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# Digitalization Level and Green-Oriented Transition Development of Highly Energy-Intensive Enterprises Based on Carbon Reduction Perspective

**Xinlin Liao [1], Yu Zhang [1], Xinyu Wang [2] and Ruijia Yuan [2,*]**

[1] School of Economics, Anhui University of Finance and Economics, Bengbu 233030, China
[2] School of Management Science and Engineering, Anhui University of Finance and Economics, Bengbu 233030, China
* Correspondence: rj.yuan@aufe.edu.cn; Tel.: +86-159-5526-9702

**Abstract:** Against the dual background of the vigorous shape of digital economy and the severe pressure for carbon reduction, exploring the mechanism of the relationship between digitalization level and carbon reduction of highly energy-intensive enterprises is one of the current hot topics in theoretical and practical circles. This paper selects panel data of listed companies with high energy consumption from 2007 to 2019 and adopts a threshold-regression method to empirically test the impact of digitalization level on corporate carbon emission reduction It turns out that the digitalization level of enterprises has both an "inverted U" effect and a heterogeneous effect on carbon emissions. Enterprise technological innovation has both a threshold action and a regulating action on the influence of digitalization level on carbon emissions. It can play a role in accelerating the digitalization level to the inhibition of the increase in carbon emissions in advance and has a reinforcing effect in accelerating the reduction of enterprise carbon emissions.

**Keywords:** digital level; highly energy-intensive enterprises; carbon emissions; technological innovation

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**Citation:** Liao, X.; Zhang, Y.; Wang, X.; Yuan, R. Digitalization Level and Green-Oriented Transition Development of Highly Energy-Intensive Enterprises Based on Carbon Reduction Perspective. *Sustainability* **2023**, *15*, 15549. https://doi.org/10.3390/su152115549

Academic Editor: Antonio Caggiano

Received: 1 August 2023
Revised: 20 September 2023
Accepted: 29 September 2023
Published: 2 November 2023



## 1. Introduction

As the economic progression of China gradually shifts to high-quality production, rapid economic development is followed by high consumption of energy and environmental deterioration. In the light of the "China Energy Development Report", China's carbon-emitting energy consumption has increased to 59 percent of total energy consumption, far higher than the global average of 30 percent of total energy consumption. An unreasonable development approach may not only endanger China's economic development but may also can harm the surroundings where we live as well as the health of the population. Therefore, promoting long-term economic progress with minimal damage to nature has grown to be a linchpin in the process of China's economic green transition [1]. At present, China's energy structure is still controlled by the use of coal, meaning that the vast majority of carbon dioxide ($CO_2$) produced by fossil fuel combustion comes from coal. Based on the "2010 Statistical Report on National Economic and Social Development", six high-intensity industries can be clearly identified. Among these, the power industry uses coal as fuel for power generation, the chemical industry incurs a great energy expense in chemical production, and the non-ferrous metal smelting industry consumes energy in the three major areas of mining, smelting, and processing. These all result in high environmental costs. In order to cope with the global climate change due to the increase of $CO_2$, various carbon reduction targets and policies have been formulated by the Chinese government. General Secretary Xi Jinping formally proposed the "double carbon" target in September 2020, which aimed for peak carbon dioxide release by 2030 and carbon neutrality by 2060. Hence, it is of great practical significance to study the carbon reduction of highly energy-intensive enterprises to realize its green-oriented transition and the national "dual carbon" target.

As the condition of global environment worsens, emissions of carbon dioxide have received increasingly widespread attention. The research on carbon emission in academic circles mainly focuses on carbon emission measurement, emission differences in different regions, and influencing factors of carbon emission. On the one hand, some scholars discuss the measurement of carbon emissions and the differences between different regions. For instance, Jiang et al. [2] argued that fossil fuel energy production in different regions has a significant influence on $CO_2$ release; hence, developed provinces should reduce energy generation and augment the import of low-carbon energy. Zhang et al. [3] predicted carbon emissions from 2018–2100 according to setting different conditions and pattern parameters and concluded that in all scenarios, the western region peaks first and the eastern coastal region peaks last. Chen et al. [4] concluded that energy-related carbon emissions differ greatly between different urban types in China, such as IC (intensity of concern) and CI (clustering intensity), which are highest in eastern China, medium in the middle region, and lowest in the western areas of China. On the other hand, some scholars analyzed the factors affecting $CO_2$ emissions from different perspectives, such as government, economic development, and urban modernization. According to the government perspective, Shi et al. [5]—by analyzing county-level panel data from 1997–2017—concluded that low-carbon policy implementation can enhance carbon reduction and show significant heterogeneity under different degrees of environmental regulation. Yao et al. [6] concluded that the government has more influence on $CO_2$ emission reduction than do enterprises, and the government's strengthening of emissions reductions is the crux to China attaining its carbon reduction targets. From an economic progression viewpoint, Du et al. [7] believed that increasing economic activity, technological development, and industrial structure are the most significant elements influencing $CO_2$ release. Jiang et al. [2] believed that economic developments are the main reasons for China's carbon emissions changes. Chen and Lin [8] argued that the increase in economic produce and per capita energy use had a positive influence on per capita carbon emission increase but that the structure and intensity of the manufacturing sector had a negative influence on carbon emission increase. Considering urban modernization, Yang et al. [9] used a spatial autoregressive model and suggested that the alteration in the number of people, urbanization, structure, and technique progress were the reasons why the south coast and east coast of China have shown a reduction in carbon dioxide emissions. Zhang et al. [10] maintained that the link between urbanization and carbon emissions was an "inverted U", so policymakers could curb carbon emissions by accelerating urbanization in the east and middle regions, where they can effectively reduce carbon emissions through regional green technological innovation. However, the cross-provincial $CO_2$ releases will have an intense negative effect due to spatial spillover.

