LUND UNIVERSITY
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# The Impact of China's Digital Economy Development on Carbon Emissions - Taking 31 Key Cities as Evidence

by

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**Abstract:** Environmental deterioration led by global warming is accelerating, and low-carbon development has become a global consensus. China, as the world's largest developing country, has also responded to low-carbon development and proposed a "30.60" dual-carbon target aimed at reducing carbon emissions. At the same time, the third industrial revolution oriented by information and communication technology (ICT) is taking place. Driven by new technologies such as the Internet and big data, the digital economy has become an important engine for high-quality economic development in China. However, while the digital economy promotes high-quality economic development, can it also promote China's low-carbon development? Based on the panel data of 31 key cities in China from 2011 to 2019, this paper explores the impact of digital economy development on carbon emissions through corresponding econometric models, and analyzes its potential mechanism based on the results. The results show that: First, there is a linear relationship between the digital economy development and carbon emissions of these 31 key cities in China, and digital economy development can restrain carbon emissions. Second, the results of this study are inconsistent with the existing research results, the reason may be the differences in model measurement scale and sample characteristics, and indirectly shows that there are differences in the level of digital economy development among Chinese cities. Third, the potential mechanism behind this relationship may be that digital economy development suppresses carbon emissions by improving innovation efficiency, promoting high-quality economic development, influencing government interventions, and applying ICT to improve energy efficiency or reduce energy consumption. Based on the above conclusions, this study draws the following practical implications: first, improve the speed and quality of digital economy development; second, improve the cultivation of digital talents; third, optimize the performance appraisal index system; fourth, formulate a digital economy development strategy that is compatible with regional differences, so as to reduce carbon emissions.

**Keywords**: Digital economy; Carbon emissions; Low-carbon development; Information and communication technology (ICT); Inverted U-shape; Environmental Kuznets Curve (EKC)

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# 1. Introduction

The continuous increase of greenhouse gases, mainly carbon dioxide, has led to accelerated global glacier melting, sea level rise, drought and flood polarization, and other extreme phenomena. In the increasingly serious global climate problem, promoting low-carbon development has become a consensus of all walks of life. As the world's largest developing country, China has responded to low-carbon development while developing its economy at a rapid pace. At the UN General Assembly, China put forward the "30.60" dual carbon goal, that is, strive to achieve carbon peak in 2030 and carbon neutrality in 2060 (Lu, Chen, Fan & Lu, 2022). Since the proposal of the dual carbon targets, many scholars have also conducted research and analysis on China's carbon emission reduction. There have been numerous studies demonstrating that economic development (Xu, Zhang, Li, Zhang & Yin, 2018; Xu & Song, 2010), population size (Chen, Wu, Ma, Liu, Cai, Liu, Jia, Zhang, Chen, Xu, Zhao & Wang, 2018; Lu et al., 2022), industrial structures (Chen et al., 2018; Xu et al., 2018), and many other factors can have an impact on carbon emissions. However, with the development of science and technology, the third industrial revolution oriented by information and communication technologies (ICT) is underway (Taalbi, 2019). Since Tapscott (1996) formally proposed the concept of the digital economy, the digital economy has sparked extensive discussion in academia. Pan, He and Pan (2021) pointed out that the digital economy is a new economic form that promotes the development of productivity and high-quality economy after the agricultural economy and industrial economy. The basic element of the agricultural economy is land, the basic element of the industrial economy is machines, and the basic element of the digital economy is data. At the same time, relevant government departments have also paid full attention to the development of the digital economy. In 2017, China's "Government Work Report" explicitly proposed "digital economy" for the first time; In April 2023, Chinese President Jinping Xi once again stressed the importance of the development of the digital economy at the 6th China Construction Summit. According to the relevant information of "China Academy of Communications", the scale of China's digital economy was 22.4 trillion yuan in 2016 and reached 35.8 trillion yuan in 2019, accounting for 36.2% of GDP, a year-on-year nominal growth of 15.6% on a comparable basis, much higher than the GDP growth rate. In the context of today's era, the development of the digital economy has a broad and far-reaching impact on the economy and society, and has become the core force leading technological change, industrial transformation and the evolution of the international competition pattern.

However, there are still certain research gaps in the academic community on the link between China's digital economy development and carbon emissions. In the field of environment, a large number of studies have explored the factors affecting carbon emissions and given corresponding policy implications. In the field of economic development, most studies have focused on the impact of China's digital economy development on high-quality economic development and scientific and technological innovation, and only a few studies have explored the impact of China's digital economy development on the environment. Although some studies have discussed the impact of the digital economy on carbon emissions, the conclusions reached in these few studies are controversial. Some studies are scaled at the provincial level in China (Zhang & Li, 2022), some on a large number of prefecture-level cities in China (Lu et al., 2022), and some on regional China (Xie, 2021). This paper explores the impact of digital economy development on carbon emissions from 31 key cities in China. Therefore, the research in this paper is of great significance: first, this research can fill the gaps in the field of environment and economic development; Second, this research can supplement the relevant conclusions from a completely new scale; Third, the proposal of the dual carbon goal and the emphasis on digital economy represent China's ambition on carbon emission reduction and the development of digital economy, so this study can provide reference suggestions for relevant policies.

## 1.1 Aim and Scope

Although existing studies have begun to explore the impact of the digital economy on the environment, there are still many questions that need to be answered urgently: How does the digital economy development in Chinese cities affect carbon emissions? Is there a linear relationship between the two? What is the underlying mechanism behind this relationship? Therefore, this paper aims to explore the impact of digital economy development on carbon emissions based on evidence from 31 key cities in China. The corresponding research questions raised in this paper are as follows.

**Research Question:** What is the impact of digital economy development on carbon emissions?
**Sub-question:** What is the potential mechanism of the impact of digital economy development on carbon emissions?

It is worth mentioning that these 31 cities are called key cities because they include all provincial capitals (except Lhasa) and municipalities directly under the central government in China, and are higher than other prefecture-level cities in terms of political level and economic development. Therefore, after obtaining the corresponding research results, the proposed policy implications will be more targeted.

In order to achieve the aim of this research, this paper attempts to fit the relationship between digital economy development and carbon emissions through historical data. This paper will use the panel data of 31 key cities from 2011 to 2019, and use the corresponding econometric model to study the impact of digital economy development on carbon emissions. After obtaining the model regression results, by comparing and discussing the results of this paper with the existing relevant research results, the potential mechanism of the impact of digital economy development on carbon emissions is analyzed. Finally, the corresponding conclusions and policy implications of this paper are obtained.

## 1.2 Delimitation

The delimitation in this paper mainly comes from two aspects: method and data collection. First, the selection of different econometric models will cause corresponding limitations and errors. At the same time, the accuracy of the model regression results cannot be guaranteed. To eliminate this problem, two econometric models are selected, one as the main regression model and the other as the robustness test. This eliminates the problems caused by model selection and ensures the accuracy of the regression results. Secondly, based on the research questions and methods in this paper, the amount of data collected will be large and multi-dimensional, so data collection will be a major challenge. In order to eliminate this problem, this paper narrows the sample size and selects 31 key cities from 2011 to 2019 as samples to ensure data integrity and reliability. However, the by-problem with shrinking the sample size is that these 31 key cities are not representative of China as a whole. Therefore, the results of this paper will only represent the pattern between digital economy development and carbon emissions in these 31 key cities, and do not represent the conclusions of this paper. After obtaining the results of this paper, the conclusions of this paper are further obtained by comparing and discussing with other research results.

### 1.3 Thesis Outline

The remainder of this paper will be divided into the following sections. The second section will review some existing relevant literature, including the current status of carbon emissions in China (section 2.1), influencing factors of carbon emissions in China (section 2.2) and digital economy (section 2.3). In section 3, the theoretical framework of this paper will be explained according to the literature review, and the corresponding hypotheses of this paper will be put forward based on theoretical analysis. The fourth section is Data and Method, which will describe the data collection and methodology of this paper, including the construction process of the digital economy development index. The fifth section will conduct an empirical analysis of the model regression results obtained in this paper, including the description of the results in section 5.1 and the discussion of the results in section 5.2, of which section 5.2.2 will discuss the potential mechanism of the impact of digital economy development on carbon emissions. Finally, this paper will end with the sixth section. On the basis of the summarized conclusions, the practical implications of this paper and the future research directions in related fields are proposed.

# 2. Literature Review

### 2.1 Current Status of Carbon Emissions in China

The increasing severity of global warming has caused major damage to the environment (Wallace, Held, Thompson, Trenberth & Walsh, 2014). Due to the rapid economic development in the past 30 years, China's carbon emissions are currently the highest in the world and are still growing rapidly (Xu et al., 2018). In the past few decades, China's total carbon emissions have experienced a rapid increase from 1980 to 1996, a stable period from 1996 to 2000, and a rapid increase from 2000 to 2005 (Hu, Huang, Zhong & Tan, 2008). Subsequently, total carbon emissions continued to grow substantially, reaching a new peak of about 10 billion tons in 2014; Total carbon emissions declined slightly from 2014 to 2016 and then increased significantly again until 2021 (Our World in Data, 2023).

