1}	-1.001 *	-0.647 *	-0.335	0.769	0.767	0.435
ΔIQ ⁺ _{t-1}	1.313	-4.601 **	-2.148	0.385 *	0.141	0.180
ΔIQ ⁻ _{t-1}	0.804	4.348 ***	2.592	-0.652 *	-0.810 ***	-0.964 *
ΔGDP_PC ⁺ _{t-1}	-0.777	-1.564 **	-0.859	0.019	0.181	0.082
ΔGDP_PC ⁻ _{t-1}	-9.041	-4.217	-4.414	0.021 *	1.324 *	-0.612
ΔD ⁺ _{t-1}	-0.115	0.032	-0.210	-0.040	-0.116 **	-0.020
ΔGHG _{t-1}	-0.212	0.911 **	0.161	-0.096	-0.010	-0.113
Long-Run Dynamics						
AC ⁺	-0.001 **	-0.005 ***	0.019 ***	0.005	-0.005 ***	-0.004
AC ⁻	0.117	0.039 ***	0.08 ***	0.006	0.006 ***	-0.005
GFC ⁺	-1.125 **	0.941 ***	0.362	0.233	0.204 ***	0.392 ***
GFC ⁻	1.186 **	1.433 ***	0.736	-0.413	-0.046	-0.293
FD ⁺	1.02 ***	1.056 ***	1.203 ***	0.196 ***	0.185 ***	0.239
FD ⁻	4.364 ***	3.804 ***	3.768 ***	0.748 ***	0.212	-0.048
TOT ⁺	-0.895 ***	-0.256 ***	-0.206	-0.96 ***	-1.035 ***	-1.096 ***
TOT ⁻	1.148 ***	0.336 ***	0.263	-0.766	-0.674 ***	-0.489
IQ ⁺	1.504	-2.388 ***	-1.689 ***	0.383 ***	0.124 ***	0.202
IQ ⁻	-0.921	-2.256 ***	-2.037 ***	0.65 ***	0.711 ***	1.083
GDP_PC ⁺	-0.891	-0.812 ***	-0.675 ***	0.018 ***	0.159	0.092
GDP_PC ⁻	10.36 *	2.189	3.469	-0.02 ***	-1.164 ***	0.688
D2	-0.132	0.017	-0.165	-0.039 **	-0.102	-0.022
Constant	12.666 *	28.007 ***	18.458 **	15.537 ***	17.616 ***	13.776 *
Diagnostic Statistics						
Adj. R2	0.840	0.860	0.732	0.924	0.992	0.972
F	16.87 ***	17.88 ***	14.31 **	14.68 ***	134.2 ***	39.63 ***
T BDM	-2.35 ***	-6.42 ***	-2.95 ***	-4.76 ***	-16.94 ***	-2.28 ***
F_PSS	11.92 ***	13.16 ***	7.840 ***	6.346 ***	134.3 ***	23.44 ***
Serial	0.010	0.7485	0.007	0.051	0.098	0.012
Het	0.109	0.855	0.781	0.135	0.703	0.828
Normal	0.301	0.346	0.858	0.950	0.148	0.574
RESET	0.228	0.423	0.455	0.136	0.662	0.138
LR Asymmetry	2.77 ***	15.6 ***	3.96 ***	3.05 ***	6.08 ***	0.41
SR Asymmetry	0.002	1.01	1.97 **	0.81	0.91	0.25

Note: For brevity *t*-statistics is not reported. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. AC: absorptive capacity, Het: Heteroskedasticity, LR: long-run, SR: short-run, D2: dummy variable representing a structural break in GHG, +/- signs indicate positive/negative change in the independent variable.

However, the result indicates that absorptive capacity based on infrastructure development has a long-term diminishing impact on the CO₂ and GHG emissions in China and the USA. Thus, we infer that there is a need to formulate the long-run policies to control the CO₂ emissions in both regions, so that the quantum surge of CO₂ may gradually be controlled. Whilst energy is “the factor” contributing substantially to socioeconomic development, it also the main culprit vis-à-vis excessive use of fossil fuels when it comes to increased GHGs in the atmosphere and consequent global warming—climate change [81].

