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Internet Usage, Human Capital and CO₂ Emissions: A Global Perspective

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Abstract: Under the background of dealing with global warming, the widespread use of the internet provides a new idea for countries to develop a low-carbon economy at the right time. Based on the panel data of 70 countries from 1995–2018, this paper empirically analyzes the relationship between internet usage, human capital, and CO₂ emissions under different levels of economic development by using system GMM and a threshold regression model. The results show that internet usage and human capital are essential drivers of low-carbon economy development, and human capital can inversely regulate the impact of internet usage on CO₂ emissions. Internet usage can increase CO₂ emissions when human capital is below the threshold value, and it can significantly inhibit CO₂ emissions when human capital exceeds the threshold value. In other words, with the accumulation of human capital, the effect of internet usage on CO₂ emissions has an inverted U-shaped nonlinear relationship. Furthermore, the empirical analysis of high-income and middle- and low-income countries indicates the hindrance effect of internet usage on CO₂ emissions is more evident in high-income countries. For both the high-income and middle- and low-income countries, the relationship between internet usage and CO₂ emissions generally shows an inverted “U-shaped” relationship, first rising and then falling as human capital accumulates.

Keywords: internet usage; human capital; CO₂ emissions; sustainable development; threshold effect

1. Introduction

Since the industrial revolution, the global economy has largely been driven by urbanization and industrialization. Long term sustainable economic growth is inevitably accompanied by vast resource consumption and environmental pollution [1]. According to the International Energy Agency, global CO₂ emissions increased from 21,373 billion tons to 33,513 billion tons during 1995–2018. Global temperatures have increased by 1 °C above pre-industrial levels due to the rapid increase in greenhouse gas concentrations in the atmosphere. At the same time, sea level rise and frequent extreme weather events pose a serious threat to human security [2]. Under the impact of COVID-19 in 2020, the global economy has undergone a slowdown, and CO₂ emissions also decreased by 17% over the same period, which will positively impact climate change in a short time [3]. However, countries may focus on stimulating economic growth in the post-pandemic era. In this context, reconciling the relationship between economic recovery after the pandemic and CO₂ emissions will be of great importance to achieving green sustainable development.

According to IWS (Internet World Stats), the number of internet users worldwide reached 4.648 billion in June 2020. As the presentation of modern information technology and the operating carrier of intellectual capital [4], the internet has been successfully integrated into all fields of social life. Additionally, it not only plays a vital role in economic development but also has a profound impact on the ecological environment [5]. The theory of internet dependency suggests that the internet influences consumers’ cognition, behavior, and emotion, changing individuals’ social interaction mode and self-awareness [6].
Therefore, environmental education through the internet can have a tremendous impact on consumer behavior [7]. People tend to choose more efficient, greener, and more environmentally friendly lifestyles, which provides an essential guarantee for achieving green sustainable development. In addition, a large number of studies and practices have shown that technological innovation and reformation are the fundamental forces for tackling climate change and reducing carbon emissions. Internet usage can make the capital of knowledge and information rapidly flow at a lower cost by reducing information asymmetry in society, thus reducing CO₂ emissions and achieving sustainable economic development [8]. For instance, the production sector can improve energy utilization efficiency and reduce CO₂ emissions by the application of internet technology [9]. Moreover, the construction of smart cities and intelligent transportation systems that use big data, blockchain, and other internet technologies will dramatically reduce CO₂ emissions [10]. In contrast, the irrational development of the internet and the massive use of related devices lead to an increase in power consumption, which may negatively impact the environment [11,12]. Can internet usage mitigate CO₂ emissions while promoting economic development? Does the impact of internet usage on CO₂ reduction vary between countries in different economic developmental stages? These questions have significant practical implications for regional CO₂ emissions as well as sustainable economic development.

Whether internet usage has a positive or negative effect on CO₂ emissions, its role must be realized through effective implementation. The essence of the influence of the internet on economic activities is the revolution of production technology and the innovation of the production model, which has knowledge-intensive characteristics. The characteristics put forward higher requirements on the quality of the labor force. In general, advanced human capital has a higher capacity for production factor allocation, technological innovation, and absorption, and the improvement of human capital levels will strengthen the positive impact of internet usage on production development and carbon emission reduction [13]. It is impossible to achieve the sustainable utilization of natural resources with an uneducated labor force [14]. Even if the internet brings the same knowledge stock in regions with a backward education level, the weak knowledge absorption and technology conversion capabilities severely constrain the technology spillover effects of the internet [15].

To sum up, this paper adopts the CO₂ emissions data of 70 countries around the world from 1995–2018, and uses system GMM and threshold models to test the effect of internet usage on CO₂ emissions empirically. This paper provides a specific factual and theoretical basis for policymakers to carry out carbon emission reduction activities and promote the “green recovery” of the post-pandemic economy. The contribution of this paper includes the following three main areas. First, this paper enriches carbon emission reduction research by putting internet usage, human capital, and CO₂ emissions in the same analytical framework. Second, according to the World Bank’s classification of countries by per capita income, the sample is divided into two groups: high-income countries and middle- and low-income countries. The regional heterogeneity of the impact of internet usage and human capital on CO₂ emissions is studied in order to find out the different roles played by internet usage and human capital in different country groups. Third, applying a threshold regression model to explore the impact of internet usage on CO₂ emissions under different human capital conditions provides a new perspective to study the relationship between internet usage and CO₂ emissions.