The digital revolution is speeding up the low-carbon transformation and upgrading development across all manner of industrial fields, and industrial digital alteration is playing a critical role in the progression of the digital economy [11]. For one thing, the 2021 China "Double Carbon" Strategy and Energy Digitalization Forum believes that digital techniques will quicken the course of energy transformation and favor the carbon dioxide peak release and carbon balance targets, thus affirming the influential position of digital technology in carbon reduction strategy. For another thing, the effect of digitalization on carbon release has also appealed to some scholars, yet the relevant literature is comparatively thin and contains different views. Ma et al. [12] argued that the degree of industrial digitization is negatively interrelated with carbon emissions. However, Belkhir and Elmeligi [13] argued that digitalization exacerbates carbon emissions and that the digitalization process itself generates a considerable carbon footprint. Meanwhile, existing studies have mainly concentrated on carbon reduction in China's industrial and manufacturing division or different regions, with less examination of the highly energy-intensive enterprises, including nonferrous metals, chemicals, and electric power enterprises, which are the focus of this paper. Therefore, this paper integrates the digitalization levels, carbon emissions of highly energy-intensive enterprises, and enterprise technology innovation into the same framework. It also finds the influence framework of enterprise digitalization level on its own carbon emissions, uses the threshold effect to search the critical point of enterprise technological innovation in the influence of digitalization level on carbon emissions, analyzes the heterogeneity of enterprise property rights and regional heterogeneity, and uses various methods of conducting robustness analysis of the results. The expectation is that this paper can maximize the role of digitalization technology levels on companies wanting to develop a low carbon footprint and provide a reference for companies and the country to forge digital low-carbon progress strategies in the future.

In contrast with other literature, there are three aspects of marginal relevance to this text. Firstly, from the research object point of view, the majority of current discussions on carbon reduction come from the macro level, such as carbon reduction studies in various provinces and regions, but this paper focuses on highly energy-intensive enterprises. Secondly, according to the research method, the bond between digitalization level and carbon release is an "inverted U", differing from the simple linear connection found in existing literature and providing empirical evidence to support the development of digitalization levels. Considering the moderating and threshold effects of technological innovation, it is clearly possible to accelerate the process of digitalization levels inhibiting the carbon emissions of enterprises. Finally, the differences in the impact of digitalization levels from heterogeneous studies can provide more effective incentives or guidance for different types of enterprises and different regions to reduce carbon emissions.

The subsequent content of this paper is divided into several parts as follows: Firstly, in Section 2, the paper emphasizes that digitalization level is related to green-oriented transition development according to the collated literature, and some research hypotheses are proposed on this basis. In Section 3, study variables and data sources are introduced on the basis of empirical models. Then, in Section 4, this study constructs the baseline regression function related to digitization level and enterprise carbon emissions and conducts a robustness test and heterogeneity analysis of the empirical results. In Section 5, the threshold regression model makes an in-depth study on the regulatory effect and threshold effect of digitization level on enterprise carbon emissions. Finally, in Section 6, the paper summarizes the research results and puts forward corresponding policy recommendations.

## 2. Theoretical Analysis and Research Hypothesis

Currently, information technology is making continuous progress, and the digital revolution is considered to be one of the effective paths for carbon reduction. At present, the Chinese economy is at a crucial point of changing to high-quality growth, and digital technology is regarded as a critical component of achieving the "double carbon" target. Development of the digital economy has tended to be a significant item in manufacturing during this period and has the advantages of trans-temporal information transmission and reducing transaction costs [14,15]. It is generally believed that on account of popularization and progress of information technology, digitalization has more and more impact on the sustainable development, and the investigation of the bond between digitalization and carbon dioxide emission has gained increasing attention [16–19]. Much research has shown the diminution effects of digital transformation, mainly on reducing energy consumption. Yang and Hu [20] argued that input digitization significantly contributes to industrial intensity reduction, but there is industry heterogeneity. Digitization can decrease energy use, lower energy strength, and optimize the energy mix. Especially for less-developed regions, digitization has a greater impact on energy use, but it has a smaller impact on energy use in developed regions [21]. Husaini and Lean [22] argued that digitization can reduce the level of total and disaggregated energy consumption and contribute to the strategic goal of energy sustainability through greater investment in digital infrastructure. Digitization is also a key driver of sustainable urban socioeconomics kinetics; it can probably promote climate-friendly urban ambient and communities [23]. At same time, through enhanced R&D investments, green digitization can significantly increase environmental innovation, driving technological innovation in energy storage and leading to a significant digitization trend in energy storage technologies [24–26].

Nevertheless, some researchers believe the blossoming digital technologies are likely to produce negative conditions on carbon emission. Some studies found that due to the rebound effect, efficiency gains from digital technology advances may not necessarily reduce the overall environmental burden, but rather increase industry $CO_2$ emissions to some extent [27,28]. Higon et al. [29] argued the bond between digital technologies and energy intensity with carbon release is a nonlinear "inverted U curvilinear". In the initial stage of switching to digital construction, the evolution of a large amount of infrastructure is inevitably energy-expensive, which significantly adds to the carbon emissions of enterprises. Moreover, after the completion of the infrastructure, maintenance and the introduction of digital talent are required, which will inevitably squeeze energy savings and carbon decreases due to limited budgets, thus giving rise to situations where carbon emissions cannot be reduced. During this time, the carbon emissions of enterprises will increase with the improvement of digital levels [30].

However, when digitalization reaches a certain scale, enterprises gradually reduce their investment in infrastructure, and their employees will master digital technology, which reduces business human capital and optimizes and upgrades their production processes, thus effectively minimizing energy consumption and resource waste creation, and increasing energy-saving and carbon-reducing investment [31]. Enterprises can now consider economic results and economic benefits, and the gradually maturing digital technology also helps to boost improvement in energy efficiency and decreases carbon release to a certain degree, Consequently, enterprises' carbon emissions will decrease with improvement digital levels [32]. Chen et al. [33] assessed the two-sided impact of digitization on the environment, arguing that it can improve the efficiency of resource utilization, but, taking into account the creation and use of hardware, it could bring about an increase in resource and energy use.

As a result, this paper proposes to study the following hypotheses:

**Hypothesis 1 (H1).** *The influence of digitization level on enterprise carbon emissions shows an "inverted U" shape, and there is heterogeneity.*

**Hypothesis 2 (H2).** *Carbon emissions of non-SOEs (state-owned enterprises) are slightly more influenced by digitization levels than SOEs.*

**Hypothesis 3 (H3).** *Carbon emissions by enterprises in the central region are affected by digitalization levels more strongly than those in the non-central regions.*

From the corporate technology innovation path leading to emission reduction, one method of boosting carbon release efficiency is through corporate technology innovation [34]. At the same time, corporate technology innovation has a threshold influence on carbon release merits. Corporate technology innovation has no appreciable devotion to carbon release by those with revenue below the threshold but produces very remarkable action on carbon reduction for those with revenue over the threshold [35]. Moreover, Du and Li [36] argued that corporate technology innovation has a high influence on carbon productivity in high-income economies. Future improvements in corporate technology innovation and the exploit of reproducible energy will be major factors following the reduction in carbon emissions, and the application of non-reproducible energy will also decrease [37]. In addition, adjacent cities have overflow effects on local carbon emission efficiency. Technological innovation can promote local carbon efficiency, but it will suppress the carbon emissions efficiency of surroundings to a certain degree. Technological innovation also has significant heterogeneity among different types of cities [38].