Interestingly the results are robust under an alternative measure of CO₂ emissions in both economies and validate the choice of the NARDL estimation as a useful tool for policy reforms.

6. Conclusions

The present study estimates the asymmetric impact of various measures of AC on CO₂ emissions in two high CO₂ emitting economies, China and the USA. The study considers the time series dataset from 1970 to 2018 for this purpose. The study accounts for the structural break in the underlying series, which has not been given due focus in related literature. We find the presence of structural breaks in our variables in both economies, and interestingly, a non-linear setting for further estimation is recommended given the mixed order of integration.

The findings document that there exists an asymmetric short- and long-run association among various measures of AC and CO₂ emissions. The results suggest an increase in technology transfer based on human resources increases CO₂ emissions in China in the short run and a decrease in technology transfer based on infrastructure decreases emissions in China as well. Our findings also show in the long term, along the lines of endogenous growth theory [41], the effects of an increase in absorptive capacity based on innovation and infrastructure developments were determined to be positive and significant to mitigate carbon intensity in China and the USA.

The results also are in support of the widely documented empirical reality of technological change's nature in decreasing GHG emissions without jeopardizing growth-oriented economic activities [43]. Previously, the literature has suggested that countries that have gone past the take-off stage when it comes to the use of renewable energy could easily take up further policy measures like feed-in tariffs, green certificates for long-run sustainable development and renewable portfolio standards [53].

Similarly, in the long term, the decrease in absorptive capacity based on innovation was shown to be positive and significant in increasing carbon intensity in China and the USA. However, the effect of a decrease in absorptive capacity based on infrastructure development is shown to be insignificant in the USA. The results of the asymmetric effects are proven to be robust and consistent using GHG intensity as an alternative dependent proxy for emissions intensity.

The findings are very useful for policy inputs and imply that curtailing CO₂ emissions regulators should prudently take into account and understand the impact of different measures of AC on CO₂ and GHG. The findings offer several directions for policymakers, for instance, and emissions trading systems should be given more attention by researchers and policymakers, so efficiency and innovation are built into the design and implementation, particularly when considering renewables for generating electricity [82]. The reforms in the industrial and transport sector have greatly contributed to reducing CO₂ in the USA [83], and those firms that are induced to invest in R&D are able to cut the carbon costs [84]. Similarly, the changes in regional structure drastically mimic the CO₂ emission [85], while the optimal utilization of innovative technology is subject to the pivotal role of the institution [86]. The mixed results pose challenges in the process of formulating the right policies to control CO₂ emissions because decreasing the AC is not going to decrease CO₂ emissions in all cases.

Every case calls for a unique policy agenda; therefore, the findings of the present study raise challenging questions to be addressed in CO₂ emissions reduction programs in China and the USA. The literature suggests that several other countries are already taking a closer look at developing a low-carbon energy mix to reduce the adverse impacts of fossil fuel misuse [48]. Interestingly, the results are robust under an alternative measure of CO₂ emissions in both economies and validate the choice of the NARDL estimation as a useful tool for policy reforms. Aligned with recent literature [87–89], we also suggest that the related studies which have taken into account the traditional linear specification, such as ARDL, may review and extend the phenomena under a non-linear setting introduced in recent literature, for better policy input.

The present study investigates one dimension of the relationship; there may be nonlinearity considerations from other factors that are not accounted for here. Moreover, the study only considers two high CO₂ emitting countries, China and the USA. Therefore, the findings lack generalizability.

However, to capture a broader picture there is a need to extend these types of models to other high CO₂ emitting countries because excessive CO₂ generation and its ensuing negative effects on human, animal, and plant wellbeing is a grave danger to the planet, let alone sustainable development [5].

