**Sustainable environment, energy and finance in China: Evidence from dynamic modelling using carbon emissions and ecological footprints**

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**Abstract**

The excess utilization of conventional energy sources and their impact on environmental degradation have compelled emerging economies to explore alternative sustainable energy sources in order to protect the environment. This study investigates the impact of sustainable finance (market capitalization) and other sustainable economic factors (exports, energy consumption, economic growth, and urbanization) on both carbon emissions/greenhouse gases emissions) and ecological footprints in China from 1970 to 2017. Considering the Environmental Kuznets Curve perspective, a novel Dynamic Autoregressive Distributed Lag technique is applied. This model is efficient enough to draw actual positive and negative simulations, while showing the change of independent variables and their impact on the dependent variable. The empirical results of this study indicate that sustainable finance exerts a positive and negative influence on carbon emissions in the long- and short-run, respectively. Likewise, the results are robust with ecological footprints through which it is evident that sustainable finance placed a lucrative cause to preserve the environment. Outcomes of additional predictors state that in the long-run, sustainable economic factors (urbanization) capture a positive impact on carbon emissions, while others, such as economic growth, energy consumption, and exports improve environmental quality. Conversely, short-run results state that urbanization supports the environment. Still, economic development, energy use, and exports tend to damage the environment, exerting a positive impact on CO2 emissions in China. The policy implications from this study can be very useful in accomplishing the widely stated global sustainable development and environment goals.

**Keywords:** Sustainable environment, energy and finance, market capitalization, Carbon/CO2 emissions, ecological footprints, DARDL, China.

1. **Introduction**

Environmental degradation is a foremost challenge for both developed and developing economies across the world. In particular, the crucial question facing businesses, environmental activists, academics, governments, managers, policy-makers and regulators is how to cut greenhouse gases (GHG)/carbon/ CO2 emissions and ecological footprints (sustainable environment/energy), while generating wealth (sustainable finance) for society. Answering this crucial policy question and preserving the environment is arguably the most demanding task for the current human generation (Collins and Zheng 2015; Bekun et al., 2019a 2019b). Environmental degradation is triggered by flood, fire, and the most prominently, GHG emissions. These events can disrupt the natural resources, infrastructure, agricultural land, and the most importantly, human lives. Within the context of the obligations imposed by the Paris Agreement in 2015, these have major implications, especially in emerging economies. Meanwhile, China as the largest emerging economy is the leading energy consumer and the first CO2 emitter in the world (Lahiani 2020). For example, China’s carbon emissions have increased from 0.94 in 1970 to 7.18 metric tons per capita in 2016, which represent~~s~~ almost seven times in growth terms over the same period (World Bank 2018). In this regard, it is essential to sustain economic and financial growth, whilst maintaining sustainable environment by curtailing CO2/GHG emissions. In this study, we contend that the answer to the questions mentioned above is committing to sustainable finance through managing stock market capitalization. The purpose of this study, therefore, is to investigate the influence of sustainable finance (market capitalization) and economy on environmental degradation with the help of carbon emissions and ecological footprints over 38 years in China. In addition, other sustainable economic factors, such as energy use, economic growth, exports, non-renewable energy use, and urbanization are taken as extra predictors in this research.

Apart from carbon emissions, ecological footprints have been proposed by Rees (1992) as a cumulative factor for environmental quality (Charfeddine 2017; Fakher 2019; Destek and Sinha 2020). Moreover, it is indicated that these were the consequences of financial and non-financial activities (Nathaniel and Khan 2020). Generally, the ecological footprint shows a part of the water and land, which is claimed to be used by the operators to manufacture products for consumption and to produce waste continually (Wackernagel and Rees 1997). Similarly, China is considered the leading country in ecological footprints in the world (Ulucak and Lin 2017). Sustainable finance i.e., market capitalization is a decent indicator of the size of firms and is corroborated by the finance literature. It contains additional elements for which the balance sheet is silent, such as company reputation, growth, and management expertise (Adom et al. 2020). Bougatef ([2017](https://jfin-swufe.springeropen.com/articles/10.1186/s40854-020-00192-3#ref-CR17)) claimed that the market capitalization is a way through which profitability can be enhanced.

To the best of our understanding, this research is unique to explore the role of sustainable finance by examining the effect of market capitalization on environment through CO2 emissions and ecological footprints. Thus and based on the review of prior research related to financial indicators and the environment, this study contributes to environmental finance literature in a number of ways. *First and foremost*, a plethora of research in EKC perspective has been done on environmental degradation with financial development (Nosheen et al. 2019; Lahiani 2020; Rahman et al. 2020), economic growth (Lau et al. 2014; Acquaye et al. 2017; Dogan et al. 2019; Khan et al. 2019; Lahiani 2020), energy consumption (Bölük and Mert 2014; Wang et al. 2016a; Bhattacharya et al. 2017; Sarkodie and Strezov 2019), non-renewable energy consumption (Bhattacharya et al. 2017; Dogan et al. 2019; Sarkodie and Strezov 2019) and urbanization (Zhang and Lin 2012; Erdoğan 2013), but the literature is silent to uncover the sustainable finance considering the rapid increases in the market capitalization of listed companies in an emerging economies.

*Secondly*, the existing research enormously utilized autoregressive distributive lag (ARDL) (Pesaran et al. 1999; Pesaran et al. 2001), Non-linear ARDL (NARDL) (Shin et al. 2014) and Quantile ARDL (QARDL) (Cho et al. 2015), while in this study we have applied novel Dynamic ARDL (DARDL) simulations to consider the effects of ong- and short-run association of among the variables that we investigate. DARDL model is robust to automatically plot positive and negative simulations (Jordan and Philips 2018). *Thirdly*, the study is exclusive in examining the influence of sustainable finance using market capitalization and sustainable economic factors with energy consumption, economic growth, urbanization, and exports on GHG emissions to validate EKC and additionally, ecological footprints in order to obtain robust results. *Lastly*, this research contributes to the Chinese Economy perspective, which is the leading manufacturer globally and hence, exporting products around the globe. It necessarily seeks to consume traditional energy sources based on fossil fuel (Lahiani 2020). In doing so, this study investigates the relationships among sustainable environment, finance and energy by applying the dynamic modelling using carbon omission and ecological footprints.