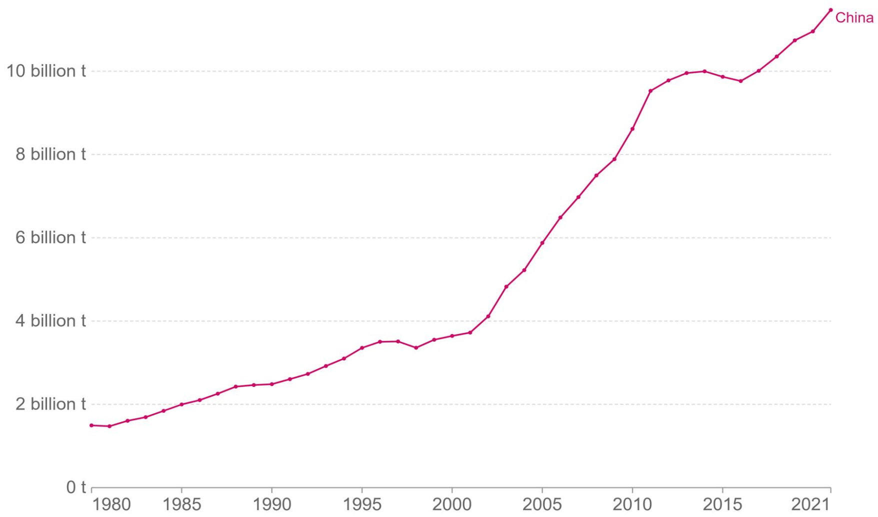


*Figure 1: The Change of Carbon Emission (Our World in Data, 2023)*

Faced with this situation, China, as a responsible major country, has made active explorations in dealing with global climate governance and made a serious commitment at the United Nations General Assembly, proposing to strive to achieve carbon peaking by 2030 and carbon neutrality by 2060. With the strategic goal of neutralization, the pressure on carbon emission reduction has been raised to unprecedented heights in China (Lu et al., 2022). The implementation of dual carbon goals means that China’s carbon emission management should gradually shift from the intensity control of "soft constraints" to total control of "hard constraints". For a long time, the Chinese government has been actively responding to the problem of carbon emissions. In 2011, it took the lead in carrying out carbon emission trading pilot projects in 7 provinces and cities across the country. On March 16, the national carbon emission rights online trading market was officially launched (Lu et al., 2022). The launch of the carbon trading market is not only conducive to the implementation of China's green concept, but also has great significance for the development of the world's low-carbon economy. Since the dual carbon goals were put forward, the issue of carbon emission reduction has become a hot topic of concern from all walks of life in China, and academic circles have also carried out research on carbon emission issues from various aspects. Scholars have found that China's carbon emissions have shown a continuous upward trend in time. In terms of space, it presents a ladder feature of high in the east and low in the west (Liu, Shao & Ji, 2021). Most scholars have found through empirical research that the implementation of environmental regulations (Wei, Pan & Li, 2021), the transformation and upgrading of industrial structure (Wang & Xiang, 2014) and the improvement of innovation level (Liu, Xu & Zhang, 2022) is a powerful means to reduce carbon emissions.

## 2.2 Influencing Factors of Carbon Emissions in China

In order to achieve China's carbon emission reduction goals, many scholars have studied the factors influencing China's carbon emissions. In the past few decades, most scholars have focused their research on the environmental Kuznets curve (EKC) (Culas, 2007; Xu et al., 2018; Xu & Song, 2010). They have been trying to determine whether China, the world's largest developing country, will experience environmental pressures that increase with economic growth, peak and then decline with economic growth. This inverted U-shaped curve between economic growth and environmental pressures is the EKC (Culas, 2007). On the basis of EKC, relevant scholars conducted empirical research on the relationship between China's carbon emissions and economic growth, confirmed that economic growth is a major factor affecting carbon emissions, and the conclusions reached are basically the same. Xu et al. (2018) found that China's carbon emissions and economic growth tend to have an inverted U-shaped relationship. Xu & Song (2010) found that although China's overall carbon emissions and economic growth have an inverted U-shaped relationship, there are regional differences. For example, the eastern and central regions of China follow this inverted U-shaped relationship, but the western region has a positive U-shaped relationship. In addition to economic growth, researchers have also found other factors influencing carbon emissions. First, energy consumption is one of the main sources of carbon emissions, so the greater the energy consumption, the higher the carbon emissions (Lu et al., 2022; Xu et al., 2018; Xu & Song, 2010; Chen et al., 2018). Second, the impact of population size and resident wealth level on carbon emissions is significant (Chen et al., 2018). In cities, the larger the population, the higher the carbon emissions, but the inverted U-shaped relationship between per capita GDP and carbon emissions in cities of different sizes is not absolutely valid. They also found that climatic conditions have a significant impact on carbon emissions, with worse climatic conditions leading to higher energy dependence and carbon emissions. In addition, industrial structure is also one of the factors affecting the level of carbon emissions. Studies have found that the higher the proportion of the secondary industry, the higher the carbon emissions (Chen et al., 2018; Xu et al., 2018). With the proposal of China's "30·60" dual carbon target, government actions play a more non-negligible role in promoting China's low-carbon emission reduction. Tian and Wang (2018) found in their research that government interventions directly affect carbon emissions. Therefore, based on the above literature review, it can be seen that the influencing factors of carbon emissions are multi-dimensional, and multiple factors should be included when considering carbon emissions.

## 2.3 Digital Economy

With the development of information and communication technology, the digital economy has increasingly become an important driving force for economic and social development. Facing the weak recovery from the economic and financial crisis, developed countries represented by the United Kingdom, Australia, Japan, Singapore, etc. have launched the national strategy for the development of digital economy, trying to promote the development of related industries through the development of the digital economy, improve the quality of economic development, enhance the country's international competitiveness, and seize the new commanding heights of world development (Pang & Zhu, 2013). Relatively speaking, China's digital economy started late and developed rapidly. In 2017, “China's Government Work Report” (China Government Network, 2019) clearly proposed "digital economy" for the first time. In 2019, “China's Government Work Report” (China Government Network, 2019) mentioned "digital economy" again, emphasizing "strengthening the digital economy" and clarifying the importance of the digital economy. The concept of the digital economy was established by Tapscoot (1996), who considered the digital economy to be activities based on the widespread use of information communication technology (ICT). At the G20 summit in Hangzhou, China, it was pointed out that the digital economy is a series of economic activities that use digital knowledge and information as key factors of production, modern information networks as an important carrier, and effective use of ICT as an important driving force for improvement and economic structure optimization (CAC, 2016). The digital economy is the main economic form following the agricultural economy and the industrial economy, and it has had a profound impact on human production patterns, lifestyles, and governance (UNCTAD, 2021). Han and Chen (2022) divide the digital economy into four parts, including data value, digital industrialization, industrial digitalization and digital governance.

With the development of digital economy, Pan, He and Pan (2021) pointed out that the current academic research on China's digital economy mainly focuses on three aspects: first, the accounting and scale measurement of the digital economy. At present, there is no unified accounting method for the digital economy, and there are generally absolute scale and relative level measurement in the measurement of the scale of the digital economy (Xu & Zhang, 2020). The second is the impact of the digital economy on high-quality economic development. Zhao, Zhang and Liang (2020) found that the digital economy can promote regional economic growth and high-quality economic development, not only improving regional total factor productivity (TFP), but also having spillover effects on surrounding cities; Third, the status quo and path of China's digital economy development. At present, China's digital economy is developing rapidly, but there is obvious regional heterogeneity (Liu, Yin & Wang, 2020), and there are unbalanced and insufficient regional heterogeneous characteristics in the development of digital economy (Gu, Tang & Liu, 2021). Besides, Chen, Yang and Wu (2022) point out that research on the digital economy is mainly analyzed from both macro and micro perspectives. From a macro perspective, the integration of digital economy and manufacturing has an optimization and promotion effect on industrial structure (Xu, Zhang & Cao, 2020), resource allocation (Zuo, Jiang & Chen, 2020), and regional innovation capability (Wen, Yan & Cheng, 2019). The digital economy can also simplify the education process and improve the quality of education and the level of human capital (Song, Qin & Long, 2022). For China, the digital economy can significantly narrow the income gap between urban and rural areas in the process of achieving shared prosperity and development (Fan, Xu & Ma, 2022). At the micro level, the digital economy also has a direct impact on businesses. Chen (2022) found in his research that the digital economy can significantly improve business performance. In addition to this, the digital economy can also improve the total factor productivity of enterprises by optimizing industrial structures and technological production processes (Xu, Zhang & Cao, 2020).

