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The Induced Effects of Carbon Emissions for China's Industry Digital Transformation

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Abstract: Studying the carbon emissions resulting from digital transformation can provide a reference for the realization of the goals of carbon peaking and carbon neutrality in the era of the digital economy. This study calculated the value added to the digital economy and carbon emissions for 97 industry divisions from 1997 to 2018. Using the input–output model, we estimated the carbon emissions induced by the digital transformation of different industries, and used the structural decomposition analysis (SDA) to identify their driving factors. The results show that the carbon emissions induced by the digital economy in agriculture, forestry, animal husbandry, and fishery decreased in 2010, those from mining increased year by year, and those from scientific research and technical services showed a decreasing trend from 2011 to 2015. The induced rate of digital economy carbon emissions for production and supply of electricity, heat, gas, and water has persistently remained high. At present, digital economy labor productivity has not shown a promoting effect on carbon emission reduction. China should strengthen the construction of a digital platform for ecological and environmental governance and build a green and low-carbon industrial chain and supply chain to promote the realization of the goals of carbon peaking and carbon neutrality.

Keywords: digital economy; carbon emissions reduction; labor productivity; input–output model; structural decomposition analysis

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1. Introduction

In September 2020, the Chinese government announced a major strategic goal to strive for peak carbon emissions by 2030 and achieve carbon neutrality by 2060 [1,2]. China's 14th Five-Year Plan proposes to support localities and key industries and enterprises with the conditions to achieve a peak in carbon emissions [3,4]. The development gap caused by different levels of technology [5], industrial structures [6], and resource endowments [7] have led to different degrees of progress in emission reduction efforts in various industries. In order to achieve the goals of carbon peaking and carbon neutrality on schedule, it is crucial to understand the results of carbon reduction efforts across different industries.

Currently, a new round of Industrial Revolution, represented by the digital economy, is sweeping across the globe at an unprecedented pace, with a very wide radiation range and depth of impact [8,9]. The Digital Carbon Neutrality White Paper points out that digital technology promotes the transformation of key industries towards digitization and greenization, empowers carbon emission reduction, and accelerates the digitalization of various sectors through information and communication technology. The potential for carbon emission reduction in the digital economy is enormous [10,11]. Therefore, it is particularly important to explore the effects of digital transformation on carbon emissions across industries in China, under the background of the goals of carbon peaking and carbon neutrality.

However, existing studies on the relationship between digital transformation and carbon emissions lack relevant research covering all industries of China's national economy, and there have been few studies analyzing the relationship between digital transformation and carbon emissions using input–output models (IOMs) and even fewer studies carried out from a supply-side perspective. Therefore, this study measured the value added to the digital economy and carbon emission volume of 97 industries classified by the (GB/T 4754-2017) [12] from 1997 to 2018. Secondly, we used the Ghosh input–output model [13] to analyze the impact of industry digital transformation on carbon emissions. Third, we used structural decomposition analysis (SDA) to decompose the carbon emissions of each industry into digital economy labor productivity, employment number, production technology level, and carbon emission intensity in order to identify the main driving factors of carbon emissions in different industries. Fourth, based on the results of the input–output model and the decomposition analysis, this study provides reasonable policy recommendations for carbon emissions reduction in Chinese industries.

This paper is expected to contribute in terms of the following three aspects. First, this study analyzed the relationship between digital transformation and carbon emissions from the supply-side using the input–output model. Replacing the value-added matrix of the four rows (employee compensation, net production tax, fixed capital consumption, and operating surplus) in the input–output table with the value-added matrix of two rows (value added to the digital economy and value added to the nondigital economy), this study used the input–output model to research the carbon emissions induced by value added to the digital economy. Second, this study covered all industries of the Chinese national economy and classified them into 97 industries according to the latest GB/T 4754-2017, released by the National Bureau of Statistics. Previous studies mainly concentrated on specific industries or sectors, but the digital economy has penetrated all industries to varying degrees [14,15], so this study adopted a more comprehensive perspective to research the relationship between digital transformation and carbon emissions. Third, we constructed two indicators, digital economy labor productivity (DP) and induced rate of digital economy carbon emissions, to explore the underlying causes of carbon emissions induced by the digital economy, and to show the carbon emissions induced by the digital economy per unit, respectively. Fourth, we provided value added to the digital economy and input–output tables of 97 industries from 1997–2018.