The remainder of the study is structured as follows. Section 2 presents the literature review, while Section 3 outlines the methodology. Furthermore, Section 4 reports and interprets the findings whilst Section 5 concludes the paper including outlining the policy implications.

1. **Literature review**

Countries' economic performance depends on energy, but the excessive usage of traditional sources of energy may result in global warming (Apergis and Garćıa 2019). Energy use and the environment have a significant relationship, and the results suggested that more use of nonrenewable energy plays a key role in the deterioration of environment (Katircioğlu and Taşpinar 2017; Baloch et al. 2019). In addition, the excessive use of traditional energy leads to environmental and ecological degradation in both developing and developed nations (Ahmed et al. 2020). Zhang et al. (2017) reported that utilization of sustainable energy improves environmental conditions, whereas non-renewable energy consumption deteriorates the environment. Renewable energy and energy efficiency play their role in mitigating the GHG emissions in BRICS countries (Akram et al., 2020). Economic complexity and non-renewable energy consumption cause detriment to the ecological footprints (Shahzad et al. 2021).

Literature shows a positive influence of sustainable economic factors such as economic growth on GHG emissions in developing economies. For instance, Nazir et al. (2018) examined that per capita income is positively significant with carbon emissions in Kyoto annex countries. As the economic growth of an economy increases, environmental pollution also increases (Katircioğlu and Taşpinar 2017; Dogan et al. 2019; Rahman et al. 2002. The relationship between carbon emissions and economic growth was analyzed using the NARDL model in China. The examined results of asymmetric relationship showed that positive and negative change in GDP brings significantly positive and negative impacts on the environment, respectively (Lahiani 2020). In addition, Fareed et al. (2018) analyzed the association between tourism, economic growth, and terrorism. The results showed statistically significant and asymmetric behavior. The impact of non-renewable energy and economic growth is positive on ecological footprints. Non-sustainable economic growth holds a significant direct effect on to the surge in ecological footprints (Sharif et al. 2020).

Zhang et al. (2017) reported that the renewable and non-renewable energy use with carbon emissions. The outcomes are evident that sustainable energy impedes environmental degradation, whereas non-sustainable energy consumption deteriorates the environment. The relationship among renewable energy use, GDP, and carbon emissions are asymmetric in both the long and short-run in Saudi Arabia (Toumi and Toumi 2019). Similarly, the outcomes of non-sustainable energy consumption and economic growth embrace a statistically significant impact on ecological footprints (Sharif et al., 2020). Dogan et al. (2019) examined the influence of non-renewable energy use on CO2 emissions, while Sharif et al. (2020) on ecological footprint, and both the studies revealed that the consumption of non-sustainable energy lead to the degradation of environment.

Hashmi et al. (2020) studied the influence of urbanization on CO2 emissions. They found that urban agglomeration has a direct and significant effect on environmental degradation in the top ten urban agglomerated countries. Urbanization holds a positively significant impact on the ecological footprints (Godil et al. 2021). Similarly, Sadorsky (2010) reported that the urbanization has a significant positive effect on CO2 emissions in panel data of emerging economics. The association of urbanization and carbon emissions is significant, leading to deteriorate the environment (Pata 2018; Dogan et al. 2019).

Mahmood et al. (2019) analyzed the nonlinear or asymmetric impact of trade on carbon emissions. The results have shown that the immediate change in trade significantly augments CO2 emissions, while the negative change improves the environment. In addition, there is a nonlinear impression of FDI and trade on CO2 emissions in Turkey (Haug and Ucal 2019). Godil et al. 2021 analyzed the influence of financial development and transportation on ecological footprints using Quantile ARDL. The outcomes of the study revealed that both transportation and financial development present reasons to preserve the environment.

In the above-mentioned literature, it is evident that a lot of work has been done to explore the sustainable environment (CO2 emissions or ecological footprints) with financial indicators (financial development and economic growth) and non- financial indicators (transportation, energy consumption, and urbanization). In contrast, the literature is silent to uncover the impact of sustainable finance on the environment.

**3. Methodology**

For this study, annual data is collected for China over 1970-2017. The description of the variables is presented in Table 1. Moreover, data for carbon dioxide emissions (CO2), economic growth (GDP), energy use (EC) (Dogan et al. 2019; Lahiani 2020), exports of products (EXP), market capitalization of listed companies (MCAP), and urban population (URB) (Pata 2018) is collected from World Bank (World Development Indicators). In contrast, data of ecological footprints (EF) (Godil et al. 2021)and non-renewable energy (NREC) are gathered from Global Footprint Network (GFPN) and BP Statistics, respectively.

For the selection of variables, this research follows the prior studies. The relationship of economic growth (GDP) (Katircioğlu and Taşpinar 2017; Pata 2018; Lahiani 2020), energy consumption (Katircioğlu and Taşpinar 2017; Nosheen et al. 2019), non-renewable energy consumption (Dogan et al. 2019), urbanization (Dogan et al. 2019), and trade (Nosheen et al. 2019) is examined with greenhouse gases (GHG) emissions. Similarly, financial development results and carbon emissions are enormously analyzed (Pata 2018; Eren et al. 2019; Rahman et al. 2020).

