

Article

Green Household Technology and Its Impacts on Environmental Sustainability in China

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Abstract: China has made a commitment to achieve carbon neutrality by 2060, and promoting a green lifestyle is an essential means to this end. The primary aim of this study is to investigate the asymmetric impact of green household technology on environmental sustainability in China. To that end, we have employed linear and non-linear auto-regressive distributed lag models to identify this complicated effect. The empirical results suggest that green household technology's positive change exerts significant and negative effect on carbon emission in the short and long terms. And the impacts of green household technology's negative change on carbon emission are significantly negative but smaller than its positive change in the long run, while insignificant in the short term. The estimates endorse the asymmetric impact of green household technology on carbon emissions both in the short and long term. This finding suggests that the improvement of green household technology can reduce carbon emissions, while a decline in it causes carbon emissions to rise, and technological retrogression plays a less influential role than its development. This research is a groundbreaking point in discussing the way towards environmental sustainability from a green household technology perspective, which considers the asymmetric effect and provides meaningful insights for China to achieve sustainable development.

Keywords: green household technology; environmental sustainability; China



Citation: Meng, Q.; Zhang, J.-W.; Wang, Y.; Chang, H.-L.; Su, C.-W. Green Household Technology and Its Impacts on Environmental Sustainability in China. *Sustainability* **2023**, *15*, 12919. <https://doi.org/10.3390/su151712919>

Academic Editors: Xin Sheng, Carolyn Chisadza and Afees A. Salisu

Received: 18 July 2023

Revised: 19 August 2023

Accepted: 23 August 2023

Published: 27 August 2023



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1. Introduction

The purpose of this study is to explore the effects of green household technology on environmental sustainability in China and further provide valuable policy insights. The accumulated amount of CO₂ emissions is strongly correlated with the expected increase in global warming. Since the middle of the last century, the world's temperature has risen noticeably, mostly due to greenhouse gas (GHG) emissions produced by human activities. Most of the world's CO₂ emissions come from power plants, which are responsible for about 75% of all pollutants. Two-thirds of total CO₂ production come from the use of fossil fuels energy sources, whereas methane (CH₄) and nitrous oxide (N₂O) is produced by the agriculture sector, and are both potent GHGs. Therefore, investing in research and development and new technologies is essential if we want to successfully combat climate change and rising temperatures. If we want to reduce GHG emissions and encourage the development of green markets, we must employ innovation and technology in more effective and sustainable ways. According to Qin et al. [1], developments in renewables, solarphotovoltaics (solar PV), and hybrid cars help cut emissions and trash. This indicates a

universal belief that advances in science and technology provide the finest opportunities for establishing eco-friendly economies [2–6]. Nevertheless, such a plan requires investment and the purposeful creation and implementation of environmentally friendly policies by both authorities and businesses [7,8]. More importantly, this study investigates the impact of green household technology on CO₂ emissions in the context of China. According to Yamano and Guilhoto [9], China is the largest emitter of CO₂ from fuel combustion among non-Organization for Economic Co-operation and Development (OECD) economies, which accounts for about 46% of non-OECD emissions in 2015. Additionally, China is the largest consumer, accounting for about 43% of non-OECD consumption-based emissions. Based on the BP Statistical Review of World Energy, China is the world's largest emitter of CO₂ emissions (10.5 billion tons), with about 30% of world's carbon emission in 2021 (the second one is the U.S. with 4.7 billion tons). Therefore, selecting China in the context of this analysis can provide fruitful results for the world's sustainable future.

World leaders and economic experts are now primarily focused on promoting global knowledge of and action for sustainable growth and environmental conservation. In the midst of rising concerns about dealing with the aforementioned environmental problems [10], considerable thought has been devoted to many important aspects, such as demographic features, energy consumption, wealth creation, and others [11]. Among these factors, green technological development at the household level is important to control the CO₂ emissions from the production and demand sides. Some researchers have focused on the issues of green technology applied in households and its influencing factors. Vorobeva et al. [12] suggest that new technological solutions (e.g., an innovative waste management system) could stimulate the higher levels of waste separation and lower household waste production. Gui and Gou [13] report that complex socioeconomic, lifestyle, and living conditions would affect the utilization of household energy technologies. Rahmani et al. [14] reveal that the subjective norms, attitudes, perceived risk, perceived behavioral control, evaluation of the regulatory framework (ERF) and perceived usefulness of power purchase agreements (PPAs) exert significant effects on households' intentions to invest in renewable energy technologies. Wu et al. [15] point out that risk, ambiguity, and time preferences significantly and positively influence the possibility of the adoption of rooftop photovoltaic technology in rural households, where time preference plays an essential favorable moderating role in the adoption of technology. Ahmad and Jabeen [16] highlight that there is a favorable impact to formal and informal credit borrowing which could increase the likelihood of biogas production technology adoption in agricultural households. Milovantseva [17] underlines that respondents with higher scores on greater engagement in pro-environmental behavior, general environmental beliefs, and positive attitudes toward recycling small electronics are more inclined to pay a premium to buy green cell phones.