2. Literature Review
2.1. Internet Usage and CO₂ Emissions

In the current global technological and industrial revolution, internet technology has gradually proliferated and penetrated into various economic and societal fields, which has become a major driving force in promoting global economic growth [16,17]. At the same time, global warming and eco-environment deterioration remain a glaring problem. The correct judgment and understanding of the relationship between internet usage and CO₂ emissions have become a hot topic for scholars worldwide [18]. Theoretically, internet
usage has an impact on CO$_2$ emissions in three ways: increasing production efficiency and energy usage efficiency and reducing the cost of energy usage [19]. In terms of improving production efficiency, data collection and resource analysis using the internet have become an essential part of any business process in the era of the digital economy [20]. May et al. [21] argued that internet usage makes the production process automated, which increases production efficiency and reduces energy consumption. With regard to promoting energy efficiency, Takase and Murota [22] found that internet usage can increase the energy efficiency of Japan and the United States. Based on this, Pradhan et al. [23] further attributed the above phenomenon to the profound impact of the internet’s “virtualization” and “dematerialization” on people’s production and lifestyles. Regarding reducing energy usage costs, Khan et al. [24] indicated that internet usage makes it possible to develop a home energy management controller and minimize energy consumption. In addition, Kumari et al. [25] pointed out that internet usage in the energy industry revolutionized the exiting grid, forming a smart grid that can meet customer demand and reduce the cost of energy usage by providing the bi-directional flow of energy and data.

Whether internet usage is beneficial to carbon reduction, the academic community has not yet reached a unanimous conclusion [26]. Some scholars believe that internet usage can stimulate economic growth and improve energy utilization. Still, the CO$_2$ and other harmful substances emitted during the process of its installation and usage will pose a serious threat to sustainable economic development [27,28]. For example, Salahuddin and Alam [10] found that OECD countries cannot effectively make use of information and communication technologies, so CO$_2$ emissions had increased. Shabani and Shahnazi [29] took Iranian economic sectors as the research object and used a panel causality model to analyze the relationship between internet usage and CO$_2$ emissions, and the results also showed that internet usage significantly increased CO$_2$ emissions. In contrast, other scholars claim that internet usage reduces CO$_2$ emissions and positively affects sustainable development [30–32]. Asongu, Le Roux, and Biekpe [33] employed panel data of Sub-Saharan Africa and performed a system GMM regression analysis to discuss this issue. They found that internet usage can reduce the potential threat of environmental pollution to human sustainable development. Haseeb et al. [18] analyzed the impact of ICT, energy consumption, and financial development on environmental quality by using panel data of BRIC countries from 1994–2014. The results of the SUR model similarly indicated that internet usage played a significant inhibitory role in CO$_2$ emissions. What is more, accompanied by the expansion of research contents, some scholars have reckoned that the relationship between internet usage and CO$_2$ emissions is not simply linear. Scholars have again successively demonstrated a nonlinear relationship between internet usage and CO$_2$ emissions [34,35].

### 2.2. Human Capital and CO$_2$ Emissions

Human capital accumulation is a crucial factor in reducing CO$_2$ emissions among many socio-economic factors [36]. In the beginning, most of the studies focused on the relationship between renewable energy usage and environmental pollution, and few studies explored the role of human capital in tackling climate change and promoting economic sustainable development [37]. Additionally, the research related to the ecological environment often used human capital to solve the estimation error caused by missing variables and endogenous problems [38]. As ecological issues become more and more serious, the relationship between human capital and sustainable development has also gradually become a hot topic in environmental protection. Generally, cognitive ability is positively related to environmental protection [39]. Advanced human capital with strong cognitive ability has a more comprehensive and correct understanding of the importance of energy security. Thus, advanced human capital is more inclined to choose environmentally friendly production methods and lifestyles [40].

The existing literature reveals that most scholars believe human capital can positively influence carbon emission reduction in the long run. At the micro-level, Kwon [41] pointed
out that human capital can reduce energy consumption by improving energy use efficiency in the production sector and play an essential role in carbon emission reduction. Yuan and Zhang [42] suggested that human capital, as an essential source of knowledge accumulation and technological innovation, can promote green production through energy-saving and technological innovation. At the macro-level, Bano et al. [43] empirically tested the relationship between human capital and CO$_2$ emissions in Pakistan by using the ECM and ARDL model. The empirical results show that the impact of human capital on CO$_2$ emissions is not significant in the short term. On the contrary, it has a positive impact on carbon emission reduction in the long term. Subsequently, Yao et al. [44] demonstrated that the relationship between human capital and CO$_2$ emissions changed over time. The effect of human capital on CO$_2$ emissions shifted from positive to negative after the 1950s. Scholars such as Khan [36] similarly argued that there is a nonlinear relationship between human capital and carbon emission reduction. When human capital is at a low level, human capital has a negative effect on carbon emission reduction. On the contrary, human capital can reduce CO$_2$ emissions when it reaches a certain level.