**Table 1** Variables of the study

|  |  |  |  |
| --- | --- | --- | --- |
| **Symbol** | **Description of Variables** | **Unit of the variables** | **Source** |
| **CO2** | Carbon emission | CO2 emissions (metric tons per capita) | WDI |
| **EF** | Ecological Footprints | Ecological consumption per capita (total) | GFP |
| **MCAP** | Market Capitalization | Capitalization of listed companies (% of GDP) | WDI |
| **GDP** | Gross Domestic Product | GDP (constant 2010 US$ per capita) | WDI |
| **EC** | Energy usage | Energy use (kg of oil equivalent per capita) | WDI |
| **NREC** | Non-Renewable Energy | Energy use (Exajoules) | BPS |
| **URB** | Urbanization | Population (Urban % of the total population) | WDI |
| **EXP** | Exports | Exports of products (% of GDP) | WDI |

*WDI, GFPN, & BPS stand for World Development Indicators (World Bank), Global Footprint Network, and BP Statistics.*

In line with existing literature, the variables such as market capitalization, exports, economic growth, energy use, and urbanization are selected to examine their impact on sustainable environment in China for 48 years, taking from 1970 to 2017. The model of this study is presented as follows.

$(CO2) \_{t}=β\_{O}+ β\_{1}MCAP\_{t}+β\_{2}GDP\_{t}+ β\_{3}EC\_{t}+β\_{4}NREC\_{t}+β\_{5}URB\_{t}+β\_{6}EXP\_{t}+ ε\_{t}$ (1)

Along with carbon emissions, this study also considered the ecological footprints as another proxy for sustainable environment. Sharif et al. (2020) examined the influence of GDP and energy consumption (renewable and non-renewable) on ecological footprints, while Godil et al. (2021) explored urbanization, transport, and financial development with ecological footprints. Hence, the second model for this study can be as follow.

$(EF) \_{t}=β\_{O}+ β\_{1}MCAP\_{t}+β\_{2}GDP\_{t}+ β\_{3}EC\_{t}+β\_{4}NREC\_{t}+β\_{5}URB\_{t}+β\_{6}EXP\_{t}+ ε\_{t}$ (2)

*3.1 ARDL bound testing*

ARDL bounds test results are utilized to demonstrate the long-run association among the study variables, and the value of f-statistics indicate the long-run relationship. If the f-value is higher than the upper limit at a 5% significance level, then long-term co-integration among variables is assumed (Pesaran et al. 2001). But, if the f-value is smaller than the lower critical limit~~,~~ then the long-run relationship is absent. If the f-value lies between the lower and upper limit, co-integration is considered un-decidable. The following hypothesis is assumed for checking long-run relationships among variables.

H0 = $δ\_{1}=δ\_{2}=δ\_{3}=δ\_{4}=δ\_{5}=δ\_{6}=δ\_{7}=0$ (3)

The bounds testing approach equation is presented below.

$∆CO2\_{t}=ɑ\_{0}+ δ\_{1}CO2\_{t-i}+δ\_{2}MCAP\_{t-i}+δ\_{3}GDP\_{t-i}+δ\_{4}EC\_{t-i}+ δ\_{5}NREC\_{t-i}+δ\_{6}URB\_{t-i}+δ\_{7}EXP\_{t-i}+\sum\_{i=1}^{r}β\_{1}MCAP\_{t-i}+\sum\_{i=1}^{r}β\_{2}GDP\_{t-i}+\sum\_{i=1}^{r}β\_{3}EC\_{t-i}+\sum\_{i=1}^{r}β\_{4}NREC\_{t-i}+\sum\_{i=1}^{r}β\_{5}URB\_{t-i}+\sum\_{i=1}^{r}β\_{6}EXP\_{t-i}+ ε\_{t} \left(4\right)$The equation mentioned above ∆ shows change operator while t – i indicates optimal lag selection based on SBIC and HQIC. And $δ\_{1}$ $to δ\_{7 }$and $β\_{1} to β\_{6}$ are coefficients that will be estimated. In addition to CO2 emissions, ecological footprints are also examined with predictor variables to robust the results. Following is the bound testing approach equation for ecological footprints.

$$∆EF\_{t}=ɑ\_{0}+ δ\_{1}EF\_{t-i}+δ\_{2}MCAP\_{t-i}+δ\_{3}GDP\_{t-i}+δ\_{4}EC\_{t-i}+ δ\_{5}NREC\_{t-i}+δ\_{6}URB\_{t-i}+δ\_{7}EXP\_{t-i}+\sum\_{i=1}^{r}β\_{1}MCAP\_{t-i}+\sum\_{i=1}^{r}β\_{2}GDP\_{t-i}+\sum\_{i=1}^{r}β\_{3}EC\_{t-i}+\sum\_{i=1}^{r}β\_{4}NREC\_{t-i}+\sum\_{i=1}^{r}β\_{5}URB\_{t-i}+\sum\_{i=1}^{r}β\_{6}EXP\_{t-i}+ ε\_{t} (5)$$

*3.2 Dynamic ARDL simulations*

ARDL model was proposed by (Pesaran et al. 1999 and Pesaran et al. 2001). It presents numerous benefits over other co-integration techniques (Duasa 2007). First of all, ARDL can be applied with different lag lengths of the variables as some model demands identical lags (Engle and Granger 1987; Johansen and Juselius 1990). Secondly, this model can be utilized if the data is stationary at I (0) or I (1) or a combination of both orders. Lastly, the ARDL model is favorable when the sample size is small (Narayan 2004).