Some research has explored how green technological development in the economy impacts environmental sustainability, and we summarize these in Table 1. Through summarizing the extant literature, we can propose a hypothesis that utilizing green technology to combat global warming and promote environmental sustainability is viable. Existing studies measure green technology by environmentally efficient technology [18], patents [19–25] and green investment [26–28], and quantified environmental sustainability through carbon emissions [18,19,22–25] and performance [21,26]. However, not enough studies have investigated green household technology's impact on CO₂ emissions. The strain that human consumption of products and services puts on the environment has contributed significantly to the current threats of environmental contamination, ecological imbalances, and global warming. Consumption of renewable energy sources and adopting green technological development at the household level are important in controlling CO₂ emissions [29]. Therefore, to combat ecological damage and lower CO₂ emission levels, there is a need to invest more in renewable and green technologies at the household level. To our limited knowledge, this is the first ever study investigating the impact of green household technology (access to clean fuels) on environmental sustainability (CO₂ emissions) in China.

Table 1. The extant literature pertaining to how green technological development impacts environmental sustainability.

Authors	Objects	Variables	Methods	Conclusions
Behera et al. [18]	18 emerging economies	environmentally efficient technology; carbon emissions	cross-sectional auto-regressive distributed lag (CS-ARDL) model	green technology significantly mitigates carbon emissions in the short and long term
Umme et al. [19]	E7 countries	registered patents related to the environment; carbon emission	cross-sectional dependence test; Panel Granger causality test	green technology decreases carbon emissions in the long term
Tan and Cao [20]	G7 and BRICS countries	patent counts of green technology; CO ₂ emissions and CO ₂ intensity	panel random and fixed effect models	a single type of green technological innovation exerts no significant effect on emission reduction, while the interaction of two types is significant
Zhang and Liu [21]	China	the amount of green patent; carbon emission efficiency	panel fixed effect model	The synergistic effect of digital finance and green technological innovation promotes local carbon emission efficiency but suppresses it in surrounding cities
Chang et al. [22]	China	total green patent count; CO ₂ emissions	panel fixed effect model	green knowledge innovation plays an essential role in decreasing CO ₂ emissions
Saqib and Dincă [23]	Leading countries in renewable energy investment	patents on environment technology; carbon emissions	cointegration tests; causality test	green technology is negatively correlated with carbon emissions
Shan et al. [24]	Turkey	registered patents related to the environment; carbon emissions per capita	bootstrapping bound ARDL test	green technological innovation declines carbon emissions
Sun [25]	China	green patents; carbon emissions	spatial econometric model	green technological innovation not only reduces local carbon intensity but also imposes spatial spillover effects
Liu et al. [26]	HJ company	HJ company's green technology innovation investment; carbon performance	nonlinear regression model	green technological innovation is an efficient way to improve carbon performance
Chen and Li [27]	–	–	differential game model	emission reduction efficiency brought about by green technology is worse than green funds when it exceeds a certain threshold

In addition, the previous studies primarily employ the panel random and fixed effect models [20–22,30], spatial econometric model [25,31], CS-ARDL model [18,32] and so on, but no research has addressed the complex asymmetric effects. Relying on the asymmetric assumption is another novelty of this study, which allows us to examine the impact of the rise and fall in green household technology, separately, on carbon emissions. To that end, we have employed the nonlinear auto-regressive distributed lag (NARDL) model of Shin and Yu [33] that can investigate both short- and long-term estimates, which makes this analysis different from all previous ones, as most existing studies only focus on long-term estimates. Moreover, this study adds to the current literature both empirically and theoretically. Finally, this research yields important results, from which we may draw important policy recommendations for interested parties.