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Appendix A

Table A1. Matrix of correlations (China).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) AC2	1.000							
(2) AC3	0.639	1.000						
(3) AC1	0.559	0.623	1.000					
(4) GFC	0.729	0.471	0.911	1.000				
(5) FD	0.401	0.769	0.882	0.877	1.000			
(6) TOT	-0.426	-0.461	-0.506	-0.512	-0.552	1.000		
(7) IQ	-0.678	-0.324	-0.656	-0.498	-0.726	0.440	1.000	
(8) GDP_PC	0.681	0.826	0.955	0.726	0.569	-0.541	-0.673	1.000

Table A2. Matrix of correlations (USA).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) AC2	1.000							
(2) AC3	-0.439	1.000						
(3) AC1	0.576	-0.713	1.000					
(4) GCF	-0.668	0.589	-0.514	1.000				
(5) FD	0.766	-0.435	0.657	-0.496	1.000			
(6) TOT	0.409	-0.502	0.560	-0.026	0.484	1.000		
(7) IQ	0.591	-0.797	0.751	-0.384	0.871	0.552	1.000	
(8) GDP_PC	0.786	-0.943	0.782	-0.475	0.973	0.579	0.892	1.000

Table A3. Variance inflation factors for China and USA.

Variable	China	USA
GDP_PC	3.424	2.068
AC1	1.765	8.931
FD	4.384	5.492
AC2	1.871	2.549
AC3	1.410	7.536
GFC	0.374	0.084
IQ	4.291	3.525
TOT	1.547	2.456

Table A4. Lag selection criteria of China.

Variable	China		USA	
	AIC	SIC	AIC	SC
0	13.70279	14.10032	-2.560704	-2.167056
1	-2.264427	6.121492	-15.56438	-8.812698
2	-6.201961 *	2.108411 *	-17.07931 *	-11.23425 *

* indicates lag order selected by the criterion.