After developing the ARDL technique, Shin et al. (2014) introduced the NARDL model to satisfy the asymmetric effects among variables. Later on, Cho et al. (2015) enhanced this model and presented the QARDL technique. In addition, Jordan and Philips (2018) proposed DARDL with dynamic simulations to consider the effects of the long and short-run association of variables. This newly developed model is competent enough to plot positive and negative simulations automatically. Hence, the following models of this study are proposed for sustainable environment using dynamic ARDL.

$$∆CO2\_{t}=φ\_{0}+ θ\_{0}CO2\_{t-1}+β\_{1}∆MCAP\_{t}+θ\_{1}MCAP\_{t-1}+β\_{2}∆GDP\_{t}+θ\_{2}GDP\_{t-1}+β\_{3}∆EC\_{t}+θ\_{3}EC\_{t-1}+β\_{4}∆NREC\_{t}+θ\_{4}NREC\_{t-1}+β\_{5}∆URB\_{t}+θ\_{5}URB\_{t-1}+β\_{6}∆EXP\_{t}+θ\_{6}EXP\_{t-1}+ΥECT\_{t-1}+ ε\_{t} (6) $$

$$∆EF\_{t}=φ\_{0}+ θ\_{0}CO2\_{t-1}+β\_{1}∆MCAP\_{t}+θ\_{1}MCAP\_{t-1}+β\_{2}∆GDP\_{t}+θ\_{2}GDP\_{t-1}+β\_{3}∆EC\_{t}+θ\_{3}EC\_{t-1}+β\_{4}∆NREC\_{t}+θ\_{4}NREC\_{t-1}+β\_{5}∆URB\_{t}+θ\_{5}URB\_{t-1}+β\_{6}∆EXP\_{t}+θ\_{6}EXP\_{t-1}+ΥECT\_{t-1}+ ε\_{t} (7)$$

**4. Results and discussion**

Table 2 displays the descriptive statistics of all the variables of this study. All the variables have a positive mean value, and it is shown that economic growth has the highest mean of 3.0440, followed by energy consumption, 2.9640. Similarly, GDP is more volatile than the rest of the given variables. On the other hand, ecological footprints and urbanization have a minimum standard deviation (0.1770). In addition, GDP has a larger range value, which is 1.5070. Skewness values show that almost all the variables are moderately skewed because given values lie between 0 - 0.5. Kurtosis values are less than 3, and hence, kurtosis has a somewhat thin tail.

**Table 2** Descriptive statistics

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Variables** | **N** |  **M** |  **Std. Dev.** |  **Min** |  **Max** | **Skewness** | **Kurtosis** |
| **CO2** | 48 | 0.4240 | 0.2750 | -0.0260 | 0.8780 | 0.2957 | 1.9487 |
| **EF**  | 48 | 0.2620 | 0.1770 | 0.0140 | 0.5700 | 0.4876 | 1.9238 |
| **MCAP** | 48 | 2.0150 | 0.3250 | 1.2450 | 2.4700 | -0.3682 | 2.1435 |
| **GDP** | 48 | 3.0440 | 0.4870 | 2.3590 | 3.8660 | 0.1577 | 1.7061 |
| **EC** | 48 | 2.9640 | 0.2230 | 2.6560 | 3.3630 | 0.5757 | 2.0308 |
| **RSS** | 48 | 1.5550 | 0.3500 | 0.9290 | 2.1010 | 0.1104 | 1.8516 |
| **URB** | 48 | 1.4750 | 0.1770 | 1.2350 | 1.7630 | 0.0838 | 1.6571 |
| **EXP** | 48 | 1.1150 | 0.3230 | 0.3960 | 1.5570 | -0.6419 | 2.2567 |

*N and M stand for the number of observations and mean of the variables used in this study. While CO2, EF, MCAP, EC, GDP, EXP, NREC, and URB stand for carbon emissions, ecological footprints, market capitalization, energy consumption, gross domestic product, exports, non-renewable energy consumption, and urbanization, respectively.*

Table 3 reveals the unit root tests of study variables using ADF and ZA (Zivot and Andrews 2002) tests. In addition, the structural break is found by using the ZA unit root test, as shown in the table. These tests represent that variables are non-stationary at I (0), whereas all of them become stationary or no unit root at I (1). Hence, both the unit root tests reject the null hypothesis when applied at I (1), representing the accomplishment of the condition for ARDL (Pesaran et al. 1999; Pesaran et al. 2001).

**Table 3** Outcomes of unit root tests

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Variables** | **ADF I(0)** | **ADF I(1)** | **ZA I(0)** | **Y** | **N** | **ZA I(1)** | **Y** | **N** |
| **CO2** | -0.6020 | -4.2140\*\*\* | -3.3410 | 1990 | 30 | -4.8960\*\* | 2010 | 41 |
| **EF**  | 0.9180 | -4.3390\*\*\* | -3.1190 | 1998 | 29 | -4.9040\*\* | 2010 | 41 |
| **MCAP** | -1.7380 | -8.2390\*\*\* | -4.3610\* | 2005 | 36 | -6.8960\*\*\* | 2002 | 33 |
| **GDP** | 2.3300 | -3.9410\*\*\* | -3.3760 | 1980 | 11 | -5.2220\*\*\* | 1986 | 16 |
| **EC** | 1.1900 | -3.6540\*\*\* | -3.2640 | 1998 | 29 | -4.2070\* | 2010 | 41 |
| **RSS** | -1.3710 | -4.0590\*\*\* | -2.6460 | 1978 | 9 | -4.5360\*\* | 2006 | 37 |
| **URB** | 2.4730 | -3.0250\*\* | -4.3370\* | 2009 | 40 | -5.1150\*\*\* | 1980 | 11 |
| **EXP** | -2.7450 | -5.2510\*\*\* | -3.6300 | 2006 | 37 | -5.8820\*\*\* | 2004 | 35 |
| **URB** | 2.4730 | -3.0250\*\* | -4.3370\* | 2009 | 40 | -5.1150\*\*\* | 1980 | 11 |