Based on the above analysis, this paper proposes research hypothesis four:

**Hypothesis 4 (H4).** *Corporate technological innovation can influence the intensity of the effect of digitization levels on carbon emissions, and there are regulating effects and threshold effects.*

## 3. Study Design and Model Construction

### 3.1. Model Setting

To explore the conditions of digitalization and technological innovation of companies on carbon emissions in its many forms, fixed-effects panel models and threshold regression models were developed based on the research hypotheses derived from the theoretical analysis, respectively.

The baseline regression model with fixed effects is:

$$\ln CO_{2_{i,t}} = \alpha_0 + \alpha_1 Digital_{i,t} + \alpha_2 Digital^2_{i,t} + \alpha_3 Patents_{i,t} + Controls_{i,t} + \varepsilon_{i,t} \tag{1}$$

where $\ln CO_{2_{i,t}}$ is the variable with the logarithm of firm $i$'s corporate carbon emissions in year $t$, $Digital_{i,t}$ is firm $i$'s digitization level of in year $t$, $Digital^2_{i,t}$ represents the digitalization level's square term in year $t$. $Patents_{i,t}$ is the technological innovation level of firm $i$ in year $t$. $Controls_{i,t}$ represents all control variables and their coefficients, $\alpha_i$ represents each variable's coefficients, $\alpha_0$ means absolute term, $\varepsilon_{i,t}$ means residual term.

The regression pattern with the introduction of the moderating effect variable is:

$$\begin{aligned} &\ln CO_{2_{i,t}} = \alpha_0 + \beta_1 Digital \times Patents_{i,t} + \beta_2 Digital^2 \times Patents_{i,t} + \alpha_1 Digital_{i,t} \\ &+\alpha_2 Digital^2_{i,t} + \alpha_3 Patents_{i,t} Controls_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{2}$$

The interaction terms $Digital \times Patents_{i,t}$ and $Digital^2 \times Patents_{i,t}$ of $Digital$ and $Digital^2$ with $Patents$ are constructed in Equation (2) to examine the adjusting action of corporate technological innovation within the link between digital level and carbon emission.

The threshold regression pattern uses $Patents$ as a threshold variable, where $\gamma_1$ is the threshold value of $Patents$.

$$CO_{2_{i,t}} = \begin{Bmatrix} \alpha_0 + \alpha_{10} Digital_{i,t} + Controls_{i,t} + \varepsilon_{i,t}, Patents < \gamma_1 \\ \alpha_0 + \alpha_{11} Digital_{i,t} + Controls_{i,t} + \varepsilon_{i,t}, Patents \geq \gamma_1 \end{Bmatrix} \tag{3}$$

### 3.2. Sample Selection and Source of Data

With respect to data availability and completeness, the study sample consisted of 1457 annual panel data came from 112 highly energy-intensive companies from 2007–2019. The data on annual carbon emissions and digitalization level are selected from a number of sources, including the annual statements of each public company from the Shanghai and Shenzhen Exchange, social responsibility reports, information on websites of companies and websites of environmental departments. The patents of enterprises are obtained from CSMAR, the CNKI Patent Database, and the State Intellectual Property Office. The other relevant information is obtained from Choice, iFinD and CSMAR. Table 1 shows the data sources.The relevant data are described as seen in Table 2 below.

**Table 1.** Carbon emissions of listed companies with high energy intensity.

| Way to Classify Carbon Emissions of Listed Companies | |
|---|---|
| Combustion and escape emissions | Release from fossil fuel burning<br>Release from biomass fuel combustion<br>Fugitive emissions from raw material extraction<br>Fugitive emissions from oil and gas machinery<br>Indirect carbon emissions from power transfers in and out |
| Production process emissions | |
| Waste emissions | Solid waste incineration emissions<br>Discharges due to sewage treatment |
| Emissions due to ground utilize change (from forest turning to industrial ground) | |

**Table 2.** Descriptive statistics of variables.

| Variables | Observations | Average | S.D. | Min | Middle | Max |
|---|---|---|---|---|---|---|
| $\ln CO_2$ | 1456 | 12.6802 | 1.587 | 6.22 | 12.62 | 17.39 |
| Digital | 1456 | 13.9588 | 20.093 | 0.00 | 8.00 | 176.00 |
| Patents | 1456 | 5.3784 | 21.442 | 0.00 | 0.00 | 307.00 |
| Location | 1456 | 1.8111 | 0.840 | 1.00 | 2.00 | 3.00 |
| Age | 1456 | 26.5357 | 3.524 | 17.00 | 28.00 | 34.00 |
| TDR | 1456 | 0.5645 | 0.428 | 0.01 | 0.56 | 12.24 |
| Ocen | 1456 | 55.9515 | 16.176 | 13.47 | 56.52 | 95.05 |
| Nature | 1456 | 0.8077 | 0.394 | 0.00 | 1.00 | 1.00 |
| Current ratio | 1456 | 1.3874 | 6.026 | 0.01 | 0.86 | 204.74 |
| MER | 1456 | 0.0892 | 0.487 | 0.00 | 0.06 | 15.00 |

### *3.3. Indicator Setting*

#### 3.3.1. Explained Variable: Carbon Emissions ($CO_2$)

Considering the current global value chain division of labor system and the increasing connection between different industries, the methods of Wang et al. [39] were adopted to gauge carbon emissions of each enterprise. According to the "Guidelines on Accounting Methods and Reporting of Greenhouse Gas Emissions by Enterprises" issued by the NDRC for different industries, the total carbon emissions usually disclosed by an enterprise refers to the sum of Scope 1 and Scope 2 emissions. Scope 1 refers to direct GHG (GreenHouse Gas) emissions, which are generated from sources owned or controlled by the enterprise, such as emissions generated from chemical production by process equipment owned or controlled by the enterprise, and Scope 2 refers to indirect GHG emissions generated from purchased electricity and heat consumed by an enterprise. the relevant data of 112 highly energy-intensive enterprises can be found manually in the annual statements of public firms, social responsibility statements of public firms, information on websites of listed companies, and websites of environmental departments each year. The sample years span from 2007–2019. The total emissions are calculated as follows, and the results were logarized and used as indicators to measure corporate carbon emissions.

Carbon emissions from listed companies with high energy consumption = combustion and escape emissions + production process emissions + waste emissions + emissions due to ground utilize change (from forest turning to industrial ground).