The rest of this paper is organized as follows. Section 2 presents the literature review. Section 3 describes the methods and data used in this study. Section 4 presents our results on the measurement of value added to the digital economy, induced effects of carbon emissions for digital transformation, and decomposition analysis of carbon emissions. Section 5 provides our conclusions and policy implications.

2. Literature Review

Research on industry carbon emissions often focuses on a specific industry, and input–output analysis (IOA) is a suitable research method for carbon emissions calculation. However, there is limited research on carbon emissions and their effects across all industries, with most focusing on a specific industry, such as the power industry [16,17], industrial sector [18], heating and power industry [19], steel industry [20], and transportation industry [21]. Currently, three main methods exist for calculating CO_2 emissions, including life cycle assessment (LCA) [22,23], intergovernmental Panel on Climate Change (IPCC), and input–output analysis (IOA) [24–28]. LCA and IPCC have high data requirements, and the accuracy of the results is difficult to guarantee. In comparison, IOA is more operable, and it can calculate direct and indirect emissions for each industry.

There is relatively few analyses that uses input–output models to study the relationship between digital transformation and carbon emissions, particularly from a supply-side perspective. Existing studies on the factors affecting carbon emissions often use econometric models [29–32], which cover population [33,34], economics [35], industry [36], space [37], residential consumption [38], and energy consumption [39]. However, research on the relationship between digital transformation and carbon emissions using an input–output model is relatively scarce [40–43], particularly from a supply-side perspective [44–47].

Regarding the impact of digital transformation on carbon emissions, there are three viewpoints currently extant in research. The first holds that digital transformation is helpful in reducing carbon emissions. Scholars claim that digital transformation can promote carbon reduction through means such as improving productivity [48], changing management and sales approaches [49], promoting industrial transformation [50], and accelerating human capital accumulation [51]. Gelenbe and Caseau [52] found that digital transformation can reduce energy consumption in industries such as transportation, construction, online learning, and healthcare. The second viewpoint is that digital transformation will exacerbate carbon emissions [53,54]. First, the widespread use of digital products directly increases carbon emissions [55]. Second, digital transformation increases energy consumption through accelerating product updates [56] and transportation, and increasing distribution demands [57]. The third viewpoint is that the relationship between digital transformation and carbon emissions follows a U-shaped pattern [58–60]. On the one hand, digital transformation will continuously increase CO_2 emissions because of factors such as digital device production [61], increases in energy consumption [62], and electronic waste recycling [63]. On the other hand, digital transformation can decrease carbon emissions by developing more intelligent cities [64], transportation systems [65], smart grids [66], and energy-efficient devices [67]. The opposing effects produce a U-shaped relationship between digital transformation and carbon emissions.

SDA is a decomposition method used for researching the driving factors of carbon emissions through input–output analysis. The commonly used carbon emission decomposition methods include structural decomposition analysis (SDA) and index decomposition analysis (IDA). In general, the advantage of IDA lies in the flexibility of selecting indicators, making it widely used in constructing comprehensive economic energy efficiency indices [68,69]. The uniqueness of SDA lies in its usability for different IO models, like the traditional Leontief I-O model, the semi-closed I-O model [70], the Ghosh I-O model [71,72], and various multiregional I-O models. In recent years, the SDA decomposition method has been widely applied to decomposing the driving factors of carbon emissions in different countries, such as Italy [73], China [74], Belt and Road Initiative countries [75], G20 countries [76], the UK [77], South Korea [78], and the EU [79]. For the driving factors of carbon emissions, most studies have analyzed the impact of structure and technology changes on energy use from the demand side. Yuan and Zhao [80] decomposed emission changes into emission intensity, technology, and demand effects. Wei et al. [81] decomposed emission changes into technology, sectoral links, economic structure, and economic scale. Xu et al. [82] believed that emission changes were caused by import and export effects, energy structure and intensity effects, technology effects, transfer effects, and investment effects. Yu et al. [83] decomposed carbon emissions from the perspectives of input structure, energy intensity, structural effects, and final demand effects.