In addition to the significant impact of digital economy on the above aspects, some scholars have found that the digital economy will also have an impact on the environment. For example, Deng and Zhang (2022) empirically found that the digital economy reduces the emission of various pollutants, among which the effect on sulfur dioxide emission reduction is the most obvious. However, there is still controversy about the impact of the digital economy on carbon emissions, with two main views: the first is that the digital economy can reduce carbon emissions. Xie (2021) found that the digital economy reduces carbon emission intensity through improvements in energy structure and technological advances, and this is more pronounced in central and western China. Yang, Wu, Ren, Ran and Zhang (2021) pointed out that the wide application of digital technology can realize intelligent environmental management, improve environmental governance capabilities, and effectively reduce carbon emissions; The second view is that the digital economy will increase carbon emissions in the short term and reduce carbon emissions in the long term (i.e., inverted U-shaped relationship). For example, Lu et al. (2022) found in his research that the development of the digital economy will increase the application of digital technologies in the early stage, thereby increasing energy consumption and increasing carbon emissions; When the digital economy matures, it will have a restraining effect on carbon emissions.

In summary, this section provides a literature review on the status quo of carbon emissions in China, influencing factors of carbon emissions in China and the digital economy. As the country with the largest carbon emissions in the world, China is committed to achieving dual carbon targets to effectively control carbon emissions. In the existing literature and research, in the field of environment, many factors affecting carbon emissions have been clarified, but the impact of the digital economy on carbon emissions is still limited; in the field of digital economy, most research focuses on the impact of digital economy on high-quality economic development and innovation capabilities, but relatively limited in terms of carbon emissions. Although some studies have explored the impact of China's digital economy on carbon emissions, the conclusions are still controversial, and only a few studies have conducted empirical research on this issue on different scales of selecting samples. Therefore, it is of great significance to study the impact of China's digital economy on carbon emissions by selecting 31 key cities as evidence in this paper. The possible contributions mainly include the following aspects: First, the research focus of this paper can supplement the gap between the field of environment and the field of digital economy; Second, there are disputes in the existing research on the impact of digital economy on carbon emissions, this paper can provide evidence for the existing theories, and deepen the relevant conclusions; Third, most of the existing literature and research are based on the empirical analysis from the scale of China's provincial or a large number of prefecture-level cities, while this paper selects 31 key cities in China for empirical analysis, which may provide relevant enlightenment for the policies issued by the central government.

# 3. Theoretical Framework

This part will build the theoretical framework of this paper on the basis of the above literature review. According to the research questions of this paper, the following section will conduct a theoretical analysis on the relationship between the digital economy and carbon emissions, and put forward corresponding hypotheses.

## 3.1 Digital Economy and Carbon Emission

The digital economy, as an emerging economic form, is a key factor in the production of digital knowledge and information, which can affect carbon emissions in two ways: one is to affect carbon emission levels by reducing energy consumption. Its mechanism is reflected in the reduction of energy consumption through the application of digital technology, upgrading the industrial structure and changing the consumption pattern. First, the application of digital technologies can increase the efficiency and dematerialization of production inputs, thereby curbing energy consumption. For example, Wen, Lee and Song (2021) found that applying digital technologies throughout the development of agroecological economy can effectively improve production efficiency and reduce unnecessary energy consumption. On the other hand, with the maturity of digital technology in various departments, they are able to build their own energy management systems, realize the orderly configuration and coordinated scheduling of multiple energy systems by controlling the digital platform, improve the overall efficiency of the energy system, and thereby reduce energy consumption (Gao, Li & Yu, 2022). And with the support of digital finance, the application of digital technology can reduce corporate financing constraints and alleviate resource allocation errors, thereby improving energy efficiency (Lu et al., 2022). Secondly, the digital economy can serve as a new driving force to promote the upgrading of industrial structure, and shift some labor-intensive and resource-intensive high-energy-consuming industries to high-tech and environment-friendly industries, thereby reducing energy consumption (Luo, Li, Cai & Luo, 2023). Finally, the development of the digital economy has promoted the efficiency and convenience of information acquisition and transmission, consumers can meet their needs through online shopping, and paper documents or reading materials can also be replaced by electronic versions, which can reduce the cost of outdoor activities. The digital economy reduces energy consumption by changing people's traditional consumption patterns (Luo et al., 2023). Carbon emissions are generated from energy consumption, and the digital economy reduces energy consumption through the above three ways, thus reducing carbon emissions.

Second, the digital economy mainly relies on digital technology, which directly forms a carbon emission reduction effect from many aspects. First of all, from the macro governance level, relevant government departments can reasonably control the total amount of carbon emissions through the digital operation of the carbon emission trading market. Secondly, from the micro-enterprise level, the application of digital technology can optimize the governance technology of enterprises on carbon emissions. For example, Stroumpoulis and Kopanaki (2022) point out that the implementation of big data and IoT technologies in the supply chain of enterprises can realize real-time monitoring of carbon emissions in each process, thereby effectively reducing carbon emissions. Therefore, based on the above theoretical analysis, this paper obtains the first hypothesis.

**Hypothesis 1:** Digital economy development has a linear relationship that has a restraining effect on carbon emissions.

However, some scholars believe that the digital economy is not only a simple carbon reduction effect, but also a certain "green blind zone", which has a negative externality effect on the environment and leads to an increase in carbon emissions (Zhang & Li, 2022; Lu et al., 2022). The EKC illustrates that there is an inverted U-shaped nonlinear relationship between economic growth and environmental pollution, that is, in the early stage of economic development, the environment will deteriorate with economic growth, and after reaching the peak, environmental pollution will decrease with economic growth (Culas, 2007) . Therefore, this may also occur when different forms of economic activity are taken into account. In the early stage of the development of the digital economy, with the vigorous promotion and application of digital technology, the construction demand of digital equipment and infrastructure will be greatly stimulated, which will directly increase the demand for energy and bring great pressure to reduce carbon emissions (Cheng, Zhang, Wang & Jiang, 2023). As digital technologies are widely used in the energy extraction industry, this will directly increase the scale of extraction, which will put great pressure on the environment (Lu et al., 2022). Second, in the process of digital industrialization, a large amount of power resources need to be consumed, and for China, the increase in power resources means an increase in coal resources, which directly increases carbon emissions (Lu et al., 2022). For enterprises at the micro level, the technological progress brought about by the digital economy will lead to a large amount of investment in the production of digital equipment in the early stage of economic development, and energy consumption and resource extraction will be greatly increased, thereby increasing carbon emissions (Lu et al., 2022). With the continuous development of the digital economy, carbon emissions will also peak, and after the development of the digital economy matures, the situation analyzed by the premise theory of hypothesis 1 appears, that is, the development of the digital economy suppresses carbon emissions. Therefore, based on the above theoretical analysis, the hypothesis 2.

**Hypothesis 2:** The impact of the digital economy development on carbon emissions has an inverted U-shaped nonlinear relationship.

# 4. Data and Method

This section presents the data and methodology for this paper, starting with a research design in the form of a quantitative research approach guided by an econometric model. Subsequently, in order to quantify the level of digital economy development, section 4.2 constructs indicators for the development of digital economy. Sections 4.3 and 4.4 describe the data and method in this paper, respectively. Finally, this section concludes with an analysis of the limitations of data and method.

## 4.1 Research Design

Based on the research questions proposed in this paper and the hypotheses obtained after theoretical analysis, this paper aims to explore the impact of China's digital economy on carbon emissions. Considering that indicators such as carbon emissions and the digital economy will be presented directly in the form of data, the quantitative research method in this paper is significantly better than the qualitative research method. In order to further determine the specific quantitative research method, this paper identifies the research sample in key cities in China, so the collected sample data must have two dimensions, namely cross-section (different cities) and time series (a certain time period, such as 2000-2023).

In economics and statistics, this kind of data that contains both sections and time series is called Panel Data (Hayashi, 2011). Based on the analysis of econometric theory and application by Hayashi (2011), this paper will use relevant econometric models to conduct regression analysis on panel data. Based on the research questions and hypotheses in this paper, the explained variables and core explanatory variables in the model are Carbon Emissions (ce) and Digital Economic Development Index (dedi), respectively. Among them, dedi is an indicator to measure the development level of the digital economy in this paper, and its specific construction process will be discussed in section 4.2. Based on the literature review in section 2.2, there are many factors that affect carbon emissions, so this paper selects Resident Wealth Level (incom) and Population Size (pop) as control variables. Specific model variable selection will be discussed in section 4.4.2.