#### 3.3.2. Explanatory Variable: Digitalization Level (Digital)

The core essence of enterprise digital diversion is to introduce digital techniques into firm production management, operation, R&D innovation and value creation, ultimately realizing enterprise efficiency improvement and empowering enterprise transformation and development. The current research on digital development level is abundant, but there is no consistent index system for measuring digital development level. Zhang and Zhou [40] mainly refer to the OECD digital economy statistical indicators and the digital economy accounting method of the China ICT Institute to build a three-dimensional indicator system, including technology readiness, business development, and social impact, to measure the digital development level. Yang and Hu [20] introduced two conceptual indicators, direct dependency and complete dependency, to gauge the digitalization level of industrial inputs. Other scholars have studied the use of the number or percentage of digitization-related keywords in annual reports to measure the digital transformation or digitization level of enterprises [41,42].

The usage of words in firms' annual statements can greatly reflect the business philosophy of the enterprise and the future development path guided by this philosophy, and they can also reflect the future strategic direction and development trend of the enterprise. When a firm publishes significant messages about digital transformation in its annual statements, it will then subsequently increase its investment in R&D for digital transformation in order to realize its development strategy. As the digital change of firms is more likely to be favored by the market in times of high-quality progression of the digital economy, firms tend to have greater motivation to put money into R&D to lay a good foundation for digital change for meeting market orientation. When the pace of digital change gradually deepens, the operational efficiency of enterprises improves, and enterprises thus achieve greater output performance [43]. Therefore, this paper adopts the enterprise digital transformation index system constructed by Wu et al. [44] and uses AI technology, big data, cloud computing, blockchain, digital technology use, and digital transformation as characteristic words to represent the degree of digital change of firms. With the Java PDFbox library, we extracted the annual reports of 112 listed highly energy-consuming enterprises in the Shanghai and Shenzhen exchanges. All text contents were searched, matched, and counted by word frequency according to the index system and then classified and aggregated these to form the final wordcount. The total words represented the extent of digital change of listed firms [45]. The squared term of digital level, $\text{Digital}^2$, was also selected to test the non-linear effect of digital level:

$$\begin{aligned} &Digital = AI\ technology + big\ data + cloud\ computing + \\ &blockchain + digital\ technology\ use + digital\ transformation \end{aligned}$$

#### 3.3.3. Threshold Variable: Corporate Technology Innovation (Patents)

The number of enterprise patents held can visually reflect the degree of enterprise technological innovation and help promote economic development and environmental improvement. In this paper, the cumulative number of patents of public companies are selected to weigh the technology innovation capability of each firm.

#### 3.3.4. Control Variables

For the purpose of exploring the impact of the digitalization level of highly energy-intensive enterprises on carbon release, some control variables were selected according to existing papers on enterprise digitalization level and carbon emissions. We controlled the location of the firm, which is split into three variables—the location of the eastern part was set as 1, that of the central part as 2, and that the western part as 3. The age of an enterprise by the cumulative time of listing is called Age. Current_ratio, using current assets/current liabilities, measures the financial risk of enterprises. Total_Debt_Ratio (TDR) uses total liabilities/total assets to measure the solvency of an enterprise. Ownership concentration (Ocen) is used to measure the ownership concentration of listed companies by the top 10 shareholders. For the nature of enterprises (Nature), the sample of 112 highly energy-intensive enterprises is allocated to state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs); SOEs are designated as 1, while non-SOEs were designated as 0. Management expense ratio (MER), management expense/operating revenue is used to measure the level of business management. The time-fixed effect variable was also set.

## 4. Empirical Studies

### 4.1. Baseline Model Regression

The regression outcomes are given in Table 3. Column (1) of the outcome without Digital2 shows that Digital is significant at the 1% level, implying that the degree of carbon emissions of enterprises is positively bound to digitalization and that the carbon emissions of firms increase with digitalization degree. Column (2), including the control variables, shows that the positive bond between enterprise carbon release and digitalization level is still significant at the 1% level. The following outcomes with the addition of the squared term Digital2 are shown in Column (3). Column (4) includes other variables, and it turns out that the Digital coefficients of all are notably positively related (0.0283) and the Digital2 values are all notably negatively related (−0.0002) at the 1% level. Additionally, the range of Digital level is [0, 176], with a slope of 0.0283 at the left endpoint and of −0.0421 at the right endpoint. After calculation, the inflection point is 70.75, which falls within the range of the digitization level. It turns out that the digital effect on a firm's carbon emission is a non-linear "inverted U" type relationship. This conclusion is consistent with previous scholars [1,46–49]. At the early stage of digital transformation, massive energy consumption is needed for infrastructure construction, and at the same time, the digitalization construction squeezes the investment in energy saving and carbon reduction, which leads to a situation in which carbon emissions cannot be reduced but increase with the growth of the digitalization level. When the digital construction reaches a certain scale, the enterprises complete the transformation and upgrading of the production process; thus, they will gradually reduce the investment in digital infrastructure and increase attention given to energy and carbon reduction. At this time, the carbon emissions decrease in line with the digital improvement. At present, the average value of the digitalization level of the sample is 13.9588, the median value is 8, but the max is 176, so it can be concluded that the majority of enterprises' digitalization level has not reached the inflection point on carbon emissions and that enterprises still need to continue to develop their own digitalization levels. The coefficients of enterprise location, gearing ratio, equity concentration, and management expense ratio are all significantly positive, and their $p$ values are all less than 0.1. Hypothesis 1 is authenticated.

**Table 3.** Regression results of digital's effect on carbon release of enterprises.

| | (1)<br>$\mathbf{lnCO_2}$ | (2)<br>$\mathbf{lnCO_2}$ | (3)<br>$\mathbf{lnCO_2}$ | (4)<br>$\mathbf{lnCO_2}$ |
|---|---|---|---|---|
| Digital | 0.0140 ***<br>(13.3558) | 0.0136 ***<br>(13.1482) | 0.0293 ***<br>(13.9394) | 0.0283 ***<br>(13.5522) |
| $Digital^2$ | | | −0.0002 ***<br>(−8.3486) | −0.0002 ***<br>(−8.0553) |
| Location | | −0.5760 ***<br>(−6.0263) | | −0.5826 ***<br>(−6.1827) |
| Age | | −0.0448<br>(−1.3187) | | −0.0439<br>(−1.2954) |
| TDR | | 0.2096 ***<br>(3.8196) | | 0.2091 ***<br>(3.8989) |
| Ocen | | 0.0092 ***<br>(4.4326) | | 0.0076 ***<br>(3.7234) |
| Nature | | 0.0936<br>(0.7574) | | 0.1209<br>(0.9983) |
| Current ratio | | −0.0002<br>(−0.0685) | | −0.0003<br>(−0.1074) |

**Table 3.** *Cont.*

| | (1) $lnCO_2$ | (2) $lnCO_2$ | (3) $lnCO_2$ | (4) $lnCO_2$ |
|---|---|---|---|---|
| MER | | −0.2273 *** (−5.0988) | | −0.2184 *** (−5.0145) |
| _cons | 12.4853 *** (92.6688) | 14.0330 *** (14.6795) | 12.3681 *** (91.3081) | 13.9757 *** (14.6765) |
| YEAR | YES | YES | YES | YES |
| ENTERPRISES | YES | YES | YES | YES |
| *N* | 1456 | 1456 | 1456 | 1456 |

Note: The $t$ statistic is in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.The same below.