In summary, in terms of research scope, few researchers have studied the relationship between digital transformation and carbon emissions in all industries in China. In terms of research methods, input–output models are used less frequently than econometric models, even though input–output models have been proven to be a more suitable research method. In terms of research perspectives, there are few studies that have explored the relationship between digital transformation and carbon emissions from the supply-side perspective, as opposed to the demand side. This article used the Ghosh input–output model to study the induced effects of digital transformation on carbon emissions from 97 industries from 1997 to 2018.

3. Materials and Methods

3.1. Ghosh Model

The Ghosh model [13] was developed as a supplement to the Leontief model. Its basic form is:

$$\boldsymbol{X} = \boldsymbol{v}(\boldsymbol{I} - \boldsymbol{B})^{-1} = \boldsymbol{v}\boldsymbol{G} \tag{1}$$

In Equation (1), $\boldsymbol{v}$ is the row vector of value added, $\boldsymbol{X}$ is the total output, and $\boldsymbol{I}$ is a suitable unitary vector. $\boldsymbol{B}$ is the direct output coefficient, representing the distribution of outputs of the original sectors. $\boldsymbol{G}$ is the Ghosh inverse matrix, and it presents the total output of downstream departments caused by 1 unit of initial input entering the production system.

This paper built an environment of the extended Ghosh model by combining the carbon emission satellite account indicator $\boldsymbol{Q}$ with the Ghosh model. Let $\boldsymbol{q_i}$ denote the carbon emission intensity vector for each industry sector i $(i \in 1 \ldots n)$, then $\boldsymbol{q}$ can be defined as:

$$\boldsymbol{q} = \boldsymbol{Q}\hat{\boldsymbol{X}}^{-1} \tag{2}$$

Carbon emission intensity $\boldsymbol{q}$ for each department represents the carbon emissions generated by the production of one unit of output in each industry sector. The element $\boldsymbol{q_i} = \boldsymbol{Q_i}/\boldsymbol{X_i}$. Therefore, by applying $\boldsymbol{q}$ to the entire economic system, the carbon emissions of each industry sector can be expressed as:

$$\boldsymbol{Q} = \boldsymbol{X}\hat{\boldsymbol{q}} = \boldsymbol{v}\boldsymbol{G}\hat{\boldsymbol{q}} \tag{3}$$

The equation above shows that the carbon emissions of each industry sector can be linked to its income through the Ghosh model. Here, $\boldsymbol{Gq}$ denotes the emission effect of the inputs of each sector and refers to the direct and indirect carbon emissions generated by the initial input of each sector through the entire economic system. It can be represented in matrix form as:

$$\begin{aligned} \boldsymbol{Q} = \hat{\boldsymbol{v}}\boldsymbol{G}\hat{\boldsymbol{q}} &= \begin{bmatrix} v_1 & & \\ & \ddots & \\ & & v_n \end{bmatrix} \begin{bmatrix} G_{11} & \cdots & G_{1n} \\ \vdots & \ddots & \vdots \\ G_{n1} & \cdots & G_{nn} \end{bmatrix} \begin{bmatrix} q_1 & & \\ & \ddots & \\ & & q_n \end{bmatrix} \\ &= \begin{bmatrix} v_1 G_{11} q_1 & \cdots & v_1 G_{1n} q_n \\ \vdots & \ddots & \vdots \\ v_n G_{n1} q_1 & \cdots & v_n G_{nn} q_n \end{bmatrix}. \end{aligned} \tag{4}$$

$\hat{\boldsymbol{v}}$ represents the diagonalized matrix of the initial inputs, while $\hat{\boldsymbol{q}}$ represents the carbon emission intensity, and its elements represent the amount of carbon emissions per unit output produced by each sector.