References

- Jordaan, S.M.; Romo-Rabago, E.; McLeary, R.; Reidy, L.; Nazari, J.; Herremans, I.M. The role of energy technology innovation in reducing greenhouse gas emissions: A case study of Canada. *Renew. Sustain. Energy Rev.* **2017**, *78*, 1397–1409. [CrossRef]
- Ang, J.B. CO₂ emissions, research and technology transfer in China. *Ecol. Econ.* **2009**, *68*, 2658–2665. [CrossRef]
- Mikayilov, J.I.; Galeotti, M.; Hasanov, F.J. The impact of economic growth on CO₂ emissions in Azerbaijan. *J. Clean. Prod.* **2018**, *197*, 1558–1572. [CrossRef]
- Yi, W.-J.; Zou, L.-L.; Guo, J.; Wang, K.; Wei, Y.-M. How can China reach its CO₂ intensity reduction targets by 2020? A regional allocation based on equity and development. *Energy Policy* **2011**, *39*, 2407–2415. [CrossRef]
- Hao, Y.; Huang, Z.; Wu, H. Do Carbon Emissions and Economic Growth Decouple in China? An Empirical Analysis Based on Provincial Panel Data. *Energies* **2019**, *12*, 2411. [CrossRef]
- Haghiri, M.; Sabau, G.; Ahmed, R. The Long Run Relationship between Economic Growth and Environmental Quality. *Asian J. Agric. Ext. Econ. Sociol.* **2019**, 1–10. [CrossRef]
- Li, H.; Wei, Y.-M.; Mi, Z. China's carbon flow: 2008–2012. *Energy Policy* **2015**, *80*, 45–53. [CrossRef]
- Wilberforce, T.; Baroutaji, A.; Soudan, B.; Al-Alami, A.H.; Olabi, A.G. Outlook of carbon capture technology and challenges. *Sci. Total Environ.* **2019**, *657*, 56–72. [CrossRef]
- Agbor, J.M. *The Relationship between Customer Satisfaction and Service Quality: A Study of Three Service Sectors in Umeå*; Umeå University, Faculty of Social Sciences: Umeå, Sweden, 2011.
- United Nations Climate Change. *The Cancun Agreements: Outcome of the Work of the Ad Hoc Working Group on Long-Term Cooperative Action under the Convention, Decision 1/CP.16*; United Nations Climate Change: Bonn, Germany, 2010; Available online: <https://unfccc.int/sites/default/files/resource/docs/2010/cop16/eng/07a01.pdf> (accessed on 15 November 2019).
- International Energy Agency. *In World Energy Statistics 2016*; International Energy Agency: Paris, France, 2016; Available online: <https://webstore.iea.org/> (accessed on 15 November 2019).
- Dauda, L.; Long, X.; Mensah, C.N.; Salman, M. The effects of economic growth and innovation on CO₂ emissions in different regions. *Environ. Sci. Pollut. Res.* **2019**, *26*, 15028–15038. [CrossRef]
- Roberts, J.T.; Grimes, P.E. Carbon intensity and economic development 1962–1991: A brief exploration of the environmental Kuznets curve. *World Dev.* **1997**, *25*, 191–198. [CrossRef]
- Antweiler, W.; Copeland, B.R.; Taylor, M.S. Is free trade good for the environment? *Am. Econ. Rev.* **2001**, *91*, 877–908. [CrossRef]
- Fang, J.; Zhang, J.; Jiang, Z.; Mao, Y. *Development of Integrated Multi-trophic Aquaculture in China*; World Aquaculture Adelaide: Adelaide, Australia, 2014.
- Zhang, Y.-J.; Liu, Z.; Zhang, H.; Tan, T.-D. The impact of economic growth, industrial structure and urbanization on carbon emission intensity in China. *Nat. Hazards* **2014**, *73*, 579–595. [CrossRef]
- Guan, D.; Klasen, S.; Hubacek, K.; Feng, K.; Liu, Z.; He, K.; Geng, Y.; Zhang, Q. Determinants of stagnating carbon intensity in China. *Nat. Clim. Chang.* **2014**, *4*, 1017. Available online: <https://www.nature.com/articles/nclimate2388> (accessed on 15 November 2019). [CrossRef]
- Wang, P.; Wu, W.; Zhu, B.; Wei, Y. Examining the impact factors of energy-related CO₂ emissions using the STIRPAT model in Guangdong Province, China. *Appl. Energy* **2013**, *106*, 65–71. [CrossRef]
- Wang, R.; Liu, W.; Xiao, L.; Liu, J.; Kao, W. Path towards achieving of China's 2020 carbon emission reduction target—A discussion of low-carbon energy policies at province level. *Energy Policy* **2011**, *39*, 2740–2747. [CrossRef]
- Soytas, U.; Sari, R.; Ewing, B.T. Energy consumption, income, and carbon emissions in the United States. *Ecol. Econ.* **2007**, *62*, 482–489. [CrossRef]
- Beckerman, W. Economic growth and the environment: Whose growth? whose environment? *World Dev.* **1992**, *20*, 481–496. [CrossRef]
- Kaika, D.; Zervas, E. The environmental Kuznets curve (EKC) theory. Part B: Critical issues. *Energy Policy* **2013**, *62*, 1403–1411. [CrossRef]
- Saboori, B.; Sulaiman, J.; Mohd, S. Economic growth and CO₂ emissions in Malaysia: A cointegration analysis of the Environmental Kuznets Curve. *Energy Policy* **2012**, *51*, 184–191. [CrossRef]