Table 4 shows regression outcome by enterprises industry classification, which are in the same direction as the overall outcome, showing digitalization's effect on enterprises' carbon emissions. It turns out that the relationship between enterprises' carbon release in each industry with digitalization is positively correlated, their $p$ values are less than 0.1, and the squared term with the level of digitalization is negatively related at the 1% level. Among them, the electric power industry is most affected by digitization level. The impact coefficient between its carbon emissions and digitization level is 0.0375, and it has a coefficient of −0.0004 with $Digital^2$.

**Table 4.** Regression outcome of the influence of digitization level on enterprises' carbon release by industry.

| | (1) Electric Power Companies $lnCO_2$ | (2) Chemical Companies $lnCO_2$ | (4) Non-Ferrous Metal Enterprises $lnCO_2$ |
|---|---|---|---|
| Digital | 0.0375 *** (6.5721) | 0.0282 *** (10.6364) | 0.0353 *** (6.3734) |
| $Digital^2$ | −0.0004 *** (−4.4216) | −0.0001 *** (−6.3250) | −0.0002 *** (−4.5486) |
| Location | −0.6629 *** (−5.6229) | −0.1631 (−1.0009) | −0.9845 *** (−5.2739) |
| Age | 0.0451 (1.1040) | 0.0080 (0.2158) | −0.2449 (−1.2706) |
| TDR | 0.8844 *** (3.4253) | 0.1729 *** (2.6261) | 0.1715 (0.3199) |
| Ocen | 0.0224 *** (6.4944) | 0.0017 (0.6572) | 0.0072 (1.0083) |
| Nature | 1.1060 *** (2.9191) | −0.0584 (−0.4531) | 0.4118 (1.0880) |
| Current_ratio | 0.0568 (1.1443) | −0.0000 (−0.0133) | −0.1016 (−1.3590) |
| MER | −0.0737 (−1.0993) | −0.2018 *** (−3.1510) | −0.6746 *** (−4.4824) |
| _cons | 8.6764 *** (7.3397) | 12.5928 *** (11.2680) | 20.4698 *** (4.0234) |
| Industry | YES | YES | YES |
| Year | YES | YES | YES |
| *N* | 520 | 767 | 169 |

### 4.2. Robustness Tests

#### 4.2.1. Dealing with Endogeneity

An inverse causal link between the growth of digitization of companies and carbon release cannot be excluded. To reduce or even eliminate the possible endogeneity problem in the model and its resulting estimation bias, as shown in Table 5, this paper takes Feng et al.'s [50] approach of adopting the introduction of digitization level's first order lagged section as an instrumental variable for 2SLS regression. The coefficient of digitization level remains positive, proving the robustness of the above results. So far, Hypothesis H1 is more comprehensively verified.

**Table 5.** Regression outcome considering endogeneity.

| | **(1)**<br>**ln$CO_2$** | **(2)**<br>**ln$CO_2$** |
|---|---|---|
| Digital | 0.033 ***<br>(0.002) | 0.027 ***<br>(0.002) |
| Location | | −0.478 ***<br>(0.046) |
| Age | | −0.043 ***<br>(0.010) |
| TDR | | 0.376 **<br>(0.188) |
| Ocen | | 0.029 ***<br>(0.003) |
| Nature | | 0.068<br>(0.100) |
| Current_ratio | | 0.013<br>(0.002) |
| MER | | −0.784 **<br>(0.304) |
| _cons | 12.387 ***<br>(0.055) | 13.084 ***<br>(0.365) |
| YEAR | YES | YES |
| ENTERPRISES | YES | YES |
| *N* | 1344 | 1344 |
| $R^2$ | 0.761 | 0.828 |

#### 4.2.2. Adjusting Sample Size

The limited sample size may lead to errors, which may have some influence on the overall regression results. Here, taking Yang and Hu's [20] approach reduces the data of some enterprises, and the coefficients are found to be positive for Digital and negative for Digital$^2$. $p$ values are less than 0.01, similar to the previous results.

#### 4.2.3. Removing the Last Two Years of Data

Also consider sample limitations and business development; the firms' data are unchanged when the last two years of their data are removed. It was found that the $p$-values for both Digital and Digital$^2$ were less than 0.01. Additionally, the coefficients are significant, and the Digital coefficient is positive while the Digital$^2$ coefficient is opposite, which is consistent with the above results and validate model robustness.

#### 4.2.4. Random Effect Model Estimation

According to the results in Table 6, the relevant analysis is as follows.The above regression results use fixed effects. Since fixed-effects models are more appropriate for examining differences between samples, while random effects are more appropriate for inferring aggregate characteristics from samples. When the random effects model is used to estimate the sample, there is no significant direction change between digitalization level and carbon release of companies, so the conclusion is consistent with the previous one, which again verifies the research findings.