2.3. Income and CO$_2$ Emissions

The conclusions of the studies that focus on the relationship between income and CO$_2$ emissions are complicated. Hatzigeorgiou et al. [45] analyzed the causal relationship between GDP per capita, energy intensity, and CO$_2$ emissions and found that GDP per capita had a positive relationship with CO$_2$ emissions. Saidi and Ben Mbarek [46] examined the impact of income on CO$_2$ emissions and also showed a positive monotonic relationship between income and CO$_2$ emissions for the panel of emerging economies over the period 1990–2013. However, it is argued that carbon emission reduction occurs inconsistently with income increases. Apergis and Payne [47] concluded that increasing income could serve to fight with CO$_2$ emissions by examining the relation between CO$_2$ emissions, energy consumption, and economic growth. Baek [48] probed the effects of energy consumption and income on CO$_2$ emissions by using panel data from 1980–2009 from 12 major nuclear generating countries, and they deemed that CO$_2$ emissions tend to decrease monotonically with income growth. Yet, others, like Sapkota, Bastola, and Ma et al. [49,50] have argued that the relationship between income and CO$_2$ emissions, whether positive or negative, would not remain unchanged with the development of economies. Indeed, CO$_2$ emissions at first tend to increase as GDP per capita rises but then decreases as GDP per capita rises further, which supports the Kuznets curve hypothesis. This provides an important reference for our study to further analyze the variability of the relationship between internet usage, human capital, and CO$_2$ emissions at different income levels.

In general, research on internet usage, human capital, and CO$_2$ emissions has been extensive, which provides essential support for this study. However, the existing research has rarely explored the effect of internet usage on CO$_2$ emissions under different income levels from a global perspective, nor has it considered the impact caused by different levels of human capital accumulation in depth. Therefore, based on the CO$_2$ emissions data of 70 countries worldwide from 1995–2018, this paper incorporates both internet usage and human capital into the study to analyze the effects of internet usage and human capital on sustainable development. Meanwhile, the paper examines whether there is a threshold effect with human capital as the threshold variable by using a nonlinear threshold regression model to provide a specific theoretical and factual basis for tackling global warming and achieving sustainable development.

3. Materials and Methods

3.1. Panel Regression Model

In order to investigate the effect of internet usage and human capital on CO$_2$ emissions, we construct an economic model that takes CO$_2$ emissions as the explained variable and internet usage and human capital as the core explanatory variables. Since CO$_2$ emissions are subject to various factors, simply considering internet usage and human capital will
where \( y \) denotes a reporter country, \( t \) refers to a specific year, \( \beta_0 \) is a constant term, and \( \mu_i \) is a random error term. \( CO_{2it} \) means the CO\(_2\) emissions of country \( i \) in period \( t \); \( NET_{it} \) and \( HC_{it} \) are the core explanatory variables, which stand for the internet usage and human capital of country \( i \) in period \( t \), respectively; the control variables \( GDP_{it} \), \( STRU_{it} \), \( URB_{it} \), \( FD_{it} \), \( FDI_{it} \), and \( TF_{it} \) express GDP, industrial structure, urbanization rate, financial development level, foreign direct investment, and trade openness in country \( i \) at period \( t \), respectively.

Consistent with Saidi and Ben Mbarek [46], considering the continuity characteristics of CO\(_2\) emissions, the previous period CO\(_2\) emissions will influence the current CO\(_2\) emissions, so we also take a lagged period of CO\(_2\) emissions into the model and use the system generalized method of moment (system GMM) for regression estimation. The specific model is expressed as follows:

\[
\begin{align*}
\ln CO_{2it} &= \beta_0 + \varphi \ln CO_{2i,t-1} + \beta_1 \ln NET_{it} + \beta_2 \ln HC_{it} + \beta_3 \ln GDP_{it} + \\
&\quad \beta_4 \ln STRU_{it} + \beta_5 \ln URB_{it} + \beta_6 \ln FD_{it} + \beta_7 \ln FDI_{it} + \beta_8 \ln TF_{it} + \mu_i 
\end{align*}
\]

where \( \varphi \) is the regression coefficient of a lagged period of the explanatory variable.

### 3.2. Threshold Regression Model

The panel regression model describes a simple linear relationship between internet usage and CO\(_2\) emissions. However, according to previous studies, internet usage may have a nonlinear relationship with CO\(_2\) emissions due to the positive externality of human capital. In the current study, the nonlinear effects mostly use a group testing and interactive testing model to estimate. Still, both models rely on subjective experiences and artificially set the cut-off points, which may bias the estimation results significantly. Therefore, this paper adopts the threshold model proposed by Hansen [53] to avoid this estimation bias. The baseline panel threshold model (single threshold) as follows:

\[
y_{it} = a_0 + a_1 x_{it} I(q_{it} \leq \gamma) + a_2 x_{it} I(q_{it} > \gamma) + \mu_i + \epsilon_{it} 
\]

where \( y_{it} \) and \( x_{it} \) denote the explained and explanatory variables, respectively, \( q_{it} \) is the threshold variable, \( I(\cdot) \) is the indicator function, and \( \gamma \) is the threshold value that divides the equation into two regimes with coefficients \( a_1 \) and \( a_2 \); \( a_0 \) is the constant term, \( \mu_i \) represents the fixed effects and \( \epsilon_{it} \) is the random error term. The paper sets the following threshold regression model based on the panel threshold theory proposed by Hansen (1999), assuming that there is only a single threshold.

\[
\ln CO_{2it} = a_0 + a_1 \ln NET_{it} \times I(\ln HC_{it} \leq \gamma_1) + a_2 \ln NET_{it} \times I(\ln HC_{it} > \gamma_1) + \\
+ \beta_1 \ln GDP_{it} + \beta_2 \ln STRU_{it} + \beta_3 \ln URB_{it} + \beta_4 \ln FD_{it} + \\
+ \beta_5 \ln FDI_{it} + \beta_6 \ln TF_{it} + \mu_i + \epsilon_{it} \quad (4)
\]