24. Ahmed, K.; Rehman, M.U.; Ozturk, I. What drives carbon dioxide emissions in the long-run? Evidence from selected South Asian Countries. *Renew. Sustain. Energy Rev.* **2017**, *70*, 1142–1153. [[CrossRef](#)]
25. OECD. *FDI in Figures*; Organisation for Economic Co-Operation and Development: Paris, France, 2016; Available online: <http://www.oecd.org/corporate/FDI-in-Figures-April-2016.pdf> (accessed on 8 December 2019).
26. Addison, T.; Mavrotas, G.; McGillivray, M. Development assistance and development finance: Evidence and global policy agendas. *J. Int. Dev.* **2005**, *17*, 819–836. [[CrossRef](#)]
27. Global Development Finance. *Mobilizing Finance and Managing Vulnerability*; The World Bank Economic Review; The World Bank: Washington, DC, USA, 2005.
28. Kobrin, S.J. The determinants of liberalization of FDI policy in developing countries: A cross-sectional analysis, 1992–2001. *Transnatl. Corp.* **2005**, *14*, 67–104. Available online: <http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.723.5288&rep=rep1&type=pdf> (accessed on 8 December 2019).
29. Meyer, K.E.; Sinani, E. When and where does foreign direct investment generate positive spillovers? A meta-analysis. *J. Int. Bus. Stud.* **2009**, *40*, 1075–1094. [[CrossRef](#)]
30. Grossman, G.M.; Helpman, E. *Innovation and Growth in the Global Economy*; MIT Press: Cambridge, MA, USA, 1991; ISBN 0262570971.
31. Sala-i-Martin, X. The classical approach to convergence analysis. *Econ. J.* **1995**, *106*, 1019–1036. [[CrossRef](#)]
32. Agustin, A.-H.; Daniel, B.-L.; Shahbaz, M.; Cantos, J.M. Energy innovation and renewable energy consumption in the correction of air pollution levels. *Energy Policy* **2017**, *105*, 386–397. [[CrossRef](#)]
33. Severo, E.A.; de Guimarães, J.C.F.; Dorion, E.C.H. Cleaner production and environmental management as sustainable product innovation antecedents: A survey in Brazilian industries. *J. Clean. Prod.* **2017**, *142*, 87–97. [[CrossRef](#)]
34. Gilli, M.; Mancinelli, S.; Mazzanti, M. Innovation complementarity and environmental productivity effects: Reality or delusion? Evidence from the EU. *Ecol. Econ.* **2014**, *103*, 56–67. [[CrossRef](#)]
35. Fernández, Y.F.; López, M.F.; Blanco, B.O. Innovation for sustainability: The impact of R&D spending on CO2 emissions. *J. Clean. Prod.* **2018**, *172*, 3459–3467. [[CrossRef](#)]
36. Stokey, N.L. Are there limits to growth? *Int. Econ. Rev.* **1998**, *39*, 1–31. Available online: <https://www.jstor.org/stable/pdf/2527228.pdf> (accessed on 8 December 2019). [[CrossRef](#)]
37. Repetto, R.C. *Promoting Environmentally Sound Economic Progress: What the North Can Do*; World Resources Institute: Washington, DC, USA, 1990; ISBN 0915825570.
38. Mazzanti, M.; Zoboli, R. Embedding environmental innovation in local production systems: SME strategies, networking and industrial relations: Evidence on innovation drivers in industrial districts. *Int. Rev. Appl. Econ.* **2009**, *23*, 169–195. [[CrossRef](#)]
39. Jaffe, A.B.; Stavins, R.N. The energy-efficiency gap What does it mean? *Energy Policy* **1994**, *22*, 804–810. [[CrossRef](#)]
40. Milkoreit, M. The Paris Agreement on Climate Change-Made in USA? *Perspect. Politics* **2019**, *17*, 1019–1037. [[CrossRef](#)]
41. Romer, P.M. Increasing returns and long-run growth. *J. Political Econ.* **1986**, *94*, 1002–1037. [[CrossRef](#)]
42. Álvarez-Herránz, A.; Balsalobre, D.; Cantos, J.M.; Shahbaz, M. Energy Innovations-GHG Emissions Nexus: Fresh Empirical Evidence from OECD Countries. *Energy Policy* **2017**, *101*, 90–100. [[CrossRef](#)]
43. Bosetti, V.; Carraro, C.; Massetti, E.; Tavoni, M. International energy R&D spillovers and the economics of greenhouse gas atmospheric stabilization. *Energy Econ.* **2008**, *30*, 2912–2929. [[CrossRef](#)]
44. Feng, F.; Peng, L. Is There Any Difference in the Effect of Different R and D Sources on Carbon Intensity in China? *Sustainability* **2019**, *11*, 1701. [[CrossRef](#)]
45. Griffith, R.; Redding, S.; Van Reenen, J. R&D and absorptive capacity: Theory and empirical evidence. *Scand. J. Econ.* **2003**, *105*, 99–118. [[CrossRef](#)]
46. Shan, W.; Zhang, C.; Wang, J. Internal Social Network, Absorptive Capacity and Innovation: Evidence from New Ventures in China. *Sustainability* **2018**, *10*, 1094. [[CrossRef](#)]
47. Ritchie, H.; Roser, M. CO₂ and Other Greenhouse Gas Emissions. Available online: <https://ourworldindata.org/co2-and-other-greenhouse-gas-emissions> (accessed on 15 November 2019).
48. Son, D.; Kim, J.; Jeong, B. Optimal Operational Strategy for Power Producers in Korea Considering Renewable Portfolio Standards and Emissions Trading Schemes. *Energies* **2019**, *12*, 1667. [[CrossRef](#)]