The analysis is structured as follows. Section 2 introduces the materials and methods. The results and discussion are given in Sections 3 and 4. Section 5 elaborates the conclusions.

2. Materials and Methods

2.1. Data

The analysis selects the annual data from 1995 to 2020 to explore the effect of green household technology on environmental sustainability in China. Table 2 contains a detailed summary of definitions, sources and descriptive statistics of concerned variables used in the regression model. Environmental sustainability is a dependent variable measured via CO₂ emissions (DCO₂), which refers to those deriving from the burning of fossil fuels and the manufacture of cement, including carbon dioxide produced in consumption of solid, liquid, and gas fuels and gas flaring. Green household technology (HT) is the variable we have primarily focused on, which is measured via access to clean fuels and technologies for cooking, as a percentage of the population. Following the definition of variable HT and Equations (3) and (4), we counted the positive change of HT as HT_POS and the negative change of HT as HT_NEG. This study has included the role of internet users, financial development (FD) measured as domestic credit to the private sector as % of gross domestic product (GDP), education (EDU) measured as tertiary school enrollment as control variables. Among them, domestic credit to the private sector reveals financial resources offered to the private sectors by financial corporations through loans, purchases of non-equity securities, trade credits, and other accounts receivable, which establishes a claim for repayment. Annual data series for all concerned variables were gathered from the World Development Indicators (WDI) and authors' calculation. To avert the adverse effect of excessive abnormal fluctuation, we transformed the selected sequences by taking the natural logarithm. The results of descriptive statistics reveal information about the mean, standard deviation (Std. Dev.), skewness, and Kurtosis. All the obtained mean values are positive. The mean values are reported as 8.522 for DCO₂, 3.919 for HT, 1.863 for Internet, 4.809 for FD, and 2.944 for EDU. The Std. Dev. values are reported as 0.496 for DCO₂, 0.311 for HT, 2.758 for Internet, 0.194 for FD, and 0.819 for EDU. The estimates of skewness measures are positive for FD and negative for DCO₂, HT, Internet, and EDU.

Table 2. Variable definitions and descriptive statistics.

Variables	Definitions	Sources	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
DCO ₂	CO ₂ emissions (tonnes, millions)	WDI	8.522	8.555	9.186	7.855	0.496	−0.127	1.410
HT	Access to clean fuels and technologies for cooking (% of the population)	WDI	3.919	3.917	4.374	3.305	0.311	−0.302	2.135
Internet	Individuals using the internet (% of the population)	WDI	1.863	2.945	4.254	−5.307	2.758	−1.389	3.829
FD	Domestic credit to the private sector (% of GDP)	WDI	4.809	4.795	5.209	4.433	0.194	0.181	2.439
EDU	School enrollment, tertiary (% gross)	WDI	2.944	3.025	4.068	1.479	0.819	−0.374	1.951

Figure 1 depicts the trends of DCO₂, HT, Internet, FD and EDU, and we can observe that the relation between DCO₂ and HT is not constant but complicated; hence, it is reliable to use a relatively advanced NARDL method to investigate the effects of green household technology on environmental sustainability in China.