In model (4), \( a_0 \) is the constant term; \( NET_{it} \) is the threshold dependent variable; \( HC_{it} \) is the threshold variable; \( \gamma_1 \) is the threshold to be estimated; \( a_1 \) and \( a_2 \) are the coefficients of the variables, when \( a_1 \neq a_2 \), it means a single threshold effect exists; \( GDP_{it} \), \( STRU_{it} \), \( URB_{it} \), \( FD_{it} \), \( FDI_{it} \) and \( TF_{it} \) are the explanatory variables, representing the same intended meaning as Equation (1); \( \mu_i \) represents the fixed effects and \( \epsilon_{it} \) is the random error term.
3.3. Variables and Data Resources

The explained variable, CO₂ emissions (CO₂\textsubscript{it}) represent carbon dioxide emissions of country \textit{i} in period \textit{t}. The data is obtained from the International Energy Agency. Carbon dioxide emissions are not only the main constituent of greenhouse gases but also reflect the method and level of energy usage. Therefore, this paper uses CO₂ emissions as an explained variable to evaluate economic sustainable development.

Core explanatory variables. Internet usage (\textit{NET\textsubscript{it}}) denotes the proportion of internet users to the total population of country \textit{i} in period \textit{t}. The data is obtained from the World Bank Database. With the development and popularization of general-purpose information technology, the internet has become an important factor affecting CO₂ emissions. In the short term, the installation and application of internet-related devices may consume a large amount of energy and increase CO₂ emissions. Conversely, the internet can reduce energy consumption and CO₂ emissions through the effective disposition of resources in the long term. Following Salahuddin and Danish [10,32], we take \textit{MP\textsubscript{it}} as a proxy variable for \textit{NET\textsubscript{it}} to conduct robustness tests, and it represents the number of mobile cellular subscriptions per 100 people. The data for \textit{MP\textsubscript{it}} has been taken from the World Bank database. Human capital (HC\textsubscript{it}) refers to the level of human capital accumulation of country \textit{i} in period \textit{t}, which is measured by the average schooling year. We expect human capital has a negative correlation with CO₂ emissions. The data comes from the United Nations Human Development Index database.

Control variables. To more precisely analyze the effects of internet usage and human capital on sustainable development, this paper also controls the following variables: gross domestic product (GDP\textsubscript{it}) indicates the level of economic development of country \textit{i} in period \textit{t}, and the data is obtained from the World Bank Database; industrial structure (STRU\textsubscript{it}) is the share of secondary and tertiary industries in the GDP of country \textit{i} in period \textit{t}, and the data are obtained from the UNCTAD Database; urbanization rate (URB\textsubscript{it}) is the proportion of urban population in the total population of country \textit{i} in period \textit{t}, the data is also obtained from the UNCTAD Database; financial development index (FD\textsubscript{it}) is the level of financial development of country \textit{i} in year \textit{t}, its value varies from 0 to 1, and the larger the value, the higher the financial development of the economy, the data comes from the International Monetary Fund; foreign direct investment (FDI\textsubscript{it}) is the stock of foreign direct investment attracted by country \textit{i} in year \textit{t}, its impact on CO₂ emissions is uncertain, the data is selected from the UNCTAD Database; the level of foreign trade openness (TF\textsubscript{it}) is the proportion of total imports and exports to GDP of country \textit{i} in period \textit{t}, which is used to measure the development of foreign trade and is expected to have a positive relationship with CO₂ emissions. This data is obtained from the UNCTAD Database.

Given the availability and reliability of data, this paper selects a panel data of 70 countries from 1995–2018. To further explore the impact of internet usage and human capital on CO₂ emissions at different income levels, this paper divides the total sample into two groups based on the World Bank’s classification of countries by income level: high-income countries and middle- and low-income countries. According to the research of Wagner [54], all the countries are listed in Table 1. The descriptive statistics of each variable are shown in Table 2.


Table 1. List of sample countries in this research.

| High-Income                      | Middle- and Low-Income                  |
|----------------------------------|-----------------------------------------|
| Australia                        | Finland                                 |
| Austria                          | France                                  |
| Belgium                          | Germany                                 |
| Canada                           | Greece                                  |
| Chile                            | Hungary                                 |
| Croatia                          | Iceland                                 |
| Cyprus                           | Ireland                                 |
| Czech Republic                   | Israel                                  |
| Denmark                          | Italy                                    |
| Estonia                          | Japan                                    |
| Korea (South)                    | Latvia                                   |
| Latvia                           | Lithuania                               |
| Lithuania                        | Nederland                               |
| Lithuania                        | New Zealand                             |
| Luxembourg                       | Norway                                  |
| Poland                           | Portugal                                |
| South Africa                     | United Arab Emirates                    |
| United States                    | Costa Rica                              |
| United Kingdom                   | Poland                                  |
| United States                    | Portugal                                |
| United States                    | Saudi Arabia                            |
| United States                    | Uruguay                                 |
| United States                    | Ecuador                                 |
| United States                    | Peru                                    |
| United States                    | Zambia                                  |

Table 2. Descriptive statistics of variables.