The advantages of setting econometric models in this paper are: 1. Econometric models can carry out structural analysis, that is, to study how changes in dedi, incom and pop, and changes in structural parameters affect ce and the entire economic system; 2. Economic forecasting, the principle of which is to simulate history and find out the law of change from the economic activities that have occurred; 3. Test and develop economic theory of the impact of digital economy development on carbon emissions, that is, use timing statistics and econometric models to empirically analyze whether the theory is correct or not. The principle is that if an econometric model established according to an economic theory can fit the actual observation data well, it means that the theory is in line with objective facts, and vice versa, it indicates that the theory cannot explain objective facts.

Therefore, according to the research questions and hypotheses, in order to explore whether there is a linear relationship between the digital economy and carbon emissions, this paper will adopt a quantitative research method, and further draw corresponding conclusions by setting an econometric model, using SPSS and Stata 17SE to process the data.

## 4.2 Measurement of the Digital Economy Development

For the measurement of China's digital economy development, due to the different research objects of scholars, for example, some scholars study prefecture-level cities, while others study provinces, so the measurement of China's digital economy development level has not yet been unified. At present, there are three most commonly used measures of China's digital economy development level. The first is the index indicators directly provided by relevant platforms, including the digital economy development index by province, region and city provided by Tencent's "Internet +" digital economy big data platform (covering the period from January 2016 to December 2017), and the 2018 Global Digital Economy Index (including indicators such as digital infrastructure, digital consumers and digital industry ecology) released by Alibaba Research Institute and KPMG (Pan, He & Pan, 2021); The second is to rebuild the evaluation index system of digital economy development, for example: Liu, Yang and Zhang (2020) constructed the evaluation index system of China's digital economy by province from the three dimensions of informatization development, Internet development and digital transaction development; Zhao, Zhang and Liang (2020) constructed a comprehensive digital economy development index using five aspects: Internet penetration rate, relevant practitioners, relevant output, mobile phone penetration rate, and digital financial development; The third is that some scholars choose the digital economy efficiency coefficient and the rate of return on digital investment serves as a proxy variable for the development of the digital economy (Pan, He & Pan, 2021).

Indicators of different dimensions of digital economy development carry different effective information on the development of digital economy, and if only one or a certain level of indicators are considered, it will lead to a one-sided understanding of the development of digital economy. Therefore, based on the practices of the above scholars, this paper will refer to Pan, He and Pan (2021) on the construction of indicators for the development of digital economy to provide guidance for subsequent data and methods. They define the evaluation index system of the development of the digital economy as follows:

"Based on the environment of digital governance, through the investment in digital economy infrastructure represented by a new generation of digital technology, vigorously promote the in-depth integration and development of digital industrialization and industrial digitalization (Pan, He & Pan, 2021, p.140)."

Based on the above, they have built an evaluation index system for the development of the digital economy from four aspects (see Table 1 below). First, the digital economy infrastructure. The development of the digital economy is inseparable from the application of digital technology, and digital technology depends on the construction of digital economy infrastructure, which can be measured by the Internet penetration rate, mobile phone penetration rate, long-distance optical cable length and other related indicators; The second is digital industrialization. Digital industrialization refers to the added value of the information industry characterized by digital technology, including digital technology innovation and digital industrial production, such as electronic information manufacturing, information and communication industry, software service industry and Internet and other related industries, which can be measured by the total amount of telecommunications business, the total amount of software business and other indicators; Third, industrial digitalization, which refers to the results of the integration of digital technology and other industries, the increase in output and efficiency brought about by the integration and penetration of Information Communication Technology (ICT) products and services in other fields, which can be measured by indicators such as enterprise informatization level and Digital Financial Inclusion Index of China; The fourth is digital governance, which refers to the implementation of relevant governance in all aspects of the digital economy through relevant government departments or enterprises and other relevant entities to ensure the healthy development of the digital economy, measured by relevant indicators such as the intensity of R&D funding and the number of patent application authorizations.

In summary, this paper constructs the digital economy development index system through four first-level indicators and 20 second-level indicators ( Table 1), which will provide guidance for the subsequent data and methods in this paper.

*Table 1: Digital Economy Development Index System ( Pan, He & Pan, 2021)*

| First-level indicators | Second-level indicators |
|---|---|
| Digital Economy Infrastructure | Internet penetration rate |
| | Mobile phone penetration rate |
| | Long-distance optical cable length |
| | Number of Internet broadband access port |
| | The number of Internet domain names |
| Digital Industrialization | Digital industry gross industrial value |
| | Digital industry practitioners |
| | Software business revenue |
| | Total amount of telecommunications business |
| | Number of digital TV subscribers |
| Industrial Digitalization | E-commerce sales |
| | The level of enterprise informatization |
| | Corporate website coverage |
| | Digital Financial Inclusion Index of China |
| | Number of courier operations |
| Digital Governance | The level of digital government |
| | R&D funding intensity |
| | Number of patent applications granted |
| | Years of schooling per capita |
| | Number of enterprises in the digital economy |

In order to further quantify the development level of the digital economy for this paper, considering the completeness and availability of data, on the basis of the 20 secondary indicators constructed in Table 1, the index selection method of Zhao, Zhang and Liang (2020) was further used for reference, to measure the comprehensive development level of the digital economy from two aspects of Internet development and digital financial inclusion. As the result, this paper was selected: the number of Internet broadband access users among 100 people, the proportion of computer service and software industry employees in urban units, the total amount of telecommunications business per capita, the number of mobile phone users in 100 people and the Digital Financial Inclusion Index of China. Then, the five indicators were first standardized, and then dimensionally reduced through the method of principal component analysis (PCA) by using SPSS, and finally the digital economy development index was obtained, which was denoted as dedi. It is worth mentioning that the purpose of the PCA method is to use fewer indicators to explain the original multiple indicators. Therefore, the dedi obtained in this paper can contain the information of the original five indicators to a certain extent, and comprehensively, dedi can be used as an index to measure the development level of the digital economy. The specific PCA method process and results will be shown in the Appendix.

## 4.3 Data and Sources

### 4.3.1 Data

In this paper, 31 key cities in China from 2011 to 2019 are selected as all samples. According to the variables selected in this paper, since the time span of the Digital Financial Inclusion Index of China is 2011-2019, the time series values of the sample data are also 2011-2019. For the selection of cross-sections in the sample, in order to basically cover all regions of China, and considering the completeness and availability of data, 31 Chinese key cities were finally selected, including provincial capitals in all provinces except Tibet and four municipalities directly under the central government. For the collection of raw data for all variables, the explained variable carbon emissions (ce) are obtained directly through the databases of the relevant institutions; For the core explanatory variable Digital Economy Development Index (dedi), because the variable is first obtained through simple quadratic calculation and got the number of Internet broadband access users among 100 people, the proportion of computer service and software industry employees in urban units, the total amount of telecommunications business per capita, the number of mobile phone users in 100 people and the Digital Financial Inclusion Index of China, and then obtained by principal component analysis method, so the raw data collected are: the number of Internet broadband access users, the number of employees in computer services and software industry, the number of employees in urban units, the total amount of telecommunications business, population, number of mobile phone users and the Digital Financial Inclusion Index of China; The raw data collected by the control variables Population Size (pop) and Resident Wealth Level (incom) are population and GDP. A statistical description of all samples is shown in Table 2.

*Table 2: Statistical Description of all Samples*

| City | Data availability |
|---|---|
| Beijing | 2011-2019 |
| Shanghai | 2011-2019 |
| Guangzhou | 2011-2019 |
| Shenzhen | 2011-2019 |
| Shijiazhuang | 2011-2019 |
| Shenyang | 2011-2019 |
| Harbin | 2011-2019 |
| Hangzhou | 2011-2019 |
| Fuzhou | 2011-2019 |
| Jinan | 2011-2019 |
| Wuhan | 2011-2019 |
| Chengdu | 2011-2019 |
| Kunming | 2011-2019 |
| Lanzhou | 2011-2019 |
| Taiyuan | 2011-2019 |
| Changchun | 2011-2019 |
| Nanjing | 2011-2019 |
| Hefei | 2011-2019 |
| Nanchang | 2011-2019 |
| Zhengzhou | 2011-2019 |
| Changsha | 2011-2019 |

| | |
|---|---|
| Haikou | 2011-2019 |
| Guiyang | 2011-2019 |
| Xi’an | 2011-2019 |
| Xining | 2011-2019 |
| Tianjin | 2011-2019 |
| Chongqing | 2011-2019 |
| Urumqi | 2011-2019 |
| Hohhot | 2011-2019 |
| Yinchuan | 2011-2019 |
| Nanning | 2011-2019 |