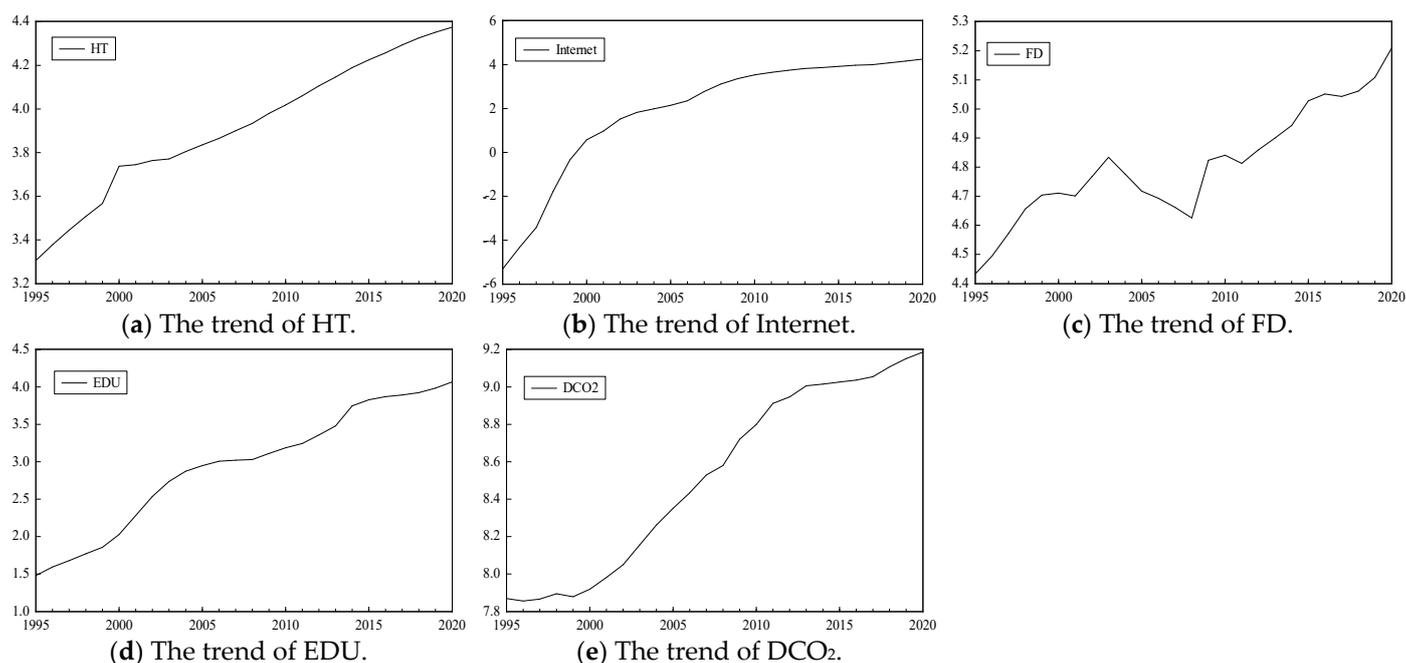


Figure 1. The trends of selected variables.

2.2. Methodology

2.2.1. The Co-Integration Regression

Generally, the ordinary least squares (OLS) estimation could be performed only when the selected sequences were stationary time series. For non-stationary sequences, a direct regression would result in “spurious regression”. The co-integration regression was developed, but it could be performed only when the selected sequences were monointegral series of the same order [34,35]. A co-integration relationship means that two or more time series are non-stationary, but a linear combination among them is a stationary quantitative relation. After conversion, it could be transformed into the auto-regressive distributed lag (ARDL) model [36–38].

2.2.2. The ARDL Model

Clean technology transitions at the household level are significant in mitigating pollution emissions. Following the work of Gupta et al. [28] and Xin et al. [39], we have assumed that household CO₂ emissions have been determined by green technology. We constructed the auto-regressive distributed lag (ARDL) model, which is used to describe the variable relationship in a single time series equation [40–46], which is written as

$$DCO_{2t} = \omega_0 + \varphi_1 HT_t + \varphi_2 Internet_t + \varphi_3 FD_t + \varphi_4 EDU_t + \varepsilon_t \quad (1)$$

where CO₂ emissions (DCO₂) in China are dependent on green household technology (HT), the development of internet (Internet), financial development (FD), and education (EDU); from the estimation of Equation (1), only long-term estimates were made.

2.2.3. The Error Correction Model (ECM)

In order to estimate the short-term effects of green household technology on CO₂ emissions, we constructed an error correction model (ECM) that enables the analysis of the regulatory mechanism of the long-term equilibrium relationship, which is constantly

adjusted according to short-term fluctuations [47–52]. A modified form of Equation (1) shows an error correction model as follows:

$$\begin{aligned} \Delta\text{DCO}_{2t} = & \omega_0 + \sum_{k=1}^n \beta_{1k} \Delta\text{DCO}_{2t-k} + \sum_{k=0}^n \beta_{2k} \Delta\text{HT}_{t-k} + \sum_{k=1}^n \beta_{3k} \Delta\text{Internet}_{t-k} \\ & + \sum_{k=0}^n \beta_{4k} \Delta\text{FD}_{t-k} + \sum_{k=0}^n \beta_{5k} \Delta\text{EDU}_{t-k} + \omega_1 \text{DCO}_{2t-1} + \omega_2 \text{HT}_{t-1} \\ & + \omega_3 \text{Internet}_{t-1} + \omega_4 \text{FD}_{t-1} + \omega_5 \text{EDU}_{t-1} + \varepsilon_t \end{aligned} \quad (2)$$

The arrangement of Equation (2) is based on the work of Pesaran et al. [53]. This approach has some benefits over other approaches. Firstly, both short- and long-term effects are estimated jointly, as in Equation (2). Short-term effects are indicated in the coefficient estimates assigned to the variables. The ultimate result is normalized estimates. The Pesaran et al. [53] method involves the application of the F-test with new critical values tabulated in the function. Another benefit of this technique is that there is no need to apply unit root tests separately, and $I(0)$ and $I(1)$ are maintained in the same model. Lastly, as a short-term dynamic alteration procedure is involved in this model, it permits any feedback effect amongst variables to be applied, which drops endogeneity and multicollinearity [53].