49. Dones, R.; Heck, T.; Hirschberg, S. *Greenhouse Gas Emissions from Energy Systems: Comparison and Overview*; Paul Scherrer Institut: Villigen, Switzerland, 2004. [[CrossRef](#)]
50. Khan, H.; Khan, U.; Jiang, L.J.; Khan, M.A.; Shah, S.H. The Role of China's Exchange Rate on the Trade Balance of Sub-Saharan Africa: A Gravity Model Approach. *Comp. Econ. Res.* **2019**, *22*, 57–72. [[CrossRef](#)]
51. Chang, K.; Chang, H. Cutting CO2 intensity targets of interprovincial emissions trading in China. *Appl. Energy* **2016**, *163*, 211–221. [[CrossRef](#)]
52. Van Vuuren, D.P.; Riahi, K. Do recent emission trends imply higher emissions forever? *Clim. Chang.* **2008**, *91*, 237–248. [[CrossRef](#)]
53. Vasylieva, T.; Lyulyov, O.; Bilan, Y.; Streimikiene, D. Sustainable economic development and greenhouse gas emissions: The dynamic impact of renewable energy consumption, GDP, and corruption. *Energies* **2019**, *12*, 3289. [[CrossRef](#)]
54. Tang, Y.; Zhang, K.H. Absorptive capacity and benefits from FDI: Evidence from Chinese manufactured exports. *Int. Rev. Econ. Financ.* **2016**, *42*, 423–429. [[CrossRef](#)]
55. Shen, X.; Lin, B.; Wu, W. R&D Efforts, Total Factor Productivity, and the Energy Intensity in China. *Emerg. Mark. Finance Trade* **2019**, *55*, 2566–2588. [[CrossRef](#)]
56. Abdulahi, M.E.; Shu, Y.; Khan, M.A. Resource rents, economic growth, and the role of institutional quality: A panel threshold analysis. *Resour. Policy* **2019**, *61*, 293–303. [[CrossRef](#)]
57. Khan, M.A.; Kong, D.; Xiang, J.; Zhang, J. Impact of Institutional Quality on Financial Development: Cross-Country Evidence based on Emerging and Growth-Leading Economies. *Emerg. Mark. Financ. Trade* **2019**, 1–17. [[CrossRef](#)]
58. Khan, M.A.; Khan, M.A.; Abdulahi, M.E.; Liaqat, I.; Shah, S.S.H. Institutional quality and financial development: The United States perspective. *J. Multinat. Financ. Manag.* **2019**, *49*, 67–80. [[CrossRef](#)]
59. Haseeb, M.; Kot, S.; Hussain, H.I.; Jermisittiparsert, K. Impact of Economic Growth, Environmental Pollution, and Energy Consumption on Health Expenditure and R&D Expenditure of ASEAN Countries. *Energies* **2019**, *12*, 3598. [[CrossRef](#)]
60. Simionescu, M.; Bilan, Y.; Krajiňáková, E.; Streimikiene, D.; Gędek, S. Renewable energy in the electricity sector and GDP per capita in the European Union. *Energies* **2019**, *12*, 2520. [[CrossRef](#)]