### 4.3.2 Sources

All the above data are the secondary data from three main sources. Except for carbon emissions and the Digital Financial Inclusion Index of China, the rest data are from the 2012-2020 “China Cities Statistical Yearbook”. The “China City Statistical Yearbook” is an informative annual publication that comprehensively reflects the socio-economic development of Chinese cities, and contains the main statistical data on the socio-economic development of cities at all levels in the country in various years, published by the National Bureau of Statistics. Raw data on carbon emissions comes from “China Emission Accounts and Datasets (CEADs)”. The database was created by the team of Professor Guan Dabo from Tsinghua University in 2016. With the support of relevant institutions such as Department of International Cooperation, Ministry of Science and Technology of China, China Agenda 21 Management Center, National Natural Science Foundation of China, UK Research Council and other relevant institutions, they are committed to building a multi-scale carbon emission accounting method system that can be cross-validated, compiling a carbon accounting inventory covering China and other developing economies, and creating a multi-scale unified, full-caliber and refined carbon accounting data platform with verifiable high spatial precision, by social and economic sector, and by energy variety quality. The Digital Financial Inclusion Index of China is derived from the “Peking University Institute of Digital Finance”, by Peking University and Ant Financial Services Group. Officially established with the approval of the President's Office of Peking University, the institution is affiliated with the National Institute of Development of Peking University, and is committed to carrying out academic research in the fields of digital finance, financial technology, inclusive finance, financial reform, etc., providing authoritative scientific research results to the society, providing theoretical guidance for industry development, and providing scientific reference for government decision-making.

### 4.3.3 Sources Criticism

Although the three main sources selected in this paper have strong reliability, the data in some sources still have limitations. First of all, for the collection of carbon emission data, since there is no unified carbon emission statistics and accounting scale, and CEADs only adopts one of the comprehensive carbon emission statistics and accounting methods, the data is controversial. However, this situation is unavoidable, and the advantage of CEADs is that it has strong authority in China's carbon emission statistics and accounting institutions, and the data completeness is relatively high. Secondly, since the Digital Financial Inclusion Index of China calculated by the Peking University Institute of Digital Finance has a short time span, only from 2011 to 2019, the sample size of this paper is limited. As for the City Statistical Yearbook, its limitations are relatively low, because the statistical scales of the "City Statistical Yearbook" in different cities are consistent, and they are all published by relevant government agencies.

## 4.4 Method

### 4.4.1 Model Setting

#### 4.4.1.1 Static Panel Model

Based on the above theoretical analysis and the two hypotheses put forward, this paper first sets a panel benchmark regression model to conduct an empirical analysis of the impact of digital economy development on carbon emissions. Considering that the data of different dimensions fluctuate greatly, on the basis of not changing the nature and correlation of the data, this paper takes natural logarithms for some of the variables, so as to reduce the variable scale, increase the stationarity and weaken the model's collinearity, variance, etc. (Hayashi, 2011). The panel benchmark model setup is as follows:

$$\ln ce_{it} = \alpha_0 + \beta_1 dedi_{it} + \beta_2 sdedi_{it} + \beta_3 \ln incom_{it} + \beta_4 \ln pop_{it} + \mu_i + \sigma_t + \varepsilon_{it}$$

Among them： $ce_{it}$ represents the carbon emissions of the i-th city in the t-year; $dedi_{it}$ and $sdedi_{it}$ are the digital economy development index and its square term, respectively; $incom_{it}$ represents the wealth level of residents in the area; $pop_{it}$ represents the population size; $\mu_i, \sigma_t, \varepsilon_{it}$ are the individual and time effects and random interference items, respectively.

#### 4.4.1.2 Unit Root Test (LLC Test)

Hayashi (2011) proposed that unit root tests should be performed on all data before performing panel data regression to ensure that all data are stationary. There are many methods of unit root test, such as LLC test, Breitung test and IPS test. This paper will use the LLC test to ensure that all data are stationary. The principle is that during process of the unit root test, the null hypothesis (H0) is non-stationary, while the alternative hypothesis (H1) is stationary. This paper uses Stata 17SE to obtain the LLC test results as follows (Table 3-6).

*Table 3: LLC Test Result of* $\ln ce$

| | Statistic | p-value |
|---|---|---|
| Unadjusted t | **-57.3721** | |
| Adjusted t* | **-54.4180** | **0.0000** |

*Table 4: LLC Test Result of $dedi$*

| | Statistic | p-value |
|---|---|---|
| Unadjusted t | **-15.5824** | |
| Adjusted t* | **-8.3334** | **0.0000** |

*Table 5: LLC Test Result of $\ln incom$*

| | Statistic | p-value |
|---|---|---|
| Unadjusted t | **-16.8085** | |
| Adjusted t* | **-13.1801** | **0.0000** |

*Table 6: LLC Test Result of $\ln pop$*

| | Statistic | p-value |
|---|---|---|
| Unadjusted t | **-40.3165** | |
| Adjusted t* | **-34.2019** | **0.0000** |

The P value of the test results of all data is 0.0000, that is, the null hypothesis (H0) is rejected. Therefore, it can be considered that all data series in the model are stable, and there is no need for cointegration test and data adjustment.

#### 4.4.1.3 Hausman Test

Based on confirming that all data series are stable, a specific model will be selected, that is, a fixed effect model or a random effect model. Therefore, the Hausman test on the model will continue (Hayashi, 2011). The principle is that the null hypothesis (H0) in the test process believes that the individual effect has no relation with the regressor variable, that is, the random effect model; while the alternative hypothesis (H1) believes that the individual effect is related to the regressor variable, that is, the fixed effect model. This paper uses Stata 17SE to obtain the Hausman test results as follows (Table 7).

*Table 7: Hausman Test Result*

**Hausman (1978) specification test**

| | Coef. |
|---|---|
| Chi-square test value | 9.398 |
| P-value | .052 |

In statistics, the significance level is usually set at 5%. The p-value of the test result is greater than 0.05, that is, the null hypothesis (H0) is accepted at the 5% significant level. However, H0 is still not 100% acceptable. Therefore, to avoid the limitation of model selection, this paper will use the random effect model as the main model of regression analysis, and use the fixed effect model for robustness testing.

### 4.4.2 Variable Selection

Explained variable: Carbon Emissions (ce). At present, there are mainly two types of measurement methods for carbon emissions, one is the departmental accounting method, and the other is the apparent emission accounting method. There are also inconsistencies in the measurement and statistical methods of carbon emissions by different agencies. In order to ensure the completeness and availability of the data, this paper directly obtained the complete data from "China Emission Accounts and Datasets (CEADs)" and used them directly.

Core explanatory variable: Digital Economy Development Index (dedi). As mentioned above, this paper draws on the method of Zhao, Zhang and Liang (2020) to select five secondary indicators to measure the development of the digital economy and uses the PCA method to obtain the digital economy development index (dedi). As mentioned above, dedi can contain the information of the original five secondary indicators to a certain extent. Therefore, the core explanatory variable dedi is a comprehensive indicator to measure the development level of the digital economy based on the original five secondary indicators. The value of dedi represents the maturity of the digital economy development. According to the hypothesis proposed in this paper, the purpose is to explore the relationship between the core explanatory variable dedi and the explained variable ce.

Control variables: Considering that there are many factors affecting carbon emissions, as well as the completeness and availability of data, based on the literature review and existing research results (Chen, Wu & Ma, 2018), this paper introduces major relevant variables to control the accuracy of the results of the impact of the digital economy on carbon emissions, including the wealth level of residents (incom) and population size (pop). The wealth level of residents is measured by the per capita income of urban residents, while the per capita income of residents is expressed by GDP per capita. The degree of wealth of a region represents the degree of economic development and income level of the region and will have an important impact on the energy consumption level and carbon emissions of the region (Chen et al., 2018). The population size is measured by the total urban population. Existing studies have shown (Chen et al., 2018) that the contribution of the household sector to carbon emissions cannot be underestimated, and population size is an important aspect that reflects the increase in carbon emissions through energy consumption at the household level.

Descriptive statistics of the variables used are shown in Table 8.