2.2.4. The Non-Linear Autoregressive Distributed Lag (NARDL) Model

As previously stated, Equation (2) assumes that the effects of variable changes on CO_2 emissions are symmetric; thus, this paper uses the non-linear autoregressive distributed lag (NARDL) model developed by Shin and Yu [33]. The NARDL model is an advanced method based on an ARDL approach, which allows the nonlinear asymmetry and cointegration relationship of small samples to be discussed in a single equation, in order to identify the effect of decomposition of explanatory variables into positive and negative changes on the explained variables [54–58]. In the extant literature, the NARDL model is widely used in the analysis of environmental problems [59–67]. Equation (2) is divided into two parts for the asymmetric analysis: a positive green household technology shock and a negative shock. As a result, we developed a structure that incorporates positive changes, specifying green household technology, and describes negative changes, suggesting green household technology. Shin and Yu [33] suggest that the partial sum idea be employed to generate the two measures given below:

$$\text{HT_POS}_t = \sum_{n=1}^t \Delta\text{HT_POS}_t = \sum_{n=1}^t \max(\Delta\text{HT_POS}_t, 0) \quad (3)$$

$$\text{HT_NEG}_t = \sum_{n=1}^t \Delta\text{HT_NEG}_t = \sum_{n=1}^t \min(\Delta\text{HT_NEG}_t, 0) \quad (4)$$

After separating the upward and downward trends of green household technology, the NARDL model can more carefully explore the asymmetric effects of core variables in different directions. With regard to error correction of the NARDL model, the long- and short-term asymmetric relationships between the explanatory variable and the explained variable can be examined. Thus, we substituted the HT variable in Equation (2) through the two partial sum variables to arrive at:

$$\begin{aligned} \Delta\text{DCO}_{2t} = & \omega_0 + \sum_{k=1}^n \beta_{1k} \Delta\text{DCO}_{2t-k} + \sum_{k=0}^n \beta_{2k} \Delta\text{HT_POS}_{t-k} + \sum_{k=0}^n \delta_{3k} \Delta\text{HT_NEG}_{t-k} \\ & + \sum_{k=0}^n \beta_{4k} \text{Internet}_{t-k} + \sum_{k=0}^n \beta_{5k} \text{FD}_{t-k} + \sum_{k=0}^n \beta_{6k} \text{EDU}_{t-k} + \omega_1 \text{DCO}_{2t-1} \\ & + \omega_2 \text{HT_POS}_{t-1} + \omega_3 \text{HT_NEG}_{t-1} + \omega_4 \text{Internet}_{t-1} + \omega_5 \text{FD}_{t-1} \\ & + \omega_6 \text{EDU}_{t-1} + \varepsilon_t \end{aligned} \quad (5)$$

The above Equation (5) is generally employed for the NARDL model, whereas Equation (2) is normally applied for linear ARDL models. Shin and Yu [33] demonstrated that

these models are used for similar estimation processes and diagnostic tests. If Equation (5) is estimated, then asymmetric assumptions can also be investigated.

3. Results

As this study aimed to explore green household technology's symmetric and asymmetric impact on environmental sustainability, it is compulsory to check the stationary properties of all variables. Thus, the study utilized the Dickey–Fuller test with generalized least squares (DF-GLS) and Phillips and Perron (PP) tests for this task, and both tests' outcomes are given in Table 3. The results under the DF-GLS test reveal that the EDU series is I (0) stationary, while DCO₂, HT, Internet, and FD series are I (1) stationary. The results under the PP test reveal that EDU and Internet series are I (0) stationary, while DCO₂, HT, and FD series are I (1) stationary. The results of unit root tests fulfill the prerequisite of the ARDL and NARDL approaches [53–67], which states that the variable series must meet the modeling requirements of the first order and below without unit roots (stationary or first-order stationary). Table 4 lists the results of the Brock–Dechert–Scheinkman (BDS) test. The BDS test was employed to check the asymmetries. The results of the BDS test reveal that the null hypothesis is rejected. It states that the variables of concern are asymmetric and nonlinear.