| Variables | Mean Value | Standard Errors | Min | Max |
|-----------|------------|-----------------|-----|-----|
| CO₂       | 345.951    | 1014.417        | 1.620 | 9528.214 |
| NET       | 39.312     | 31.819          | 0.000 | 99.011  |
| HC        | 9.620      | 2.539           | 2.800 | 14.100  |
| GDP       | 727.229    | 1962.680        | 1.468 | 20,580.170 |
| STRU      | 85.274     | 6.419           | 51.600 | 99.461  |
| URB       | 67.768     | 18.287          | 18.196 | 100.000 |
| FD        | 0.473      | 0.232           | 0.065 | 1.000   |
| FDI       | 202.073    | 525.715         | 0.032 | 7844.205 |
| TF        | 85.700     | 57.862          | 15.600 | 437.300 |
| MP        | 75.387     | 51.037          | 0.000 | 212.639 |

4. Results and Discussion

4.1. Unit Root Test

With the aim of avoiding the phenomenon of pseudo-regression results, it is necessary to conduct the stationarity test before regression analysis. In this paper, LLC-Test and IPS-Test are used to examine the stationarity of the data. The results of the first-order difference estimation of each variable are shown in Table 3. The original hypothesis of “unit root” is rejected, indicating that the variables are stable.

Table 3. Results of the unit root test.

| Variables | LLC | IPS |
|-----------|-----|-----|
| LnCO₂     | −1.740 ** | −15.085 *** |
| LnNET     | −19.723 *** | −16.907 *** | −13.325 *** | −18.791 *** |
| LnHC      | −6.688 *** | −11.481 *** | −3.915 *** | −23.168 *** |
| LnGDP     | −2.657 *** | −17.688 *** | 0.450 | −19.660 *** |
| LnSTRU    | −5.898 *** | −17.428 *** | −2.415 *** | −28.546 *** |
| LnURB     | −9.262 *** | −5.997 *** | −1.975 ** | −23.924 *** |
| LnFD      | −5.322 *** | −16.018 *** | −4.137 *** | −28.364 *** |
| LnFDI     | −5.952 *** | −17.672 *** | −5.545 *** | −21.690 *** |
| LnTF      | −4.086 *** | −14.579 *** | −0.685 | −24.669 *** |
| LnMP      | −19.212 *** | −24.012 *** | −15.069 *** | −15.757 *** |

Note: "***", and "**" mean significance at the level of 1%, and 5%, respectively; standard errors in parentheses.

4.2. Panel Regression Results

When dealing with panel data, we can relax the assumptions that the random items are independent and identically distributed if the sample has a long time span. The long period
of the sample data in this paper may have the problems of serial correlation and between-group heteroskedasticity. Therefore, this paper first adopts the feasible generalized least squares (FGLS) method to estimate model (1). On this basis, to improve the estimation accuracy and mitigate the estimation bias caused by the endogeneity problem, this paper then introduces instrumental variables and estimates model (2) again by using the system GMM estimation method. Blundell and Bond [55] recommend to use the second and higher order lags of the regressors as instruments when applying the system GMM method. In our study, we employ the second and third lags of the regressors as instrumental variables and apply the two-step estimator to achieve a consistently valid estimation. Additionally, we have collapsed the instrumental variables to make sure that the number of instrumental variables do not get much larger than the number of groups [56]. The estimated coefficients of internet usage and human capital remain consistent with the FGLS estimation. The system GMM estimation results have passed the autocorrelation and Hansen test, indicating that the estimation results are robust. The specific results are listed in Table 4.

From Table 4, the one-period lagged estimate of CO$_2$ is positive and statistically significant in the estimated outcomes in column (4), indicating that CO$_2$ emission is a continuous and accumulated process. Even though individuals or households are more aware of environmental protection and tend to choose more environmentally friendly products, the living habits cannot be changed rapidly in a short time due to a time lag effect. Therefore, a positive correlation is shown between the previous and current periods CO$_2$ emissions. This finding is consistent with the result of Saidi and Ben Mbarek [46]. The estimated coefficient of internet usage is $-0.025$ and statistically significant, which is consistent with expectations. It shows that the internet, with the development of general-purpose information technology, can actively guide resources flowing to high-efficiency sectors through data collection and organization, improve resource utilization, and reduce CO$_2$ emissions. The estimated coefficient of human capital is also significantly negative, which means that human capital accumulation can significantly reduce CO$_2$ emissions. The result is similar to the findings of Ozcan and Apergis [35]. Advanced human capital has a more comprehensive environmental awareness of and proficiency in green production techniques, which has a curtailing effect on CO$_2$ emissions, and this result is in line with the research of Bano et al. [43].