61. Khan, H.; Khan, U. Financial Development and FDI Inflows in China; Economics Discussion Papers. 2019. Available online: <http://www.economics-ejournal.org/economics/discussionpapers/2019-54> (accessed on 29 December 2019).
62. Huang, J.; Liu, Q.; Cai, X.; Hao, Y.; Lei, H. The effect of technological factors on China's carbon intensity: New evidence from a panel threshold model. *Energy Policy* **2018**, *115*, 32–42. [[CrossRef](#)]
63. Cohen, W.M.; Levinthal, D.A. Absorptive capacity: A new perspective on learning and innovation. *Adm. Sci. Q.* **1990**, 128–152. [[CrossRef](#)]
64. Almfraji, M.A.; Almsafir, M.K. Foreign Direct Investment and Economic Growth Literature Review from 1994 to 2012. *Procedia Soc. Behav. Sci.* **2014**, *129*, 206–213. [[CrossRef](#)]
65. Keynes, J.M. *The General Theory of Employment, Interest and Money*; Springer: London, UK, 1936.
66. Schorderet, Y. *Revisiting Okun's Law: An Hysteretic Perspective*; University of California, San Diego Department of Economics: California, CA, USA, 2001; Available online: <https://escholarship.org/uc/item/2fb7n2wd> (accessed on 15 November 2019).
67. Li, C.; Pervaiz, K.; Khan, M.A.; Rehman, F.U.; Oláh, J. On the Asymmetries of Sovereign Credit Rating Announcements and Financial Market Development in the European Region. *Sustainability* **2019**, *11*, 6636. [[CrossRef](#)]
68. Rehman, F.U.; Khan, M.A.; Khan, M.A.; Pervaiz, K.; Liaqat, I. The Causal, Linear and Nonlinear Nexus Between Sectoral FDI and Infrastructure in Pakistan: Using A New Global Infrastructure Index. *Res. Int. Bus. Financ.* **2020**, 101129. [[CrossRef](#)]
69. Shin, Y.; Yu, B.; Greenwood-Nimmo, M. Modelling Asymmetric Cointegration and Dynamic Multipliers in a Nonlinear ARDL Framework. In *Festschrift in Honor of Peter Schmidt: Econometric Methods and Applications*; Sickles, R.C., Horrace, W.C., Eds.; Springer: New York, NY, USA, 2014; pp. 281–314.
70. Pesaran, M.H.; Shin, Y.; Smith, R.P. Pooled mean group estimation of dynamic heterogeneous panels. *J. Am. Stat. Assoc.* **1999**, *94*, 621–634. [[CrossRef](#)]
71. Kriskkumar, K.; Naseem, N.A.M. Analysis of Oil Price Effect on Economic Growth of ASEAN Net Oil Exporters. *Energies* **2019**, *12*, 3343. [[CrossRef](#)]