Taking sector i as an example, in terms of the results, the row direction represents the carbon emissions generated by sector i's initial inputs. Each column of the first row represents the carbon emissions generated in all the sectors connected to sector $i's$ initial inputs, generated after running through the entire economic system. In terms of column direction, each row of the first column represents the carbon emissions generated by sector i, initiated by all sectors' initial inputs.

This study mainly examined the carbon emissions generated by digital value added from various industry sectors. Thus, we chose the sum of each industry sector's $\boldsymbol{rows}\sum_i^n v_i \sum_j^n \boldsymbol{G_{ij} q_{ij}}$ to represent the carbon emissions generated by their digital value added.

Therefore, the carbon emissions generated by the digital value added of sector i can be represented as:

$$\boldsymbol{Q_i} = \sum_j^n v_i \boldsymbol{G_{ij} q_j}. \tag{5}$$

In order to study the socioeconomic driving factors of changes in the amount of carbon emissions, the $\boldsymbol{v}$ in Equation (5) was decomposed into the following two influencing factors: digital economy labor productivity (D) and employment number (E). The SDA model was used to decompose the changes in carbon emissions Q into the sum of various factors, namely:

$$\Delta \boldsymbol{Q} = \Delta \boldsymbol{DEGq} + \boldsymbol{D}\Delta \boldsymbol{EGq} + \boldsymbol{DE}\Delta \boldsymbol{Gq} + \boldsymbol{DEG}\Delta \boldsymbol{q} \quad (6)$$

Among them, $\Delta \boldsymbol{D}$, $\Delta \boldsymbol{E}$, $\Delta \boldsymbol{G}$, and $\Delta \boldsymbol{q}$ represent the contribution of digital economy labor productivity, employment number, production technology level, and carbon emission intensity to the change incarbon emissions when other variables remained unchanged.

3.2. Input–Output Tables for 97 Industries

The 97 industries input–output table is a modification of the 42 industries input–output table [84], compiled by the Chinese Industrial Ecology Laboratory (IELab). The refinement of the industry classification standards from 42 to 97 industries enabled the development of the 97 industries input–output table. Harmonized matrix methods were used for industry adjustments in the intermediate-use matrix (T), final-use matrix (Y), and initial-input matrix (V) in the input–output table. In this paper, the employment structures of the 97 industries were selected as the proxies for matrices T, Y, and V. The assumption underlying the selection of the employment structures of the 97 industries as proxies for matrices T, Y, and V was that the employment structure was consistent with the industry division classification structure of T, Y, and V within the industry section. This assumption was reasonable for two reasons. First, in the absence of data for industry division, employment was the closest available indicator in proximity to the intermediate-use, final-use, and initial-input measures. Second, this assumption did not change the industry section structure of the T, Y, and V matrices. The use of the employment structure for industry classification as based on the original data of different industry sections as the control total, which avoided the change of the original industry section structure.

3.3. Measurement of Industry Value Added to the Digital Economy

According to the practice of the China Academy of Information and Communications Technology (CAICT), this paper divided the national economy into the basic industries of the digital economy and the convergent industries of the digital economy. Combining the selection of the digital economy's basic industries by BEA [85], this paper specified six industries for the basic industries of the digital economy by the GB/T 4754-2017 standard: computer, communication, and other electronic equipment manufacturing industries (39) (the numbers represent the industry division codes in Table A1 of Appendix A); telecommunications, broadcasting, television, and satellite transmission services (63); internet and related services (64); software and information technology services industry (65); and radio, television, film, and video production industry (87). The convergent industries of the digital economy were the industries other than the basic industries.