For the other control variables, the coefficient of GDP is $-0.016$, which is significant at the 5% level. To some extent, GDP can represent the economic development stage of an economy, and different economic development stages imply different energy consumption characteristics. In pace with the increasing level of economic development, the structure of energy consumption has also been constantly adjusted. The use of low-carbon, non-polluting green energy has dramatically reduced CO$_2$ emissions. This result partly coincides with the outcome of Khan et al., who reported a significant impact of economic development on CO$_2$ emissions [57]. The estimated coefficient of industrial structure is significantly positive, which is inconsistent with Chang [58]. The index of industrial structure used in this paper is measured by the share of secondary and tertiary industry in the GDP. The positive estimated coefficient of industrial structure indicates that the share of secondary industry is still large in the process of industrial restructuring in the sample countries, and the production patterns of high input and high pollution has led to increasing CO$_2$ emissions. The estimated coefficient of urbanization rate is 0.156 and statistically significant. The urbanization process is associated with the rapid expansion of population, land, and industrial scale, and the resulting scale effect leads to a significant increase in CO$_2$ and other pollutant emissions. Hence, authorities should focus on CO$_2$ emissions in the process of urbanization [50]. The estimated result of financial development is significantly negative at the 1% level. A 1% increase in financial development would lead to a 0.144% reduction in CO$_2$ emissions. This finding indicates that financial development can broaden the financing channels of enterprises, increase R&D investment, and produce more low-carbon products. This finding on the importance of financial development is the same with Park et al. for European Union countries [28]. The coefficient of foreign
direct investment is estimated to be significantly positive, which further supports the “pollution refuge” hypothesis that foreign direct investment will degrade the host country’s environment by transferring high pollution industries to it. This finding was also confirmed by Sapkota et al., who hold that the introduction of FDI would increase CO\(_2\) emissions in Latin American \[49\]. Foreign trade openness is positively correlated with CO\(_2\) emissions. The development of foreign trade has undoubtedly brought great impetus to economic development. Still, it has also brought more prominent side effects, such as excessive energy consumption in the trade process, which seriously restrict the sustainable development of national economies.

Table 4. Results of the panel regression model estimation.

| Variables | (1) Total | (2) High-Income | (3) Middle- and Low-Income | (4) Total | (5) High-Income | (6) Middle- and Low-Income |
|-----------|----------|-----------------|---------------------------|----------|-----------------|---------------------------|
| L.LnCO\(_2\) | 0.957 *** | 0.903 *** | 0.988 *** | 0.014 | 0.020 | 0.023 |
| LnNET | −0.147 *** | −0.219 *** | −0.045 *** | −0.025 *** | −0.015 * | −0.014 * | 0.002 | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 |
| LnHC | 0.126 *** | 0.259 *** | 0.173 *** | −0.480 *** | −0.888 *** | −0.613 *** | 0.009 | 0.012 | 0.018 | 0.054 | 0.093 | 0.012 |
| LnGDP | 1.283 *** | 0.989 *** | 0.879 *** | −0.016 ** | 0.028 ** | −0.015 ** | 0.004 | 0.008 | 0.008 | 0.008 | 0.013 | 0.033 |
| LnSTRU | −1.334 *** | 2.734 *** | −0.700 *** | 0.449 *** | 0.415 | −0.378 | 0.030 | 0.142 | 0.142 | 0.403 | 0.552 |
| LnURB | −0.132 *** | −0.754 *** | 0.034 * | 0.156 *** | 0.320 * | 0.071 | 0.007 | 0.020 | 0.020 | 0.047 | 0.166 | 0.114 |
| LnFD | −0.413 *** | −0.444 *** | 0.207 *** | −0.144 *** | 0.115 *** | −0.466 *** | 0.008 | 0.142 | 0.142 | 0.142 | 0.027 | 0.075 |
| LnFDI | −0.178 *** | −0.041 *** | −0.039 *** | 0.091 *** | 0.032 *** | 0.181 *** | 0.003 | 0.006 | 0.006 | 0.004 | 0.011 | 0.045 |
| LnTF | 0.430 *** | −0.002 *** | 0.301 *** | 0.145 *** | 0.191 *** | 0.161 *** | 0.007 | 0.004 | 0.004 | 0.013 | 0.016 | 0.045 |
| CONS | 4.710 *** | −7.921 *** | 1.061 *** | −1.666 *** | −2.251 | 3.089 | 0.134 | 0.263 | 0.263 | 0.578 | 1.586 | 2.365 |
| Wald | 237,354.380 | 961,635.930 | 22,846.020 | 961,635.930 | 22,846.020 | 22,846.020 |
| Prob > Chi\(_2\) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| AR(1) | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| AR(2) | 0.319 | 0.318 | 0.407 | 0.319 | 0.318 | 0.407 |
| Hansen Test | 0.492 | 0.841 | 0.246 | 0.492 | 0.841 | 0.246 |
| Obs | 1680 | 960 | 720 | 1680 | 960 | 720 |

Note: "***", "**", and "*" mean significance at the level of 1%, 5%, and 10%, respectively; standard errors in parentheses.

Regarding the World Bank’s classification of countries by income level, the sample is divided into ‘high-income’ and ‘middle- and low-income’ groups for separate regression estimation in this paper. In the system GMM regression results of the subsample, the regression coefficients of the core explanatory variables, internet usage and human capital, are significantly negative for both high-income and middle- and low-income countries, displaying significant inhibitory effects on CO\(_2\) emissions. Further comparing the two types of regressions, it is found that internet usage and human capital have a more significant inhibitory effect on CO\(_2\) emissions in high-income countries than in middle- and low-income
countries. The main reason is that the internet was developed and generally applied earlier in high-income countries. The internet has penetrated all spheres of production and life and created a strong scale effect. Digital finance, online education, cross-border e-commerce, and other activities all contribute to the development of a low-carbon economy. Then, the environment sustainability can be maintained even if output of a high-income country increases. While for the middle- and low-income countries, the internet usage has not played the same role in coping with environmental pollution. This is probably because the technological advancement of the internet is not enough to decline CO$_2$ emissions by improving productivity, and consumers in middle- and low-income countries do not have sufficient income to purchase and consume internet related products. Therefore, the curbing effect of internet usage on CO$_2$ emissions is more evident in high-income countries. Human capital also plays an important role in reducing emissions by increasing energy efficiency and improving the economy’s readiness to adopt energy-efficient technologies in production and daily life [14]. Compared with middle- and low-income countries, high-income countries, which have a better living environment and perfect compensation system, can attract high-skilled labor and take full advantage of their role in achieving sustainable economic development [59].