*All the variables are in logarithm form. ZA and ADF stand for Zivot & Andrews and Augmented Dickey-Fuller, respectively. Y and N is the year and observation number at which t-statistics is minimum while I (0) and I (1) indicate stationary at the level and 1st difference. \*, \*\*, \*\*\* demonstrate significance level at 10%; 5% and 1%, respectively.*

Fig 1 presents the line graphs of study variables, including carbon emissions, market capitalization, economic growth, non-renewable energy use, exports, energy use, and urbanization in China from 1970 to 2017. All the given variables are increasing except market capitalization. Apparently, the percentage of market capitalization is decreased from 2.5 % to 2% from 1970 to 2017. This does mean that market capitalization is curtailed, but the value is enlarged because of a change in the real value of GDP over four decades. In addition, market capitalization shows more volatility, and GDP per capita is larger following by energy consumption in 2017.

**Figure 1.** *Dynamics for the selected variables for China (1970-2017). MC is the market capitalization of listed companies, GDP is a gross domestic product, NREC is non-renewable energy consumption, EXP is exports, CO2 is carbon dioxide emissions, EC is energy consumption, and URB is urbanization.*

Table 4 shows lag selection indication based on Vector Auto-Regressive (VAR) model (Khan et al. 2019). It presents the results of LR, FPE, AIC, SBIC, and HQIC criteria. As per the SBIC and HQIC, the first lag is appropriate, while AIC indicates that the second lag is satisfactory. Hence, for the model selection, SBIC and HQIC are used with lag one.

**Table 4** ARDL model- Lag selection

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|   | **CO2** | **EF**  | **MCAP** | **GDP** | **EC** | **EXP** | **NREC** | **URB** |
| **LR** | 8.9446\*  | 7.1515\*  |  73.7000\*  |  8.5374\* |  13.1830\* | 143.5400\* |  22.5190\* | 6.2434\* |
| **FPE** | 0.0005\* | 0.0002\*  | 0.0192\* |  0.0002\*  | 0.0002\* | 0.0031\* | 0.0002\* | 2.4e-06\* |
| **AIC** |  -4.8105\*  |  -5.9493\* | -1.1133\* | -5.9037\* | -5.6351\* | -2.9548\* |  -5.7966\* | -10.1136\* |
| **SBIC** | -4.6888\* | -5.8277\*  | -1.0322\* | -5.7820\* | -5.5134\*  | -2.8737\* | -5.6750\* | -9.9109\* |
| **HQIC** | -4.7654\*  |  -5.9042\* | -1.0832\*  |  -5.8586\* | -5.5899\* |  -2.9247\* |  -5.7515\* | -10.0384\*  |
| **p-value** | 0.0030 | 0.0070 | 0.0000 | 0.0030 | 0.0000 | 0.0000 | 0.0000 | 0.0120 |
| **Decision** | I (1) | I (1) | I (1) | I (1) | I (1) | I (1) | I (1) | I (1) |

*All the variables are in logarithm form. FPE, LR, AIC, HQIC, and SBIC represent sequentially Final prediction error, modified LR test statistic, Akaike information criterion, Hannan-Quinn information criterion, and Schwarz Bayesian information criterion, respectively. Moreover, \* shows the selected lag based on the p-value for each selection criteria.*

Table 5 indicates the ARDL bounds testing results to demonstrate the long-term relationship among variables. F-statistics value is 20.9330, and it is greater than the upper limit at 1% *p*-value (Pesaran et al. 2001). The model has sufficient evidence to accept the alternative hypothesis representing that the variables of this study embrace long-run cointegration and equilibrium. Moreover, the error correction term (ECT) -0.1991\*\*\* in Table 6 corroborates the cointegration when the value of ECT is negatively significant (Kanjilal and Ghosh 2013).

**Table 5.** Bounds testing for ARDL

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Test statistics** |   |   | **Value** | **k** |
| F-statistics |  |  | 20.9330 | 6 |
| t-statistics |  |  | -1.8730 | 6 |
|  | **F-statistics** | **t-statistics** |
| Significance level | Lower limit | Upper limit | Lower limit | Upper limit |
| 10% | 2.31 | 3.51 | -2.57 | -4.04 |
| 5% | 2.73 | 4.06 | -2.86 | -4.38 |
| 1% | 3.66 | 5.33 | -3.43 | -4.99 |

*The lower limit and upper limit show the lower and upper boundary limits, respectively.*

Table 6displays the results of dynamic ARDL simulations. The model outcomes indicate that market capitalization has a significant association with carbon emissions for both the long and short-run. China represents a 4% to 5% contribution of market capitalization (percentage of GDP) towards the environment. The relationship indicates that market capitalization behaves negatively and positively in the short and long-run. This is because China is an emerging economy, and an increase in market capitalization helps to save the environment. Then, in the long run, this impact becomes adverse and shifts to negative due to more investment and consumption of traditional sources of energy. Hence, China is leading in energy consumption and is the biggest carbon emitter country across the world (Lahiani 2020).

The outcome of short-run economic growth shows the positive and insignificant influence on CO2 emissions in China. The 1% increase in GDP influences to increase of 0.26% environmental degradation per year. The positive effect of GDP on carbon emission shows that currently, China falls at the first stage of EKC and is moving towards industrial richness. On the other hand, in the long run, economic growth shows a negative impact on CO2 emission in China because there will be a threshold point when CO2 emissions would start to decline even though GDP per capita is increasing (Grossman and Krueger 1991). These outcomes are consistent with the literature, which explains that economic growth might lead to environmental degradation (Sharma 2011; Acquaye et al. 2017; Pata 2018; Dogan et al. 2019; Lahiani 2020).