**Table 6.** Robustness tests.

| | **Reduction of Some Enterprises** | | **Removing the Last Two Years** | | **Random Effects Model** | |
|---|---|---|---|---|---|---|
| | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** |
| | **ln$CO_2$** | **ln$CO_2$** | **ln$CO_2$** | **ln$CO_2$** | **ln$CO_2$** | **ln$CO_2$** |
| Digital | 0.0288 ***<br>(13.5773) | 0.0278 ***<br>(13.0644) | 0.0250 ***<br>(10.5814) | 0.0244 ***<br>(10.3791) | 0.0291 ***<br>(13.7920) | 0.0281 ***<br>(13.4161) |
| Digital$^2$ | −0.0002 ***<br>(−8.1658) | −0.0002 ***<br>(−7.8191) | −0.0001 ***<br>(−6.5430) | −0.0001 ***<br>(−6.3638) | −0.0002 ***<br>(−8.2881) | −0.0002 ***<br>(−7.9812) |
| location | | −0.5821 ***<br>(−6.1539) | | −0.5392 ***<br>(−5.4844) | | −0.6001 ***<br>(−4.8387) |
| age | | −0.0386<br>(−1.1171) | | −0.0392<br>(−1.1414) | | 0.0000<br>(.) |
| TDR | | 0.1391 **<br>(2.5273) | | 0.1846 ***<br>(3.4765) | | 0.1989 ***<br>(3.7020) |
| Ocen | | 0.0069 ***<br>(3.2844) | | 0.0063 ***<br>(2.7832) | | 0.0067 ***<br>(3.2007) |
| nature | | 0.1624<br>(1.1755) | | 0.0852<br>(0.6632) | | 0.1140<br>(0.8735) |
| Current_ratio | | −0.0000<br>(−0.0160) | | 0.0004<br>(0.1368) | | −0.0004<br>(−0.1269) |
| MER | | −0.1453 ***<br>(−3.1588) | | −0.1874 ***<br>(−4.3647) | | −0.2109 ***<br>(−4.8425) |
| _cons | 12.3976 ***<br>(87.0759) | 13.8911 ***<br>(14.3111) | 12.3681 ***<br>(90.5340) | 13.8817 ***<br>(14.3314) | 12.3705 ***<br>(481.5080) | 12.9056 ***<br>(46.8641) |
| Control | | √ | | √ | | √ |
| ENTERPRISES | √ | √ | √ | √ | | |
| YEAR | √ | √ | √ | √ | | |
| $N$ | 1365 | 1365 | 1232 | 1232 | 1456 | 1456 |
| Adj. $R^2$ | 0.897 | 0.812 | 0.882 | 0.865 | 0.860 | 0.821 |

### *4.3. Heterogeneity Test*

To consider the influence of heterogeneity of samples, the research data are classified into state-owned enterprises (SOEs) and non-state-owned enterprises (non-SOEs). The outcomes of SOEs and non-SOEs are displayed in Columns (1) and (2), respectively, of Table 7 below, and these show that the level of digital development of the vast majority of enterprises in China have not yet hit the knee point and that digital development of enterprises with respect to carbon emissions is still in the promotional stage. The factor of Digital in Column (1) is notably positive, and the $p$ value is under 0.01. The factor of Digital in Column (2) is notably positive, and the $p$ value is under 0.05. These figures imply that the level of digitalization differs in the sample of enterprises with the different nature of property rights, among which the carbon emissions of non-SOEs are slightly more affected by the level of digitalization than those of SOEs. Thus, Hypothesis 2 is valid. Columns (3), (4), and (5) classify companies based on their location into east, middle, and west companies, respectively. The coefficient of carbon release and digitalization level in the eastern region is notably positive, and the *p* value is under 0.05. At the same time, the coefficient between carbon emissions and digitalization level in central is significantly positive, and the *p* value is less than 0.01. The coefficient in the western region is not significant. The reason for these results is that the east was the first to develop its digitalization level, and it has been effective to a small extent. Thus, the trend of the positive influence of digitization on carbon release decreases relatively. The development of the central region ushered in new opportunities for digital development, so the construction of a large amount of digital infrastructure will add carbon release, creating a coefficient as high as 0.033. With central industry's digital change and the elimination of backward production capacity, the effect of carbon reduction will become increasingly significant. The reason why the digitalization level of enterprises from the west is unremarkable may be that the digital industry foundation is relatively weak, so the industry chain has not formed yet, and the digital economy's pivot industries are small in scale. Therefore, they are not yet able to have an impact on enterprise carbon emissions. In addition, from the regression results, it can be seen that the development of the Digital level of most enterprises in China has not yet reached that point, and the impact of enterprise digital development on enterprise carbon emissions is still in the promotion stage. The sub-sample regression only considers the linear relationship between digital level and carbon dioxide emissions, at which time the impact of digital development on corporate carbon emissions has obvious subregional sub-property heterogeneity promotion. Similarly, due to the limited development of digital level, it is still in the development stage, the inhibition of carbon emissions has not yet fully come into play, so the R square value will be relatively small, but the regression results are significant can indicate that the improvement of digital level can significantly promote carbon emission reduction.

**Table 7.** Sub-sample regression results.

| | **(1)**<br>**$lnCO_2$** | **(2)**<br>**$lnCO_2$** | **(3)**<br>**$lnCO_2$** | **(4)**<br>**$lnCO_2$** | **(5)**<br>**$lnCO_2$** |
|---|---|---|---|---|---|
| Digital | 0.011 ***<br>(0.003) | 0.015 **<br>(0.006) | 0.006 **<br>(0.002) | 0.033 ***<br>(0.005) | 0.007<br>(0.005) |
| Location | −0.139<br>(0.105) | −0.808<br>(0.611) | 0.000<br>(.) | 0.000<br>(.) | 0.000<br>(.) |
| TDR | 0.039<br>(0.107) | 0.826 ***<br>(0.092) | 0.598 ***<br>(0.181) | −0.007<br>(0.042) | 0.231<br>(0.211) |
| Ocen | 0.009 ***<br>(0.002) | 0.005<br>(0.004) | 0.012 ***<br>(0.003) | 0.006 *<br>(0.003) | 0.003<br>(0.003) |
| Nature | 0.000<br>(.) | 0.000<br>(.) | 0.104<br>(0.165) | 0.156<br>(0.227) | 0.382 **<br>(0.147) |
| Current_ratio | −0.038 **<br>(0.015) | 0.002 ***<br>(0.001) | 0.002 **<br>(0.001) | −0.267 ***<br>(0.083) | −0.040 **<br>(0.018) |
| MER | −0.146<br>(0.113) | −0.639 ***<br>(0.083) | −7.878 ***<br>(0.705) | −0.026<br>(0.027) | −0.907 ***<br>(0.175) |
| _cons | 12.368 ***<br>(0.197) | 13.100 ***<br>(1.001) | 12.420 ***<br>(0.278) | 12.162 ***<br>(0.267) | 11.425 ***<br>(0.261) |
| YEAR | YES | YES | YES | YES | YES |
| ENTERPRISES | YES | YES | YES | YES | YES |
| *N* | 1176 | 280 | 677 | 377 | 402 |
| $R^2$ | 0.914 | 0.834 | 0.932 | 0.889 | 0.870 |

Note: The *t* statistic is in parentheses; ** $p < 0.05$, *** $p < 0.01$.

Hypothesis H3 is verified.