Table 3. DF-GLS and PP tests.

	DF-GLS			PP		
	I (0)	I (1)	Decision	I (0)	I (1)	Decision
DCO ₂	−1.456	−2.987 ***	I (1)	−0.278	−2.875 *	I (1)
HT	−0.023	−1.654 *	I (1)	−0.234	−4.251 ***	I (1)
Internet	−0.954	−1.785 *	I (1)	−5.652 ***		I (0)
FD	−0.187	−1.674 *	I (1)	−0.621	−3.854 ***	I (1)
EDU	−2.354 **		I (0)	−2.678 *		I (0)

Note: * $p < 0.1$; ** $p < 0.05$; and *** $p < 0.01$.

Table 4. BDS test.

Dimension	DCO ₂				HT			
	BDS Statistic	S.E	z-Stat	Prob.	BDS Statistic	S.E	z-Stat	Prob.
2	0.192	0.009	20.36	0.000	0.196	0.009	20.92	0.000
3	0.318	0.015	20.77	0.000	0.327	0.015	21.29	0.000
4	0.402	0.019	21.65	0.000	0.414	0.019	22.03	0.000
5	0.455	0.020	23.07	0.000	0.478	0.020	23.70	0.000
6	0.490	0.019	25.15	0.000	0.523	0.020	26.09	0.000

Table 5 lists the results obtained with the ARDL and NARDL models, and the latter contains two new variables: the positive change of HT (HT_POS) and the negative change of HT (HT_NEG). The long-term results obtained via the ARDL model suggest that HT has a negative and significant impact on DCO₂. It states that a 1% increase in HT reduces DCO₂ by 0.598% in the long term. The long-term results obtained via the NARDL model indicate that an increase in HT has a significantly negative impact on DCO₂, revealing that increases in HT tend to reduce DCO₂ in China. A 1% increase in positive shock of HT tends to reduce DCO₂ by 0.714% in China. However, a negative shock in HT has a significantly positive impact on DCO₂, meaning that an upsurge in HT tends to enhance DCO₂ in China. A 1% increase in negative shock of HT tends to increase DCO₂ by 0.474% in China. Through the ARDL model, the internet was found to be negatively and significantly associated with DCO₂ in the long term. It was found that a 1% increase in the use of the internet tends to decrease DCO₂ by 0.154% in the long term. The results obtained via the NARDL model reveal that the internet has a significantly negative impact on DCO₂, meaning that

internet use plays a significant role in reducing DCO₂ in China. A 1% increase in internet use tends to reduce DCO₂ by 0.262% in China in the long term. The impact of EDU on DCO₂ was found to be statistically insignificant via both the ARDL and NARDL models, revealing that EDU has no impact on environmental sustainability in China in the long run. The impact of FD on DCO₂ was found to be significantly negative with both the ARDL and NARDL models, revealing that financial development significantly improves environmental sustainability in China in the long run. Coefficient estimates indicated that a 1% increase in FD reduces DCO₂ by 0.279% in the ARDL model and 0.223% in the NARDL model.

Table 5. ARDL and NARDL estimates.

ARDL					NARDL				
Variable	Coefficient	S.E	t-Stat	Prob.	Variable	Coefficient	S.E	t-Stat	Prob.
Short-term									
HT	−0.086	0.180	−0.478	0.641	HT_POS	−0.251 **	0.122	−2.057	0.046
Internet	−0.041	0.031	−1.323	0.213	HT_POS (−1)	−0.043	0.173	−0.249	0.809
Internet (−1)	−0.023	0.049	−0.469	0.642	HT_NEG	−0.062	0.116	−0.534	0.601
Internet (−2)	−0.097 ***	0.034	−2.853	0.010	Internet	−0.006 **	0.003	−2.000	0.045
EDU	−0.262 *	0.136	−1.926	0.076	Internet (−1)	−0.054	0.064	−0.844	0.414
EDU (−1)	−0.054	0.179	−0.302	0.768	EDU	−0.118	0.143	−0.825	0.428
FD	0.344 ***	0.117	2.940	0.009	EDU (−1)	−0.069	0.172	−0.401	0.694
FD (−1)	0.153	0.109	1.404	0.183	FD	0.190 *	0.109	1.743	0.098
Long-term									
HT	−0.598 *	0.313	−1.911	0.095	HT_POS	−0.741 ***	0.223	−3.323	0.006
Internet	−0.154 **	0.066	−2.333	0.047	HT_NEG	−0.474 **	0.225	−2.107	0.047
EDU	−0.496	0.531	−0.934	0.386	Internet	−0.262 *	0.135	−1.941	0.074
FD	−0.279 *	0.162	−1.722	0.100	EDU	−0.149	0.111	−1.342	0.203
C	−6.029 **	2.577	−2.340	0.048	FD	−0.223 *	0.122	−1.828	0.099
					C	−9.646 ***	1.998	−4.828	0.000