*Table 8: Descriptive Statistics of the Variables*

| Variables | Variables | Mean | Observation | Std.dev. | Min | Max |
|---|---|---|---|---|---|---|
| Carbon Emission | $\ln ce$ | 17.9205 | 279 | 0.7727 | 15.2252 | 19.2814 |
| Digital Economy Development | $dedi_{it}$ | 0.1307 | 279 | 0.3814 | -0.4119 | 3.7227 |
| Square of Digital Economy Development | $sdedi_{it}$ | 0.1620 | 279 | 0.9842 | 0.0000 | 13.8536 |
| Resident Wealth Level | $\ln incom$ | 15.8505 | 279 | 0.3917 | 10.3473 | 12.2234 |
| Population Size | $\ln pop$ | 11.2787 | 279 | 0.6724 | 14.3041 | 17.2774 |

### 4.5 Limitation

Based on the above content of this section, the limitations of the data and method in this paper are mainly reflected in two aspects. First, from the perspective of methodology, this paper adopts the PCA method to construct the digital economy development index dedi. Since the cumulative contribution rate of the extracted principal components cannot reach 100%, the information from all indicators will be reduced. For the setting of the model, this paper selects the random effect model as the main model according to the results of the Hausman test. Compared with fixed-effect models, random-effect models have stronger assumptions (H0: Individual effect has no relation with the regressor variable), which can easily violate common economic theories (Wooldridge, 2010). Second, from the perspective of data, there are the following limitations. First, since different institutions have different statistics on specific carbon emissions, the absolute values of the coefficients in the regression results of this paper do not have strong reference significance. Second, due to the completeness and availability of data, this paper only selects 31 key cities in China as samples. Although these 31 key cities basically cover all provinces and municipalities in China, they still cannot represent the whole of China. Third, this paper only selects five secondary indicators of digital economy development to measure the level of digital economy development due to the completeness and availability of data, so its explanatory power will also be weakened. Fourth, the time series span of the sample is short, which indirectly leads to insufficient sample size, which may lead to inaccurate results.

# 5. Empirical Analysis

### 5.1 Result

In order to be able to intuitively and clearly see the correlation between carbon emissions and digital economy development, this paper first draws scatter plots of carbon emissions and digital economy development, and the results are shown in Figure 2. Among them, the Y axis in the figure is ce (carbon emissions) of 31 key cities from 2011 to 2019, and the X axis is dedi. The results show that the slope of the trend line is negative (that is, the downward trend), indicating that with the increase of dedi, ce will decrease, which is in line with the hypothesis 1 proposed in this paper. In addition, it can be clearly seen from Figure 2 that most of the scattered points are concentrated between -0.5 and 0.5 of dedi, and the distribution is uneven. For the scattered points distributed above the trend line in this interval, it may be because the value of dedi is relatively low, the development of the digital economy is weak, so the value of ce is relatively large. At the same time, this distribution may also be due to the differences between cities. Some cities are heavy industrial cities, and the carbon emission level is naturally high, so these scattered points are distributed above the trend line. As for the scatter points distributed below the trend line in this interval, it may be because the cities represented by these scatter points are small in scale or have a low industrial level, so although the value of dedi is small, they still have low carbon emission. When the value of dedi gradually increases from 0.5, the value of ce of the corresponding scatter point mostly tends to a lower level. However, the results in Figure 2 can only represent the correlation between ce and dedi, and cannot verify the hypothesis of this paper, because drawing this scatter plot cannot scientifically and rigorously explain the change in carbon emissions is due to the change in digital economy development. Therefore, the hypothesis of this paper must be verified through the analysis of the regression results of the model below.

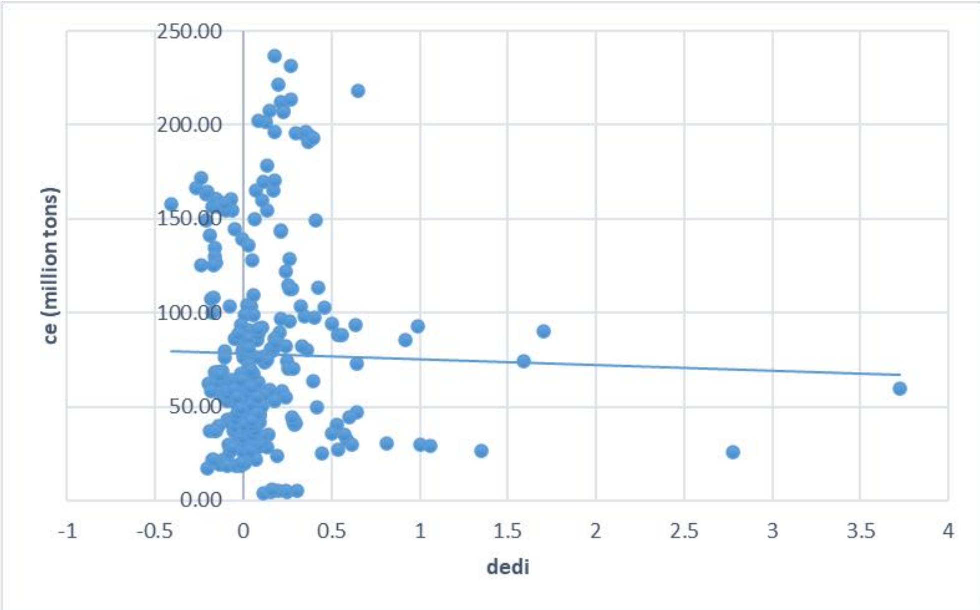


*Figure 2: Scatter plots of carbon emissions and digital economy development*

The model regression results are shown in Table 9. In this paper, the linear term of digital economy development is first included in the main regression model (random effect model). After controlling other variables that may affect carbon emission levels, as well as time and individual effects, the regression results are shown in column (1) of Table 9. The results found that the regression coefficient of digital economy development on carbon emissions was -0.0694, and passed the 1% significance test, indicating that digital economy development has a linear relationship with carbon emissions, and digital economy development will inhibit carbon emissions. This verifies the previous hypothesis 1, that is, the development of the digital economy will reduce carbon emissions by reducing energy consumption through the application of digital technology, or directly intervene in carbon emissions to achieve carbon emissions reduction. At the same time, this result is also in line with the correlation between carbon emissions and digital economy development in Figure 2. Next, the quadratic term of digital economy development is added to the model to investigate whether digital economy development affects carbon emissions in a non-linear relationship. The regression results are shown in column (2) of Table 9. It was found that the coefficient of the linear term of the digital economy development was negative and passed the 10% significance test; the coefficient of the quadratic term of the development of the digital economy was positive, but it didn't pass the significant test. This indicates that there is no inverted U-shaped relationship between digital economy development and the level of carbon emissions. Therefore, the previous hypothesis 2 was rejected. At the same time, the coefficient of dedi in column (2) failed the significance test of less than 5%, but passed the significance test of 10%, which still has a certain degree of convincingness to verify hypothesis 1.

Columns (3) and (4) in Table 9 are the robustness test results of columns (1) and (2) respectively, using a fixed effect model. First, the linear term of digital economy development is included in the model, and the results are shown in column (3). It was found that the coefficient of dedi was negative and passed the 1% significance test. Then, the quadratic term of digital economy development was incorporated into the model, and the results are shown in column (4). It was found that the coefficient of dedi was negative, and it passed the 10% significance test; the coefficient of sdedi was positive, and it failed the significance test. The above robustness test results show that the results in columns (1) and (2) are both reliable enough to pass the robustness test.

*Table 9: Model Regression Result*

| Variables | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | lnce (REM) | lnce (REM) | lnce (FEM) | lnce (FEM) |
| dedi | $-0.0694^{***}$ | $-0.1232^{*}$ | $-0.0688^{***}$ | $-0.1311^{*}$ |
| | (0.0086) | (0.0893) | (0.0093) | (0.0720) |
| sdedi | | 0.0183 | | 0.0212 |
| | | (0.4255) | | (0.3579) |
| lnpop | $0.3154^{***}$ | $0.3028^{***}$ | $0.2202^{**}$ | $0.1981^{*}$ |
| | (0.0005) | (0.0011) | (0.0370) | (0.0673) |
| lnincom | $0.1168^{***}$ | $0.1287^{***}$ | $0.1183^{***}$ | $0.1324^{***}$ |
| | (0.0037) | (0.0027) | (0.0037) | (0.0024) |
| _cons | $11.6129^{***}$ | $11.6830^{***}$ | $13.1044^{***}$ | $13.3014^{***}$ |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| *Obs* | 279 | 279 | 279 | 279 |
| $R^2$ | 0.3182 | 0.3246 | 0.3290 | 0.3403 |

*Notes: 1.* $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$; 2. $p$-values in parentheses 3. REM refers to Random Effect Model, FEM refers to Fixed Effect Model

Among the remaining control variables, the regression coefficient of population size is 0.3154, which is significant at the 1% significance level, indicating that every 1% increase in population size will increase carbon emissions by 0.3154%. In addition to the carbon dioxide emissions exhaled by people themselves, the larger the population size, the greater the concentration of the living circle and the scope and intensity of people's activities, thereby increasing carbon emissions. For example, the large-scale use of transportation and the output of domestic waste will increase the output of carbon emissions. The coefficient of the resident wealth level is 0.1168, and it is significant at the 1% significance level. This shows that for every 1% increase in the wealth level of residents, carbon emissions will increase by 0.1168%. When the income level of residents increases, the consumption of living energy will increase for individuals and families; at the same time, the increase in family wealth will further increase consumption demand will lead to an increase in the supply level of enterprises, resulting in an increase of carbon emissions.