4.3. Threshold Regression Results

4.3.1. Threshold Effect Test and Threshold Value Estimation

Advanced human capital has a unique capacity for resource allocation, technological innovation, and absorption, which can promote resource utilization and reverse the inhibitory effect of internet usage on CO$_2$ emissions. According to model (4), this paper takes the human capital as the threshold variable and the internet usage as the threshold-dependent variable to test the threshold characteristics of the relationship. We use the bootstrap method to test whether the threshold effect is significant and the number of threshold effects. In addition, we conduct the same test for high-income and middle- and low-income samples. The estimation results are shown in Table 5. There is a single threshold in the total sample and middle- and low-income country samples. At the same time, a double threshold exists in high-income country samples. The effect of internet usage on CO$_2$ emissions shows a nonlinear variation depending on human capital accumulation.

Based on the threshold effect, the research further estimates the threshold value and confidence interval. The results are described in Table 6. There is a single threshold in the total sample and the threshold value is 2.380, which lies within the confidence interval of [2.370, 2.389]; the threshold values estimated by the double threshold model for high-income countries are 2.342 and 2.501, which lie within the confidence interval of and [2.493, 2.510], respectively. The threshold estimation for the single threshold model in middle- and low-income countries is 2.361, and the confidence interval is [2.351, 2.370].
### Table 6. Results of the threshold value and confidence interval.

| Region                | The Number of Thresholds | The Value of Threshold | 95% Confidence Intervals   |
|-----------------------|--------------------------|------------------------|----------------------------|
| Total                 | Single                   | 2.380                  | [2.370, 2.389]             |
| High-income           | Single                   | 2.342                  | [2.337, 2.366]             |
|                       | Double                   | 2.501                  | [2.493, 2.510]             |
| Middle- and low-income| Single                   | 2.361                  | [2.351, 2.370]             |

#### 4.3.2. Threshold Model Regression Results

The threshold regression results are listed in Table 7. In the total sample regression results, the effect of internet usage on CO$_2$ emissions has a threshold characteristic, when human capital is below the threshold value of 2.380, internet usage is positively correlated with CO$_2$ emissions at the significance level of 1%; while human capital is above the threshold of 2.380, the estimated coefficient of internet usage is $-0.015$, significantly negative at the level of 1%. A 1% increase in internet usage would lead to a 0.015% decrease in CO$_2$ emissions. With the continuous accumulation of human capital, internet usage can effectively reduce CO$_2$ emissions. The improvement of physical capital efficiency needs to be matched with human capital. Thus, the extensive use of the internet has put forward higher requirements and challenges to human capital. Only when an economic society has enough advanced human capital can they truly absorb and innovate internet technologies and make full use of the internet usage’s positive effects on carbon emission reduction. It is believed that building a mature talent training system can fully take advantage of internet usage in the sustainable development of society. The results are similar to the findings of Mouelhi, who explores the increasing impact of information and communication technologies (ICT) on firm efficiency in the Tunisian manufacturing sector with the accumulation of human capital, and suggests that achieving benefits from ICT requires investments in human capital [60].

From the sub-sample regression results, there are two human capital thresholds in high-income countries. The estimated coefficient of internet usage is significantly positive when human capital is below the first threshold value of 2.342. When human capital exceeds the first threshold, between 2.342 and 2.501, the coefficient of internet usage is negative but statistically insignificant. However, after human capital exceeds the second threshold value, the effect of internet usage on CO$_2$ emissions is significantly negative at the level of 1%. For middle- and low-income countries, there is only a single threshold for human capital. When human capital is below 2.361, the effect of internet usage on CO$_2$ emissions is significantly positive. A 1% increase in internet usage would lead to a 0.032% increase in CO$_2$ emissions, which is not conducive to socially sustainable development. When human capital is greater than 2.361, the coefficient of internet usage is $-0.067$, significant at the 1% level. Moreover, the increase in internet usage can slow down CO$_2$ emissions. In summary, the analysis finds that human capital has a strong positive externality, which is obviously different between high-income and middle- and low-income countries. The quality of human capital directly limits the effect of internet usage on CO$_2$ emissions in both high-income and middle- and low-income countries. Under the influence of human capital, there is a general inverted U-shaped relationship between internet usage and CO$_2$ emissions. Only when human capital exceeds a certain threshold can the green effect of internet usage be fully realized. Therefore, the positive impact of the interaction between internet usage and human capital on sustainable development suggests that economies should continuously increase human capital investment and support the development of internet technology to reduce CO$_2$ emissions [61].
Table 7. Results of threshold regression.