Note: * $p < 0.1$; ** $p < 0.05$; and *** $p < 0.01$.

The short-term dynamics demonstrate that HT has no impact on DCO₂, according to the results from the ARDL model. According to the NARDL model, a positive shock in HT causes a significant reduction in DCO₂ in the short term. However, a negative shock in HT has an insignificant impact on DCO₂ in the short term. Internet use is insignificantly associated with DCO₂ in the ARDL model, but the association is significantly negative in the NARDL model. In contrast, EDU is significantly and negatively associated with DCO₂ in the ARDL model, but the association was found to be insignificant in the NARDL model. The impact of FD is reported to be significant and positive on DCO₂ in the short term in both the ARDL and NARDL models.

Table 6 lists the results of the diagnostic estimates, including those from the F-test, ECM, lagrange multiplier (LM), Breusch-Pagan (BP), stability test, and regression specification error test (RESET test). These tests are compulsory in order to validate the findings of ARDL and NARDL estimates. The outcomes of the F-test and ECM tests with negative symbols confirm the long-term cointegration relationship among variables. The outcomes of the LM and BP tests confirm the absence of autocorrelation and heteroskedasticity issues. Both models are correctly specified, as demonstrated through the results of the RESET test. The results of the CUSUM and CUSUM-sq tests reveal that both models are stable.

Table 6. Diagnostic tests.

Variable	ARDL				NARDL			
	Coefficient	S.E	t-Stat	Prob.	Coefficient	S.E	t-Stat	Prob.
F-test	13.21 ***				9.658 ***			
ECM (−1) *	−0.254 ***	0.021	−12.11	0.000	−0.194 ***	0.033	−5.922	0.000
LM	1.652				2.012			
BP	0.302				1.650			
RESET	0.320				0.021			
CUSUM	S				S			
CUSUM-sq	S				S			

Note: * $p < 0.1$; and *** $p < 0.01$.

4. Discussion

Previous studies have only identified monotonic and positive relations between green technology and carbon emissions [18–27], which not only lacks a household-level analysis, but also ignores the asymmetrical effects. Thus, the inclusion of this analysis would add to the current literature both empirically and theoretically, which addresses two research questions that also reinforce the existing work.

On the one hand, few studies have explored the way towards environmental sustainability via green household technology [18–28], and this analysis investigates the effect of green household technology on CO₂ emissions. Due to the rapid increase in production and consumption activities worldwide, the industrial revolution has significantly contributed to increasing the nations' affluence. However, the massive rise in production and consumption have also proved to be significant factors in the large-scale infusion of carbon into the atmosphere. As a result, the issue of climate change and global warming has erupted, which has jeopardized the subsistence of life on Earth. Several factors have been proposed by the empiricists and policymakers to tackle the issue of climate change and global warming, among which green technological development is widely acknowledged as a significant factor in curbing carbon emissions, and the vast majority of the literature supports this notion [18,26,27,68]. The shift to clean and green technology is regarded as being among the most effective ways to combat global warming and excessive energy consumption [69], making it an important factor in determining energy efficiency. One of the greatest advantages of green technology is that it might significantly decrease the expense of carbon reduction by creating more economical and energy-efficient devices [70]. In addition, Song et al. [71] suggested that the most reasonable choice available to nations in mitigating climate change and global warming is to rely more on green technologies, because green technologies help improve production efficiency by reducing waste. Households are an important component of the economy and contribute significantly to carbon emissions. Therefore, the adoption of green technology by households, such as clean energy and fuels, can play a significant role in reducing CO₂ emissions.