## 5.2 Discussion

### 5.2.1 Regression Result Criticism

The regression results in Section 5.1 show that digital economy development can significantly restrain the level of carbon emissions, and there is a linear relationship between the two variables. Although this result has passed the robustness test, it is still worth discussing further, because the pattern of the results in this paper does not match those of some existing studies. Among them, Lu et al (2022) selected 278 prefecture-level cities in China from 2011 to 2019 as samples in their research, and explored the relationship between digital economy development and carbon emissions by setting a panel regression model similar to this paper. Their research first found that the digital economy may have a certain negative impact on carbon emissions, but this linear relationship has not been verified in their statistical model. Later, when they incorporated the quadratic term of the digital economy into the model, they found that the coefficient of the linear term of the digital economy was positive and passed the 5% significance test, and the coefficient of the quadratic term of the digital economy was negative and passed the significance of 1%. The test shows that there is a significant inverted U-shaped relationship between the digital economy and carbon emissions. They believe that the reasons for the above results are: in the early stage of the development of the digital economy, due to the relatively immature development of the digital economy, in the process of digital industrialization and industrial digitization, the high investment and high cost caused by the development of the digital economy have increased the carbon consumption in production and life, resulting in an increase of carbon emissions. Moreover, while forcing enterprises to carry out green technology research and development, it also further forms the superimposed impact of energy consumption investment, resulting in the level of carbon emissions in the early stage only rising but not falling. When the development of the digital economy continues to mature, the initial investment in capital, manpower, and technology will gradually produce a positive net effect, the efficiency of energy utilization and technology research and development will be improved, the industrial structure will be optimized and upgraded, the production cost of enterprises will be reduced, thereby significantly reducing the level of carbon emissions.

There may be the following reasons for the discrepancy between the pattern of the results in this paper and the pattern of the above results. First, this paper selected 31 key cities in China as samples, while Lu et al (2022) selected 278 prefecture-level cities as samples (there are 293 prefecture-level cities in China, so their samples can basically cover the whole China). It is worth mentioning that in the process of collecting source data in this paper, it is found that these 31 key cities have the following characteristics: This paper selects five indicators to construct the digital economy development index, and the value of the five indicators of these 31 cities are higher than those of other prefecture-level cities in their provinces, respectively. Among which the Digital Financial Inclusion Index of China is the most obvious. Therefore, it can be considered that the digital economy development of these 31 key cities is more mature than that of 278 prefecture-level cities. However, Lu et al. (2022) believe through empirical research that after the development of China's overall digital economy is more mature, carbon emissions will gradually decline from the peak, and the development of digital economy will curb carbon emissions at this time. As discussed in Section 4.5, there are limitations in this paper. Since this paper only selects these 31 key cities as samples, the results obtained cannot generalize the situation in China as a whole. Therefore, although the results of this paper are different from those of Lu et al. (2022), this paper does not deny their conclusion that China's digital economy development and carbon emissions have an inverted U-shaped relationship. On the contrary, based on their conclusion, the result pattern of this paper may due to the selected 31 key cities have reached a relatively mature level of digital economy development during 2011-2019, so they are distributed on the right side of the peak of the inverted U-shaped curve, that is, the development of the digital economy directly inhibits carbon emissions. Judging from the regression results of the model in this paper, it may be due to the small sample size and the relatively mature development of their digital economy, so the results show that digital economy development has a simple linear relationship to restrain carbon emissions. It may also be due to differences in sample selection that the linear relationship in the regression results of Lu et al. (2022) is not significant. At the same time, the difference in results also represents the difference in the level of digital economy development between different cities in China. However, the above point of view is only a conjecture after comparing and discussing the results, and has not been verified, because there is no research so far that uses the same data indicators and methods as this paper to draw corresponding conclusions on the basis of selecting samples that can basically cover the whole of China.

Second, Lu et al. (2022) selected population size, resident wealth level, environmental pollution index, energy consumption and government intervention as control variables in their model, but this paper only included the first two of them in the model as control variables. And as mentioned above, the purpose of introducing control variables is to improve the accuracy of the results of the impact of digital economy development on carbon emissions. Therefore, this paper preliminarily believes that the reasons for different result patterns is the difference in control variables. As mentioned earlier in this paper, Chen et al. (2018) found that although EKC exists in China, the inverted U-shaped relationship between GDP per capita and carbon emissions in cities of different sizes is not absolutely valid. This indicates that when control variables such as population size are included in the model, the EKC pattern between cities will change, and even the inverted U-shaped relationship no longer exists. Similarly, this situation may also occur in the model of this paper. First of all, in Section 2.2, it has been clarified that there are many factors that will affect the level of carbon emissions. Secondly, Lu et al. (2022) found in their model regression results that both environmental pollution and energy consumption will significantly increase carbon emissions, which is consistent with reality; government intervention will significantly inhibit carbon emissions. The possible reason is that, under the constraints of "30.60" dual carbon targets, government intervention shows a clear tendency to reduce carbon emissions, which is also in line with reality. Therefore, after the above discussion, this paper further believes that it is the control variables that cause the regression result pattern of this model to be different from that of Lu et al. (2022).

### 5.2.2 Potential Mechanisms of the Restraining Effect of Digital Economy Development on Carbon Emissions

The results of this paper have fully verified Hypothesis 1, that is, digital economy development has a linear relationship that has a restraining effect on carbon emissions. This section will discuss the potential mechanisms of the restraining effect of digital economy development on carbon emissions based on the regression result and existing relevant literature. First of all, it must be clear that the driving force for digital economy development comes from ICT, and the first four indicators in the digital economy development index constructed in this paper (excluding the Digital Financial Inclusion Index of China) can all represent the maturity of ICT to a certain extent (Gao, Li & Yu, 2022). Combined with the above theoretical analysis, this paper first believes that digital economy development has improved energy efficiency and reduced energy consumption through the full application of ICT, thereby reducing carbon emissions. Gao, Li and Yu (2022) found through empirical research that digitization can significantly improve the efficiency of green energy utilization. They believe that this may be due to the positive impact of ICT development, because ICT can realize automatic control in the production process, thereby optimizing the production process and effectively reducing energy consumption; at the same time, in the process of enterprise management, some operation-oriented ICT equipment may be introduced, which can optimize the operation mode of enterprises, thereby reducing energy consumption of enterprises.

Secondly, this paper believes that in the process of digital economy development, carbon emissions will be suppressed by improving innovation efficiency. Some studies have confirmed that with the development of the digital economy, the innovation efficiency of enterprises will increase (Gao, Li & Yu, 2022; Lu et al., 2022). The improvement of innovation efficiency can drive the development of green environmental protection technology, promote the use of environmental protection materials, recycling technology and pollution control equipment, so as to improve the efficiency of energy utilization and the monitoring of carbon emissions, and curb the growth of carbon emissions (Lu et al., 2022). The improvement of innovation efficiency can also alleviate technical problems such as insufficient new energy storage and power consumption, and increase the collection of new energy through technological improvement, thereby optimizing the energy structure and reducing carbon emissions (Lu et al., 2022). In addition, under the impetus of innovation efficiency, it is conducive to promoting the formation of high-tech industries, and gradually eliminating high-energy consumption and high-pollution enterprises in the process of continuous transformation and upgrading of the industrial structure, thereby curbing carbon emissions (Gao, Li & Yu, 2022; Lu et al., 2022).

Third, digital economy development can promote high-quality economic development, thereby curbing carbon emissions. Zhao, Zhang and Liang (2020) have confirmed in their research that the development of the digital economy can promote the high-quality development of China's economy. Besides, the literature review section of this paper has already made it clear that many scholars have confirmed the existence of EKC in China. Therefore, this paper speculates that the potential mechanisms of the restraining effect of digital economy development on carbon emissions is as follows: digital economy development first promotes the development of high-quality economy. When the development of digital economy matures, the development of high-quality economy will also mature, which is reflected in the right part of the carbon emission peak on the EKC, that is, gradually reduces carbon emissions. Finally, this paper believes that digital economy development curbs carbon emissions by directly affecting government intervention. The development of the digital economy can promote the maturity of digital technology. Relevant government departments need to use digital technology to optimize management and monitor the carbon emissions trading market, so as to effectively control carbon emissions in real time.