| Variables                        | (1) Total                  | Variables                        | (2) High-Income             | Variables                        | (3) Middle- and Low-Income |
|----------------------------------|----------------------------|----------------------------------|-----------------------------|----------------------------------|----------------------------|
| LnNET (LnHC ≤ 2.380)            | 0.038 *** (0.004)          | LnNET (LnHC ≤ 2.342)            | 0.025 *** (0.007)          | LnNET (LnHC ≤ 2.361)            | 0.032 *** (0.004)          |
| LnNET (LnHC > 2.380)            | -0.015 *** (0.005)         | LnNET (2.342 < LnHC ≤ 2.501)    | -0.010 (0.007)             | LnNET (LnHC > 2.361)            | -0.067 *** (0.010)         |
| LnGDP                            | 0.204 *** (0.015)          | LnGDP                            | 0.144 *** (0.020)          | LnGDP                            | 0.313 *** (0.021)          |
| LnSTRU                           | 0.161 (0.121)              | LnSTRU                            | -0.542 * (0.322)           | LnSTRU                            | 0.407 *** (0.128)          |
| LnURB                            | 1.161 *** (0.085)          | LnURB                             | -0.380 ** (0.176)          | LnURB                             | 0.987 *** (0.102)          |
| LnFD                             | 0.034 (0.027)              | LnFD                              | 0.085 ** (0.041)           | LnFD                              | 0.090 ** (0.035)           |
| LnFDI                            | -0.042 *** (0.008)         | LnFDI                             | 0.015 * (0.009)            | LnFDI                             | -0.082 *** (0.013)         |
| LnTF                             | -0.049 ** (0.025)          | LnTF                              | -0.142 *** (0.034)         | LnTF                              | 0.149 *** (0.032)          |
| CONS                             | -2.051 *** (0.676)         | CONS                              | 7.720 *** (1.585)          | CONS                              | -3.486 *** (0.728)         |
| R^2                              | 0.606                      | R^2                               | 0.767                      | R^2                               | 0.802                      |
| F Value                          | 307.860                    | F Value                           | 36.080                     | F Value                           | 344.720                    |
| Obs                              | 1680                       | Obs                               | 960                        | Obs                               | 720                        |

Note: ***", **", and *" mean significance at the level of 1%, 5%, and 10%, respectively; standard errors in parentheses.

4.4. Robustness Test

To ensure the reliability of the research results, this paper uses the method of replacing the core explanatory variables for robustness testing. Mobile cellular subscriptions (MP_{it}) is selected as a proxy variable for internet usage in model (1) and model (2). We use FGLS and system GMM methods to estimate the models again. The outcomes are shown in Table 8. Although we replaced the core explanatory variables, the empirical results are consistent with those reported previously, indicating that internet usage and human capital have a suppressive effect on CO_{2} emissions. The model is robust in the long run.

Table 8. Results of the robustness test.

| Variables | (1) GLS | (2) GLS Middle- and Low-Income | (3) System GMM | (4) System GMM Middle- and Low-Income |
|-----------|---------|--------------------------------|----------------|-------------------------------------|
| LnCO_{2}  | 0.948 *** (0.013) |                               | 0.995 *** (0.024) |                      |
| LnMP      | -0.150 *** (0.002) | -0.212 *** (0.002) | -0.055 *** (0.004) | -0.024 *** (0.003) | -0.025 *** (0.007) | -0.019 * (0.010) |
| LnHC      | 0.043 *** (0.007) | -0.079 *** (0.012) | 0.362 *** (0.020) | -0.503 *** (0.045) | -1.298 *** (0.119) | -0.563 *** (0.114) |
5. Conclusions

With the booming development of global information and communication technologies, countries are facing the problem of how to reconcile the relationship between internet usage and CO$_2$ emissions along with global warming. Based on cross-country panel data of 70 countries from 1995–2018, this paper empirically examines the relationship between internet usage, human capital, and CO$_2$ emissions using system GMM and a threshold regression model. The main findings are as follows: (1) Internet usage and human capital play a significant inhibitory role on CO$_2$ emissions, and the hindrance effect is more evident in high-income countries. In addition, the regression outcomes of replacing core explanatory variables confirm the robustness of these findings; (2) For both the high-income and middle- and low-income countries, the relationship between internet usage and CO$_2$ emissions generally shows an inverted “U-shaped” relationship that first rises and then falls as human capital accumulates. There is a significant nonlinear relationship between internet usage and CO$_2$ emissions with human capital as the threshold variable.

The widespread use of general information technologies such as big data, cloud computing, and blockchain can improve the efficiency of resource allocation, reduce energy consumption, and ultimately promote green economic development. In order to improve the ability of the positive impacts of the technological spillover and scale effect of internet on carbon emission reduction, this paper proposes the following countermeasures: (1) In the early stages of internet development, the installation and usage of internet-related equipment may increase energy consumption and CO$_2$ emissions. Carbon reduction efforts need to emphasize the orderly construction of internet infrastructure. Governments should accurately implement policies and tailor the overall layout of internet industries to curtail the adverse effect of overlapped construction on CO$_2$ emissions. The application
of the core technologies of the internet such as big data and cloud computing can reduce resource consumption on the production side. Therefore, policies should be implemented to strengthen financial support for the key areas of internet technology. Under the influence of these policies, manufacturers may be inclined to use internet technology reasonably and increase investment in green information technology. (2) The estimation results of the threshold regression model prove the correctness of the view that the internet, as a significant technological innovation, has an essential dependence on human capital accumulation. Therefore, we should emphasize the threshold effect of human capital on the green development of the internet. If possible, the whole society ought to provide more opportunities for education to increase the level of human capital and spread among the public about the dangers of pollution, improve the public’s environmental awareness and responsibility, and create favorable social conditions for the development of a low-carbon economy. In addition, enterprises can pay more attention to human capital accumulation, and it is necessary to actively reserve human capital through skills training according to their own development goals. In these ways, the threshold of human capital can be exceeded as soon as possible, and the positive effect of internet usage on carbon emission reduction can be fully achieved.

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