## 5. Moderation Effect and Threshold Effect

### 5.1. Analysis of Reconciliation Effects

The interaction terms Digital × Patents and Digital$^2$ × Patents are introduced to test Hypothesis H4. Table 8 below implies a regression outcome of moderating effect. It indicates that the Column (1) Digital coefficient is notably positive and that the $p$ value is under 0.01. Digital$^2$ is notably negative under the 1% level as well. Digital × Patents in (3) is notably negative, and the $p$ value is under 0.05, but Digital$^2$ × Patents is not significant. These indicate that enterprise technological innovation has an adjustment action concerning the impact of enterprise digitalization level on carbon emissions, and a firm's technical innovation ability can flatten the relationship curve of the positive influence of enterprise digitalization level on carbon release. As enterprise technological innovation strengthens, the inflection point of the impact of the digitalization level will move to the left, thus promoting the decrease of enterprise carbon release.

**Table 8.** Regression outcome of the moderated effects.

| | **(1)**<br>**ln$CO_2$** | **(2)**<br>**ln$CO_2$** | **(3)**<br>**ln$CO_2$** |
|---|---|---|---|
| Digital | 0.0366 ***<br>(9.1995) | 0.0315 ***<br>(8.0431) | 0.0354 ***<br>(8.8762) |
| Digital$^2$ | −0.0002 ***<br>(−5.4866) | −0.0002 ***<br>(−4.5100) | −0.0002 ***<br>(−5.1124) |
| Digital × Patents | | | −0.0007 ***<br>(−2.9196) |
| Digital$^2$ × Patents | | | 0.0000<br>(1.5146) |
| Patents | | 0.0152 ***<br>(8.9238) | 0.0278 ***<br>(7.7576) |
| Location | −0.5127 ***<br>(−11.2692) | −0.5076 ***<br>(−11.4562) | −0.5160 ***<br>(−11.7107) |
| Age | −0.0360 ***<br>(−3.4179) | −0.0252 **<br>(−2.4339) | −0.0245 **<br>(−2.3855) |
| TDR | 0.5488 ***<br>(5.1910) | 0.5843 ***<br>(5.6714) | 0.5791 ***<br>(5.6541) |
| Ocen | 0.0188 ***<br>(7.9184) | 0.0162 ***<br>(6.9673) | 0.0154 ***<br>(6.6372) |
| Nature | 0.0331<br>(0.3458) | 0.0611<br>(0.6550) | 0.0674<br>(0.7273) |
| Current_ratio | 0.0045<br>(0.7260) | 0.0045<br>(0.7502) | 0.0046<br>(0.7752) |
| MER | −0.5573 ***<br>(−6.0141) | −0.5694 ***<br>(−6.3082) | −0.5607 ***<br>(−6.2503) |
| _cons | 12.8348 ***<br>(36.0537) | 12.6041 ***<br>(36.2551) | 12.5974 ***<br>(36.4701) |
| YEAR | √ | √ | √ |
| ENTERPRISES | √ | √ | √ |
| $N$ | 1456 | 1456 | 1456 |
| Adj. $R^2$ | 0.834 | 0.874 | 0.883 |

### 5.2. Threshold Effect Analysis

As shown in Table 9, the analysis in this section is as follows.To further look into enterprise technology innovation and the influence of digitalization level on enterprise carbon release, the threshold regression pattern is used to empirically examine whether there is a significant threshold value for enterprise technology innovation. Furthermore, to determine whether a remarkable variance exists in the influence of digitalization level on enterprise carbon emissions in different level ranges of enterprise technology innovation, and to verify Hypothesis H4, enterprise technology innovation is used as the threshold. The threshold examination is conducted through the self-sampling test of the threshold effect, and it was found that there is a significant single threshold action in the electric power industry and the chemical industry. From the F-statistic and the *p*-value obtained via the bootstrap method, it appears that only technological innovation under the single threshold regression model passes at a 5% remarkable level. This shows that the moderating effect of technological innovation in the mechanism will be strengthened when the patents of the sample in the electric power industry reach 45 and above and when the patents of the sample in the chemical industry reach 26 and above. Hypothesis 4 is verified.

**Table 9.** Single-threshold influence self-sampling test.

| Industry | Variable | Threshold | F | *p*-Value | Critical 1% | Critical 5% | Critical 10% | Threshold |
|---|---|---|---|---|---|---|---|---|
| Power Industry | patents | Single | 35.36 | 0.0067 | 29.8732 | 18.8868 | 13.3412 | 45 |
| Chemical industry | patents | Single | 25.01 | 0.0233 | 29.7040 | 18.9582 | 16.9859 | 26 |

Note: BS count is 300.

Table 10 shows the model outcome for the threshold values. Column (1) shows the outcome of the model with Patents as the threshold variable in the electric power industry. When Patents exceeds 45, the digitalization level's correlation on enterprise carbon release converts from positive to negative, the coefficient decreases from 1870.802 to $-5.0 \times 10^4$ and changes from insignificant to significant. Column (2) implies the regression outcome of the model with Patents as the threshold value in the chemical industry. When Patents exceeds 26, the active action of digitalization level on firms' carbon emissions is significantly weakened; the coefficient decreases from 97.774 to $3.5 \times 10^4$ and turns from insignificant to significant. This shows that enterprises with higher level of technological innovation can mitigate the active action of the digitalization level on enterprises' carbon release in early stages, so the digitalization level can exert the inhibitory effect on carbon emissions in advance.

**Table 10.** Threshold model regression results.

| | (1)<br>Power Industry<br>$CO_2$ | (2)<br>Chemical Industry<br>$CO_2$ |
|---|---|---|
| Digital$^2$ | −34.669<br>(63.378) | 16.280<br>(40.413) |
| Patents | $1.4 \times 10^4$ ***<br>(1480.854) | $1.1 \times 10^4$ ***<br>(3696.530) |
| TDR | $1.6 \times 10^5$<br>($1.8 \times 10^5$) | $2.4 \times 10^5$ **<br>($1.1 \times 10^5$) |
| Ocen | −509.720<br>(2396.030) | 4172.574<br>(4522.120) |

**Table 10.** *Cont.*

| | (1) Power Industry $CO_2$ | (2) Chemical Industry $CO_2$ |
|---|---|---|
| Current_ratio | $-3.2 \times 10^3$ ($3.2 \times 10^4$) | 272.580 (4550.988) |
| MER | $-1.2 \times 10^4$ ($4.3 \times 10^4$) | $-2.4 \times 10^5$ ** ($1.0 \times 10^5$) |
| Digital (Patents < 45) | 1870.802 (4345.364) | |
| Digital (Patents > 45) | $-5.0 \times 10^4$ *** (9841.989) | |
| Digital (Patents < 26) | | 97.774 (5120.596) |
| Digital (Patents > 26) | | $3.5 \times 10^4$ *** (8398.625) |
| _cons | $2.0 \times 10^5$ ($2.0 \times 10^5$) | $1.9 \times 10^5$ ($2.9 \times 10^5$) |
| Control | √ | √ |
| YEAR | √ | √ |
| INDUSTRY | √ | √ |
| Sample size | 520 | 767 |
| F | 10.048 | 11.592 |
| $R^2$ | 0.904 | 0.852 |