The results of dynamic ARDL simulations report a direct and significant association between energy use and carbon emissions in the short run. China is an emerging economy and the largest producer of manufactured goods in the world. Hence, an increase of 1% in energy use pollutes the environment by 0.51% due to more traditional energy sources in the short run. On the other hand, this relationship shifts and becomes negatively insignificant in the long run. The coefficient is also decreased from 0.51 to 0.28 in the long run, which indicates that China tends toward~~s~~ more renewable energy use (Shahbaz et al. 2013; Wang et al. 2016a; Bhattacharya et al. 2017; Sarkodie and Strezov 2019). It is indicated that emerging countries of the world are impatient for economic growth. These economies use traditional ways of energy sources based on fossil fuels and hence, causing the quality of the environment (Khan et al. 2019).

The results of Table 6 show that between non-renewable energy use and GHG emissions, there exists a significantly positive and negative association in the short and long-run, respectively, in China. An increase of 1% in non-renewable energy use brings a surge of 0.64% in carbon emissions in the long-run. In the short run, the outcomes are aligned with Dogan et al. (2019). A surge in non-renewable energy consumption leads to pollute the environment (Bhattacharya et al., 2017; Khan et al., 2019). On the other hand, an increase of 1% in non-renewable energy use supports the environment by about 0.59%. This is due to the long-lasting effect of non-renewable energy use on the environment.

Results of urbanization represent insignificant relation with carbon emissions. This relationship is direct in the long-run whereas inverse in the long-run. The coefficient shows that urbanization is more robust in the long-run than in the long-run in China. Outcomes indicate that an increase of 1% in urbanization helps to save the environment about 0.61% in the short run per year. This effect of urbanization shifts from negative to positive in the long-run and reports that an increase of 1% in urbanization may reason 0.43% of environmental degradation. Huang and Wang (2016) examined urbanization and its role in the environment. Wang et al. (2016b) studied the association of energy use and urbanization with CO2 emissions, and the outcomes of the study presented that urbanization is a key indicator of environmental degradation. There exists a direct impact of urbanization on GHG emissions (Zhang and Lin 2012; Erdoğan 2013). The outcomes of urbanization are similar to (Pata 2018; Dogan et al. 2019) but opposite to (Khan et al. 2019).

The results of dynamic ARDL simulations state a positive and significant relationship between exports and carbon emissions in the short-run. China is one of the leading manufacturers and exporter countries in the world. An increase of 1% in exports adds to environmental degradation by 0.06% in the short run. Whereas in the long run, this relationship is negatively insignificant. An increase of 1% in exports leads to reduce the GHG emissions by 0.003%. Trade has a bidirectional relationship with CO2 emissions (Mirza and Kanwal 2017; Chandia et al. 2018). In addition, developed countries shift their CO2 emissions-related technologies to emerging economies (Khan et al., 2019).

ECT is negatively significant (-0.1991), which states the speed of adjustment parameter aftershock. ECT narrates that in one year, the rate of adjustment to the preceding equilibrium exists almost -20%. R-squared value presents that the independent variables of the study explained 88% variation in CO2 emissions. For the ECT algorithm, this study utilized 5000 simulations for the variables vector as recommended (Sarkodie et al., 2019). The P-value of the overall model is significant at a 1% level. Root mean square error (RMSE) and F-statistics values of the model are also favorable, which are 0.0091 and 19.24, respectively.

**Table 6** Dynamic ARDL Simulations (Carbon Emissions)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable Name | Coefficients | Standard Error | t-Statistics | *p*-value |
| Cons | -0.5488 | 0.2564 | -2.1400 | 0.0400 |
| MCAPt | -0.0449 | 0.0137 | -3.2700 | 0.0020 |
| ∆MCAP t-1 | 0.0589 | 0.0125 | 4.7100 | 0.0000 |
| GDPt | 0.2593 | 0.1664 | 1.5600 | 0.1290 |
| ∆GDP t-1 | -0.2473 | 0.1746 | -1.4200 | 0.1660 |
| ECt | 0.5167 | 0.1831 | 2.8200 | 0.0080 |
| ∆EC t-1 | -0.2882 | 0.1905 | -1.5100 | 0.1400 |
| NRECt | 0.6374 | 0.1894 | 3.3700 | 0.0020 |
| ∆NREC t-1 | -0.5884 | 0.1807 | -3.2600 | 0.0030 |
| URBt | -0.6072 | 0.5913 | -1.0300 | 0.3120 |
| ∆URB t-1 | 0.4319 | 0.5965 | 0.7200 | 0.4740 |
| EXPt | 0.0612 | 0.0345 | 1.7800 | 0.0850 |
| ∆EXPt-1 | -0.0032 | 0.0312 | -0.1000 | 0.9180 |
| ECT(-1) | -0.1991 | 0.1063 | -1.8700 | 0.0700 |
| R2 |  |  |  | 0.5834 |
| Adj. R2 |  |  |  | 0.5375 |
| N |  |  |  | 47 |
| Simulations |  |  |  | 5000 |
| Prob. |  |  |  | 0.0000 |
| F-Statistics |  |  |  | 19.24 |
| RMSE |   |   |   | 0.0091 |

*All the variables are in logarithm form. MCAP is market capitalization, GDP indicates gross domestic product, EC is energy consumption, NREC shows non-renewable energy consumption and URB is urbanization, and EXP displays exports. ∆ Represents difference while N stands for the number of observations used. ECT is an error correction term, RMSE is the root mean square error, while R2 shows the goodness of fit of the model.*

Fig 2indicates the ecological footprints consumption per person for China from 1960 to 2017. The value of ecological footprint consumption global hectares per person was initially favorable, and it became adverse in 1970. The value of ecological footprint consumption increased and reached from 1 to 2 global hectares per person in 33 years. Then, it increased exponentially and crossed the next unit in just six years. Therefore, ecological footprint consumption in China continues to grow. The reason behind this is twofold. Firstly, China is the largest populated country globally, and this massive population demands more natural resources. Secondly, China is the largest manufacture and exporter globally.