# 6. Conclusion

In the context of China's "30.60" dual carbon goals, this paper uses 31 key cities in China as evidence to explore the impact of digital economy development on carbon emissions. By selecting 31 key cities from 2011 to 2019 as panel data, the results were obtained after regression analysis using the relevant econometric model: Digital economy development has a linear relationship that has a restraining effect on carbon emissions, and this result passed the robustness test. However, the pattern of the regression results of the model in this paper is not consistent with the result patterns of existing related studies, and the results obtained are that there is an inverted U-shaped relationship between China's overall digital economy development and carbon emissions (Lu et al., 2022). The difference in results can indirectly indicate the difference in the level of digital economy development between different cities in China. In view of this result, this paper believes that it is due to the difference in model measurement scale and sample characteristics. The difference in the measurement scale of the model is reflected in the different selection of control variables, resulting in inconsistent result patterns; The difference in sample characteristics is reflected in the fact that the sample size in this paper is much smaller than theirs, and the 31 key cities selected in this paper are more mature in the development of digital economy than the 278 prefecture-level cities selected by them, and the sample they selected is more extensive and more differentiated between samples. Therefore, this paper does not deny the conclusion that there is an inverted U-shaped relationship between China's overall digital economy development and carbon emissions, and on this basis, this paper further concludes that for these 31 key cities with relatively mature digital economy development, digital economy development can suppress carbon emissions. In addition, this paper argues that the potential mechanisms behind this relationship are: first, the development of the digital economy improves energy efficiency through the application of ICT, thereby curbing carbon emissions; Second, the development of the digital economy can improve the efficiency of innovation, and the improvement of innovation efficiency can improve energy efficiency or reduce energy consumption, thereby curbing carbon emissions; Third, the development of the digital economy promotes high-quality economic development, and the EKC shows that when the economic development matures, it will have a restraining effect on carbon emissions; Fourth, the digital economy development directly affects government interventions through digital technologies, enabling better monitoring and control of carbon emissions.

Based on the above conclusions, the policy implications obtained in this paper are as follows.

First, improve the speed and quality of digital economy development. China must accelerate the development of the digital economy, which is based on digital platforms and produces a wide range of scale effects and scope economy, and it is necessary to increase the construction of new infrastructure facilities carrying digital technologies and platforms, such as 5G network base stations, big data centers, blockchain services and artificial intelligence, etc., to comprehensively promote the digital transformation of the economy. At the same time, it is necessary to accelerate the progress of digital government construction, use efficient digital governance to strengthen environmental monitoring, optimize government environmental governance methods, and help achieve the "dual carbon" goal. Second, digital talent is the key to improving the speed and quality of the development of the digital economy. In the long run, the learning cycle of digital technology is long and the threshold is high, so it is necessary to pay attention to the field of education related to the digital economy, by opening related majors, cultivate national digital awareness and input more talents for the sustainable development of China's future digital economy. Third, optimize the performance appraisal index system. The behavior of local governments is greatly affected by the performance evaluation index system formulated by the central government, and the proportion of environmental pollution and carbon emissions in the performance evaluation indicators of local officials should be increased, and the performance evaluation indicators should be further optimized, so as to promote healthy competition among local governments. At the same time, trying to take the introduction of high-quality foreign investment as one of the performance evaluation indicators. The advanced low-carbon technologies brought by high-quality foreign direct investment and the enterprise management concept that attaches importance to environmental protection can help enterprises transform green, thereby reducing carbon emissions. Finally, formulate a digital economy development strategy that is compatible with regional differences. As things stand, there are differences in the level of digital economy development between different cities in China. These 31 key cities with a mature level of digital economy development, as cities with priority pilot policies of the government, should adhere to the concept of "central leads local areas", develop their own digital economy and drive the development of surrounding cities, so as to promote the development of China's overall digital economy and curb carbon emissions.

For future research directions, this paper makes the following suggestions. First, c. This study can verify the differences between the results of this paper and existing research results, and at the same time further verify the pattern between China's digital economy development and carbon emissions. Second, explore the intermediary effect of digital economy development on carbon emissions. For example, government intervention is included in the model as an intermediary variable, and the pattern of the regression results is further analyzed to verify the potential mechanism of the impact of digital economy development on carbon emissions proposed in this paper. Third, explore other influencing factors of carbon emissions in the context of the third industrial revolution. The measurement scale of the research method in this paper is 31 key cities in China, and future research can explore the impact on carbon emissions from the enterprise level. For example, what impact does the digital transformation of enterprises have on carbon emissions? How does mass digital awareness affect carbon emissions?

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# 8. Appendix

## 8.1 PCA Method Process and Result

After collecting the five secondary indicators data of all samples, this paper imports them into SPSS for PCA. The KMO and Bartlett's Test results obtained first are shown in Table 10. Among them, the value of the test result is 0.656. Kaiser and Rice (1974) pointed out that when the value is greater than 0.6, it can be considered that the case is suitable for PCA, so the five secondary indicators selected in this paper can be processed by PCA method for dimension reduction.

*Table 10：KMO and Bartlett's Test Result*

**KMO and Bartlett's Test**

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | .656 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 166.995 |
| | df | 10 |
| | Sig. | .000 |

Table 11 and Table 12 are Total Variance Explained and Component Matrix respectively. Among them, Table 11 shows that a total of 2 principal components have been extracted, with a cumulative contribution of 60.756%, which means that the final dedi will carry 60.756% of the information of the original five secondary indicators. A, B, C, D and E in Table 12 respectively represent the original five secondary indicators, namely: the total amount of telecommunications business per capita, the proportion of computer service and software industry employees in urban units, the number of Internet broadband access users among 100 people, the number of mobile phone users in 100 people and the Digital Financial Inclusion Index of China. The values in this table represent the loading numbers of the corresponding indicators of principal component 1 and principal component 2.

*Table 11: Total Variance Explained*

**Total Variance Explained**

| Component | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|
| | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 1.990 | 39.798 | 39.798 | 1.990 | 39.798 | 39.798 |
| 2 | 1.048 | 20.958 | 60.756 | 1.048 | 20.958 | 60.756 |
| 3 | .847 | 16.941 | 77.697 | | | |
| 4 | .603 | 12.064 | 89.760 | | | |
| 5 | .512 | 10.240 | 100.000 | | | |

Extraction Method: Principal Component Analysis.

*Table 12: Component Matrix*

**Component Matrix[a]**

| | Component 1 | Component 2 |
|---|---|---|
| A | .638 | .394 |
| B | .289 | .791 |
| C | .711 | -.414 |
| D | .690 | .048 |
| E | .720 | -.304 |

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

Subsequently, this study imported Table 11 and Table 12 into Excel, first calculated the coefficients of each indicator in the linear combination of the two principal components through the calculation of the loading number, and then obtain the coefficients of all indicators in the comprehensive score model through the calculation of the variance contribution rate of the principal components. Finally, since the sum of the weights is 1, the coefficients in the comprehensive score model are normalized to obtain the corresponding weights of each indicator. The final result is:

Digital Economy Development Index (dedi) = the total amount of telecommunications business per capita***0.2700** + the proportion of computer service and software industry employees in urban units***0.2523** + the number of Internet broadband access users among 100 people***0.1199** + the number of mobile phone users in 100 people***0.2118** + the Digital Financial Inclusion Index of China***0.1460**

## 8.2 Multicollinearity Analysis (Pearson Test)

For the purpose of this study, this paper only needs to focus on the nature of the coefficients in the regression results (i.e., the positive and negative coefficients), and does not need to pay much attention to the values of the specific coefficients. Chen (2014) pointed out that for regression of panel data, if the case does not care about the specific regression coefficients, but only about the predictive power of the entire equation, then multicollinearity can be usually ignored. The main consequence of multicollinearity is that the contribution to the individual variables is not accurately estimated, but the overall effect of all variables can still be accurately estimated. Based on this, although multicollinearity analysis of variables is not required in this paper, Pearson's test can still enhance the robustness of the regression results. The Pearson test results are shown in Table 13.

*Table 13: Pearson Test Result*

| | lnce | dedi | lnincom | lnpop |
|---|---|---|---|---|
| lnce | 1.0000 | | | |
| dedi | -0.0361 | 1.0000 | | |
| lnincom | 0.3864 | 0.3679 | 1.0000 | |
| lnpop | 0.5276 | 0.0047 | 0.3468 | 1.0000 |

Among them, the value of Pearson's test (r value) ranges from -1 to 1, and the positive and negative signs represent the positive or negative correlation between the two variables, and the larger the absolute value, the stronger the collinearity between the variables. Sdedi is not tested because sdedi is the square term of the core explanatory variable dedi, and there is a certain mathematical relationship between the two variables, so the test of sdedi is meaningless. In this paper, the absolute value of r is defined as 0.8-1 as extremely strong correlation, 0.6-0.8 as strong correlation, 0.6-0.4 as moderate correlation, 0.4-0.2 as weak correlation, and 0.2-0 as extremely weak correlation. The results in Table 13 show that the r values between the core explanatory variable dedi and other variables are all less than 0.4, so the collinearity between dedi and other variables is considered to be weak. This result can enhance robustness to the model regression results.