On the other hand, the existing efforts neglect the complicated effects of the selected variables [18–28,30–32], and this study relies on the asymmetric assumption, allowing us to determine the impact of the positive and negative shocks in green household technology on environmental sustainability in China, represented by carbon emissions. The results of the DF-GLS and PP tests confirm that the selected variables meet the modeling requirements of the ARDL and NARDL approaches, and the results of the BDS test prove that the sequences are asymmetric and nonlinear; thus, it is reliable to use the NARDL model to conduct the empirical analysis. In addition, the results of the F-test, ECM, LM, BP stability test, and RESET test indicate that the results of the ARDL and NARDL approaches are robust. From the ARDL and NARDL model estimates, we can infer that household use of green technology helps reduce carbon emissions. The use of environmentally friendly technology has the potential to convert the source of a household's energy supply from non-renewable to renewable sources, contributing to a reduction in CO₂ emissions. Green household technology has the potential to provide beneficial external effects in the form of increased

awareness, making it easier for renewable energy sources to be accepted and disseminated at the household levels [71]. In addition, the influence of green household technology on CO₂ emissions in the long term is greater than in the short term, mainly due to the fact that the adoption of new technology would have a continuous incentivizing effect [72,73]. More importantly, the results suggest that positive changes in green household technology have a more positive influential effect on carbon emissions than negative in the short and long term, emphasizing the asymmetric impact of the NARDL model.

5. Conclusions

The primary aim of this study was to investigate the relationship between green household technology and environmental sustainability in China. To that end, we have employed linear and non-linear ARDL models, but before that, we tested the stationary status of the variables via DF-GLS and PP tests, which suggested that our variables are either I (0) or I (1). The results of the stationary test permits us to employ the ARDL model because it can deal with the combination of I (0) and I (1) variables. Then, to confirm whether we can apply the NARDL model or not, we utilized the BDS test, which validates the application of the NARDL model. The of the results obtained via the ARDL model suggest that the long-term effects of HT are negative and significant, while the short-term estimates are negative but insignificant. On the other side, the long-term estimates from the NARDL model suggest that the estimate attached to HT_POS is negatively significant, and the estimate of HT_NEG is also significant and negative. This finding suggests that a positive change in green household technology could help to reduce CO₂ emissions, while the reduction in green household technology causes CO₂ emissions to rise. Hence, households' higher usage of green technology has a significant positive impact on the environment in the long term. In the short term, the estimate of HT_POS is negatively significant; however, the estimate of HT_NEG is insignificant. The estimates attached to positive and negative components emphasize the asymmetric impact of green household technology on CO₂ emissions both in the short and long term. Furthermore, higher levels of internet usage and education have a positive impact on the environment, while greater financial development has a negative impact.

The above findings can offer policy advice to the concerned parties. Given the disparate effects of the positive and negative shocks on green technology adoption at the household level, the findings imply that policymakers should approach these two types of changes independently. Moreover, the relevant authorities in China should try to invest more in research and development activities that can help generate more green and renewable technologies that are crucial in lowering CO₂ emissions. Furthermore, the role of information and communication technology (ICT) should be increased because that can lead to the digitalization and dematerialization of the economy, which can help to ameliorate environmental issues. Lastly, education levels must be increased in order to increase awareness about environmental degradation, which will encourage people to adopt pro-environmental practices that promote environmental sustainability.

The limitations of the analysis are twofold. On the one hand, we have focus too much on reducing greenhouse gas emissions, instead of speaking out against all kinds of environmentally harmful emissions and wasteful economic activities in general. On the other hand, this paper primarily focuses on China, but there is no comparison between China's effect and other countries around the world (Asia, America, Europe or Australia). In future research, we would consider other environmentally harmful emissions (e.g., sulfur dioxide) and wasteful economic activities, in order to represent environmental sustainability more comprehensively. Moreover, we would include data from all over the world to compare and put forward specific implications, which is an essential topic that deserves further exploration.

Author Contributions: Conceptualization, C.-W.S. and Y.W.; methodology, Q.M.; software, J.-W.Z.; validation, H.-L.C. and C.-W.S.; formal analysis, Q.M.; investigation, Y.W.; resources, Q.M.; data curation, J.-W.Z.; writing—original draft preparation, Q.M.; writing—review and editing, H.-L.C.; visualization, Y.W.; supervision, C.-W.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data could be found here: <https://data.worldbank.org/> (accessed on 28 July 2023).

Conflicts of Interest: The authors declare no conflict of interest.

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