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 *Ecological Footprints in China over 1960-2017.*

Table 7shows the outcomes of dynamic ARDL simulations for sustainable environment taking ecological footprint as a dependent variable. This indicates that market capitalization has an insignificant relationship with ecological footprints for both the long and short-run. The 1% increase in market capitalization saves the environment by 0.01%. Sharif et al. (2020) presented a direct association of economic growth, while Godil et al. (2021) explored the negative relationship of financial development with ecological footprints. In the short-run, economic growth outcomes show a significant association with ecological footprints in China. The 1% increase in GDP effects 0.38% natural resources. In the long-run, economic growth shows a negative influence on ecological footprints similar to (Sharif et al. 2020), while financial development leads to ignoring the environment (Godil et al., 2021).

Moreover, the results show a significantly positive association between energy consumption and ecological footprints in the short-run. An increase of 1% in energy consumption influences the expansion of environmental degradation by about 0.75%. On the other hand, this relationship is negatively insignificant in the long-run. Sharif et al. (2020) examined the negatively significant relationship between the environment and renewable energy consumption. In addition, it is found that emerging countries of the world look keen to use traditional ways of energy production based on fossil fuels, irrespective of the environment, to fulfill their energy demand (Khan et al., 2019).

The results of Table 7 display that between non-renewable energy consumption and ecological footprints, there is an insignificantly negative and positive association in the short and long-run, respectively. An escalation in non-renewable energy use leads to polluting the environment (Bhattacharya et al., 2017). Non-renewable energy consumption shows a positively significant effect on natural resources (Sharif et al. 2020).

The results of urbanization represent insignificant relation between environmental degradation and urbanization. This affiliation is direct in the short-run whereas inverse in the long-run. The coefficients show that the influence of urbanization is stronger in the long-run in China. Examined outcomes indicate that an increase of 1% in urbanization distresses the environment by 0.01% per year, but the impact of urbanization shifts from positive to negative in the long run. Short-run results are aligned with Godil et al. (2021) explained that urbanization is positively connected with ecological footprints and Erdoğan 2013 explained the positive impact of urbanization on GHG emission. Similarly, the results of dynamic ARDL simulations show that there exists a positive and insignificant connection between exports and ecological footprints. The 1% increase in exports causes to spoil the environment by 0.01% in the short-run while and 0.04% in the long-run. There is a bidirectional relationship between trade and environmental degradation (Shahzad et al., 2017; Chandia et al., 2018).

Besides, ECT is negatively significant (-0.7561). In this model, ECT narrates that the speed of adjustment to the preceding equilibrium is almost 76% in one year. R-squared value presents that the independent variables explain -76% variation in ecological footprints. The P-value of the overall model is significant at 1%. F-statistics and RMSE values are 8.31 and 0.0071, respectively.

**Table 7** Dynamic ARDL Simulations (Ecological Footprints)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable Name | Coefficients | Standard Error | t-Statistics | *p*-value |
| Cons | -1.5530 | 0.4253 | -3.6500 | 0.0010 |
| MCAPt | -0.0176 | 0.0111 | -1.5800 | 0.1240 |
| ∆MCAP t-1 | -0.0105 | 0.0102 | -1.0300 | 0.3110 |
| GDPt | 0.3788 | 0.1462 | 2.5900 | 0.0140 |
| ∆GDP t-1 | -0.1300 | 0.1361 | -0.9500 | 0.3470 |
| ECt | 0.7459 | 0.1476 | 5.0500 | 0.0000 |
| ∆ECt-1 | -0.0785 | 0.1696 | -0.4600 | 0.6470 |
| NRECt | -0.2541 | 0.1688 | -1.5100 | 0.1420 |
| ∆NRECt-1 | 0.0047 | 0.1358 | 0.0300 | 0.9720 |
| URBt | 0.0116 | 0.4496 | 0.0300 | 0.9800 |
| ∆URBt-1 | -0.4148 | 0.4819 | -0.8600 | 0.3960 |
| EXPt | 0.0084 | 0.0269 | 0.3100 | 0.7560 |
| ∆EXP t-1 | 0.0357 | 0.0267 | 1.3300 | 0.1910 |
| ECT(-1) | -0.7567 | 0.1847 | -4.1000 | 0.0000 |
| R2 |  |  |  | 0.6659 |
| Adj. R2 |  |  |  | 0.6537 |
| N |  |  |  | 47 |
| Simulations |  |  |  | 5000 |
| Prob. |  |  |  | 0.0000 |
| F-Statistics |  |  |  | 8.3100 |
| RMSE |   |   |   | 0.0071 |

*All the variables are in logarithm form. MCAP is market capitalization, GDP indicates gross domestic product, EC is energy consumption, NREC shows non-renewable energy consumption and URB is urbanization, and EXP displays exports. ∆ Represents difference while N stands for the number of observations used. ECT is an error correction term, RMSE is the root mean square error, while R2 shows the goodness of fit of the model.*

*4.1 Graphs of dynamic ARDL simulations*

Fig. 2 shows positive and negative 10% change in economic growth and its impact on carbon emissions in China for 1970-2017. The 10% rise in GDP has positive and negative effects on carbon emissions in the long and short-run, respectively. Whereas the right graph directs that a decrease in GDP helps to save the environment in China. Fig. 3 shows positive and negative 10% change in energy use and its impact on carbon emissions. The left graph represents that growth in energy use makes the environment deteriorate both in the long and short-run. But, the right graph presents that a 10% decrease in energy use helps to support the environment.