72. Marques, A.C.; Fuinhas, J.A.; Tomás, C. Energy efficiency and sustainable growth in industrial sectors in European Union countries: A nonlinear ARDL approach. *J. Clean. Prod.* **2019**, *239*, 118045. [[CrossRef](#)]
73. Khan, M.A.; Ilyas, R.M.A.; Hashmi, S.H. Cointegration between Institutional Quality and Stock Market Development. *NUML Int. J. Bus. Manag.* **2018**, *13*, 90–103. Available online: <https://search.proquest.com/openview/4574ad20282b490a8ae2326e378f48ba/1?cbl=2050138&pq-origsite=gscholar> (accessed on 8 December 2019).
74. Dickey, D.A.; Fuller, W.A. Distribution of the estimators for autoregressive time series with a unit root. *J. Am. Stat. Assoc.* **1979**, *74*, 427–431. [[CrossRef](#)]
75. De Long, J.B.; Summers, L.H. Equipment investment and economic growth. *Q. J. Econ.* **1991**, *106*, 445–502. [[CrossRef](#)]
76. Phillips, P.C.; Perron, P. Testing for a unit root in time series regression. *Biometrika* **1988**, *75*, 335–346. [[CrossRef](#)]
77. Zivot, E.; Andrews, D.W.K. Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *J. Bus. Econ. Stat.* **2002**, *20*, 25–44. [[CrossRef](#)]
78. Alola, A.A. Carbon emissions and the trilemma of trade policy, migration policy and health care in the US. *Carbon Manag.* **2019**, *10*, 209–218. [[CrossRef](#)]
79. Koçak, E.; Ulucak, Z.Ş. The effect of energy R&D expenditures on CO2 emission reduction: Estimation of the STIRPAT model for OECD countries. *Environ. Sci. Pollut. Res.* **2019**, *26*, 14328–14338. [[CrossRef](#)]
80. Adamu, T.M.; Shafiq, M. Analyzing the Impact of Energy, Export Variety, and FDI on Environmental Degradation in the Context of Environmental Kuznets Curve Hypothesis: A Case Study of India. *Energies* **2019**, *12*, 1076. [[CrossRef](#)]
81. Armeanu, D.Ş.; Gherghina, Ş.C.; Pasmangiu, G.J.E. Exploring the Causal Nexus between Energy Consumption, Environmental Pollution and Economic Growth: Empirical Evidence from Central and Eastern Europe. *Energies* **2019**, *12*, 3704. [[CrossRef](#)]
82. Wolff, G.; Feuerriegel, S. Emissions Trading System of the European Union: Emission Allowances and EPEX Electricity Prices in Phase III. *Energies* **2019**, *12*, 2894. [[CrossRef](#)]
83. Wang, Q.; Wang, S. Decoupling economic growth from carbon emissions growth in the United States: the role of research and development. *J. Clean. Prod.* **2019**. [[CrossRef](#)]
84. Yenipazarli, A. Incentives for environmental research and development: Consumer preferences, competitive pressure and emissions taxation. *Euro. J. Oper. Res.* **2019**, *276*, 757–769. [[CrossRef](#)]
85. Zheng, J.; Mi, Z.; Coffman, D.M.; Milcheva, S.; Shan, Y.; Guan, D.; Wang, S. Regional development and carbon emissions in China. *Energy Econ.* **2019**, *81*, 25–36. [[CrossRef](#)]
86. Khan, M.A.; Máté, D.; Abdulahi, M.E.; Sadaf, R.; Khan, M.A.; Popp, J.; Oláh, J. Do Institutional Quality, Innovation and ICT Technologies Promote Financial Market Development? *Eur. J. Int. Manag.* **2019**, *46*. [[CrossRef](#)]
87. Bala, U.; Chin, L. Asymmetric impacts of oil price on inflation: An empirical study of African OPEC member countries. *Energies* **2018**, *11*, 3017. [[CrossRef](#)]
88. Liu, Y.; Dong, H.; Failler, P. The oil market reactions to OPEC's announcements. *Energies* **2019**, *12*, 3238. [[CrossRef](#)]
89. Chen, S.; Du, X.; Huang, J.; Huang, C. The Impact of Foreign and Indigenous Innovations on the Energy Intensity of China's Industries. *Sustainability* **2019**, *11*, 1107. [[CrossRef](#)]