## 6. Conclusions and Implication

### *6.1. Conclusions*

With the digital change and Industrial Revolution 4.0 driving the osmosis of digital learning and information technology in all areas of the society [51–53], and according to practical examination enterprises of low carbon change, we selected 112 highly energy-intensive enterprises in China from 2007–2019 as the observation sample. We incorporated the effect of digitalization level on $CO_2$ release into the study and explored the regulation mechanism of enterprise technology innovation on digitalization level affecting enterprise carbon emissions. The study determined that:

(1) The digitalization levels of firms have an "inverted U" effect on carbon emissions and that after the inflection point the carbon release by firms decreases as the digitalization level increases; the effect has heterogeneous; the carbon release by non-SOEs are less influenced by the digitalization level than those of SOEs; and the carbon release of enterprises in the central region are more influenced by the digitalization level than those in the non-central areas.

(2) Enterprise technical innovation has a reinforcing moderating action on digitalization level to promote a decrease in enterprise carbon release; under the impact of enterprise technology innovation, the digitalization level will show the inhibiting influence on carbon release in advance, but the impact is limited at present, which means the progress of Chinese digital economy still needs to be strengthened [54].

(3) The empirical research on the threshold pattern found that when the enterprise technological innovation reaches a certain level, the digitalization level makes a greater contribution to decreasing enterprise carbon release.

### 6.2. Implications

According to findings of this paper, from the research object's point of view, the majority of current discussions on carbon reduction come from the macro level, such as carbon reduction studies in various provinces and regions, but this paper focuses on highly energy-intensive enterprises. Secondly, according to the research method, the bond between digitalization level and carbon release is an "inverted U", differing from the simple linear connection found in the existing literature and providing empirical evidence to support the development of digitalization levels. Considering the moderating and threshold effects of technological innovation, it is clearly possible to accelerate the process of digitalization levels inhibiting the carbon emissions of enterprises.

To make the goal of carbon reduction development come true and to help China achieve the target of carbon peaking and carbon balance, we need to improve the digitalization level of highly energy-intensive enterprises through various means. At the micro-enterprise level, the progress of digital economy should be accelerated. Firstly, we can add to the construction of infrastructure to carry digital technology platforms, lay out new infrastructure in a targeted manner, and establish digital management platforms and development platforms for enterprises [45]. Additionally, we can raise digital management levels and operation within enterprises, promote the change and escalation of the traditional industrial chain, and accelerate the formation of a digital management systems with data mining, analysis, and application as the core [55]. Secondly, management experience and strengthened staff training need to be introduced. Enterprises can improve the motivation and efficiency of employees by introducing advanced management experience and conducting regular training on digital technology for employees. Thirdly, we should increase the investment in technology and scientific innovation in the digital field. As the digital development stage has certain energy consumption characteristics, while vigorously developing enterprise digitalization, we should avoid extensive growth. We can also introduce advanced low-carbon technology and increase the investment in R&D, strengthen the training of digital talents, and maximize cooperation between research institutes, business, and research universities to develop more talent for the future digital development of enterprises [56,57].

Macro national policy implementation can introduce policies that can inspire firms to complete digital transformation. The state should combine the characteristics of industry development and increase policy support, such as introducing preferential policies to encourage low-carbon adoption by firms, and improving the enthusiasm of firms, especially state enterprises. Furthermore, considering the regional heterogeneity of firms, differentiated and targeted incentives and subsidy policies that help enterprises in different regions to successfully achieve low-carbon changes need to be implemented. Reforms to the market mechanism for SOEs and non-SOEs, such as the carbon emission trading mechanism to eliminate outdated and inefficient enterprises and effectively realize supply-side reform, also need to be promoted [26]. Finally, we should increase funding assistance for the technological innovation behavior of firms as well as protection property rights, create a fair market environment to improve the aggressiveness of firms for technological innovation in energy saving and emission decrease, and encourage firms to realize breakthroughs in low-carbon technologies, production processes, and research and development of production equipment.

### 6.3. Limitations

The digital economy in China is developing faster and faster, and the impact of digitalization level on enterprises is deepening. Due to the immaturity of digitalization level measurement methods and the limitation of industry-level data acquisition and digital economy statistics, this paper has some limitations. This paper focuses on the empirical study of the bearing of digitalization on the carbon release of firms with high energy consumption and only proposes qualitative judgment and research hypotheses regarding digitalization on firms' carbon release, but it does not study the mechanism of the influence of digitalization on firms' carbon release. In the future, there will be a need to carry out an in-depth theoretical exercise in order to grasp more comprehensively and systematically the effect of digitalization on the promotion of the "double carbon" target.

**Author Contributions:** Conceptualization, X.L.; Method, X.W.; Software, X.W.; Verification, Y.Z.; Resources, X.L. and R.Y.; Data Management, X.W.; Writing—Original manuscript preparation, X.W.; Writing—Review and editing, X.L. and R.Y.; Visualization, X.W.; Supervising, X.L. and R.Y.; Project management, R.Y. All authors have read and agreed to the published version of the manuscript.

**Funding:** This paper obtained the Key Project of Social Science Planning of Anhui Province (approved No. AHSKZ2021D14), the General Project of Social Science Planning of Anhui Province (approved No. AHSKY2021D50), the research topic of Social Science Federation of Anhui Province (approved No. 2021CX038), and the Anhui Provincial University Scientific Research Plan on Social Science Key Project (approved No. 2022AH050542), Anhui Province New Era Education and Training Program for Postgraduates Quality Engineering Project (approved No. 2022shsjsfkc016, 2022jyjxggyj278), Anhui Provincial Quality Engineering Project for Higher Education Institutions (approved No. 2022zybj001, 2021sx005), Anhui University of Finance and Economics general project (approval No. ACKYC22052), Anhui BIM Engineering Center Open Subject (approval No. AHBIM2022KF01).

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Informed consent was obtained from all subjects involved in the study.

**Data Availability Statement:** Not applicable.

**Acknowledgments:** The authors are grateful to the host institution for providing the necessary assistance in conducting this study. This is also the joint efforts of all research members.

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

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