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| ***Figure 2.*** *Economic growth and carbon dioxide emissions. The paired graphs represent ± 10 % change in growth (GDP per capita) and its impact on environmental degradation. Dots display ordinary forecasts, whereas the blue lines indicate a 95% confidence interval, which decreases to 90% and 75% confidence interval as the line becomes thin in two stages.* |
|  |  |
| ***Figure 3.*** *Energy use and carbon dioxide emissions. The paired graphs represent ± 10 % change in energy use and its impact on environmental degradation. Dots display ordinary forecasts, whereas the blue lines indicate a 95% confidence interval, which decreases to 90% and 75% confidence interval as the line becomes thin in two stages.* |

Fig. 4 shows positive and negative 10% change in non-renewable energy use and its impact on carbon emission in China for 1970-2017. It is shown that the rise in non-renewable energy use has a direct influence on carbon emissions in the short-run. Still, an inverse impact in the long-run as non-renewable sources save the environment. Moreover, a 10% decrease in non-renewable energy use supports the environment. Fig. 5 reports positive and negative 10% change in exports of products and its impact on carbon emissions in China over 1970-2017. A rise in exports has a direct effect on carbon dioxide emissions. In contrast, the right graph leads that a 10% decrease in exports has an opposite influence on carbon emissions.

Fig. 6 shows positive and negative 10% change in urbanization and its impact on carbon emissions in China. The left graph represents that the rise in urbanization has a positive influence on carbon emissions. On the other hand, a 10% decrease in urbanization helps to minimize environmental degradation in the short-run than in the long-run. Fig. 7, presents positive and negative 10% change in market capitalization and its impact on carbon emissions in China for 1970-2017. A 10% increase in market capitalization saves the environment in a shorter period but deteriorates in the long-run, on the opposite, the decrease in urbanization assets a negative influence on environmental quality.

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| ***Figure 4.*** *The above-shown graphs represent ±10 % in non-renewable energy consumption and its impact on carbon emissions. The Dots display average forecast while the dark blue line indicates 95% confidence interval, which decreases to 90% and 75% confidence interval as the line becomes thin in two stages.* |
|  |  |
| ***ure 5.*** *Exports of products and carbon dioxide emissions. The paired graphs represent ± 10 % change in exports and its impact on environmental degradation. Dots display ordinary forecasts, whereas the blue lines indicate 95% confidence interval, which decreases to 90% and 75% confidence interval as the line becomes thin in two stages.* |
|  |  |
| ***Figure 6.*** *Urbanization and carbon dioxide emissions. The paired graphs represent ± 10 % change in urbanization and its impact on environmental degradation. Dots display ordinary forecasts, whereas the blue lines indicate 95% confidence interval, which decreases to 90% and 75% confidence interval as the line becomes thin in two stages.* |
|  |  |
| ***Figure 7.*** *Market capitalization and carbon dioxide emissions. The paired graphs represent ± 10 % change in market capitalization and its impact on environmental degradation. Dots display ordinary forecasts, whereas the blue lines indicate a 95% confidence interval, which decreases to 90% and 75% confidence interval as the line becomes thin in two stages.* |

Fig 8 indicates CUSUM (cumulative sum) and CUSUM squares graphs at a 5% significance level. These two graphs are utilized to know the reliability of the coefficient. Both the graphs represent the upper and lower boundary lines, and between these limits, residual values are shown. These residual values are between the boundaries and prove that the examined DARDL model is stable and reliable at a 5% significance level.

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| ***Figure 08.*** *CUSUM and CUSUM square graphs indicate a 5% significance level. Upper and lower dotted lines represent the upper and lower limits of stability.*  |

**5. Conclusion**

This study has sought to extend the extant literature on sustainable environmental, energy and finance by applying a dynamic model to evaluate the effects of sustainable finance and other economic factors on environment in China using annual data from 1970 to 2017. The main findings are as follows. First, the results indicate that the study’s variables are stationary at the first order that leads to long-run cointegration and equilibrium. Second, empirical outcomes of this study show that the novel measure of sustainable finance (market capitalization) exerts a negative and positive influence on carbon emissions in the short- and long-run, respectively. Similarly, these results in the short-run are robust with ecological footprints through which it is evident that sustainable finance placed a reasonable cause to preserve the environment. In the long-run, on the contrary, sustainable finance leads to observable degradation of the environment. This might be due to the more use of non-renewable energy production sources in China. In the long run, other sustainable economic factors, such as urbanization capture a positive impact on CO2 emissions, while economic growth, energy use, and exports are worthy indicators to improve environmental quality. Finally, these results have adverse effects in the short-run. Urbanization negatively impacts on the environment, while economic growth, energy consumption, and exports have positive impact on CO2 emissions in China.

*Firstly,* our findings will be of interest to investors, especially Chinese investors as they are required to attain optimal level of sustainable finance in order to achieve sustainable economic growth. *Second*, since economic growth has a negative influence on GHG emissions, in the long-run, it seems appropriate to work towards increasing GDP so that maximum economic growth along with a sustainable environment can be accomplished to in order to fulfil the target of net-zero CO2 emissions by 2060. *Third*, in the short-run, energy consumption adds to pollute the environment by emitting more carbon emissions in China. It is pertinent, therefore, to replace the conventional energy production techniques with renewable and sustainable energy consumption methods. Hence, policymakers in China, as well as other leading CO2 emitters’ economies, can accomplish sustainable economic growth by providing subsidies on low carbon-emitting technologies and the availability of smart energy-efficient methods by imposing a ban on the use of fossil fuels in order to improve the community's lifestyle. Future research can be applied with the same set of variables in other leading GHG emitter countries following China, especially in the Asian region or with additional sustainable factors to further explore sustainable growth by persevering the environment.

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