According to whether each industry belonged to the basic industries of the digital economy or the convergent industries of the digital economy, this paper divided the acquisition methods of the digital economy's value added into two types. The value added of the nondigital economy in that industry was the total value added of the industry minus the value added of the digital economy in that industry. The first method of acquiring the value added to the digital economy of the industry is to use the scale of the national digital economy's basic part as the control total. According to the industry's digital economy scale distribution structure under the BEA framework, the value added to the digital economy is allocated. The scale of the national digital economy's basic part can be directly or indirectly obtained from the relevant data released by the CAICT. The accounting of the industry's digital economy scale under the BEA framework refers to the accounting framework of the BEA. The second method of acquiring the value added to the digital economy of the industry is to use the scale of the national convergent part of the digital economy as the control total. Based on the distribution structure of information and communications technology (ICT) capital services, the value added to the digital economy of the industry is allocated. The scale data of the national convergent part of the digital economy can be directly or indirectly obtained from the relevant data released by the CAICT. The ICT capital service value added of the industry is calculated by multiplying the industry value added by the proportion of the ICT capital service to the total capital service. The value of industry value added is provided by the 97 industries input–output table. According to Wang an Wang [86], the proportion of ICT capital services in the total capital services was calculated.

3.4. Measurement of Industry Carbon Emissions

The industry carbon emissions data in this paper were from the Carbon Emission Accounts and Datasets (CEADs) in China [87–89], which provides carbon emissions data categorized by industry in the *National Industry Classification (GB/T 4754-2011)* [90] standard, with 47 industries. To unify the data of industry value added to the digital economy, this paper adjusted the industry carbon emission data to the 97 industry classifications in the *National Industry Classification (GB/T 4754-2017)* standard.

3.5. Indicator Construction

3.5.1. Digital Economy Labor Productivity

This paper constructed the digital economy labor productivity (DP) to measure the amount of value added to the digital economy (DV) produced by each employed labor (L). The higher the DP, the more DV each employed labor produces and vice versa. The expression of DP is shown as Equation (7):

$$\text{Digital Economy Labor Productivity} = \frac{\text{Value} - \text{added to the Digital Economy}}{\text{Labor}} = \frac{\text{DV}}{\text{L}} \tag{7}$$

3.5.2. Induced Rate of Digital Economy Carbon Emissions

This paper built the induced rate of digital economy carbon emissions (IR), which refers to the carbon emissions (CE) induced by one unit of DV in the Ghosh model. The IR represents the carbon emissions induced by one unit of DV in downstream production processes. The higher the IR, the greater the carbon emissions induced by the input of the digital economy, and the weaker the carbon reduction ability of the digital economy.

The expression of IR is shown as Equation (8):

$$\begin{aligned} &\text{Indeced Rate of Digital Economy Carbon Emission} \\ &= \frac{\text{Carbon Emissions Induced by Value} - \text{added to the Digital Economy}}{\text{Value} - \text{added to the Digital Economy}} \\ &= \frac{\text{CE}}{\text{DV}} \end{aligned} \tag{8}$$

4. Results

4.1. Value Added to the Digital Economy in Different Industries

4.1.1. National Value Added to the Digital Economy

In this chapter, the scale of the digital economy from 1997 to 2018, and its proportion of GDP, were calculated using data from the CAICT on the proportion of the digital economy to GDP and the GDP data released by the National Bureau of Statistics (Table 1). The proportions of the digital economy's basic and integrated parts to the total scale of the digital economy were also calculated.

From 1997 to 2018, China's overall digital economy scale, basic part scale, and integrated part scale showed a rapidly increasing trend, with the integrated part's annual growth rate being higher than the basic part. From 1997 to 2018, China's digital economy scale increased rapidly from CNY 51.4 billion to CNY 16,983.3 billion, with an average annual growth rate of 31.8%, and its proportion to GDP increased from 0.6% to 34.8%. In 21 years, the basic part of the digital economy increased from CNY 25.3 billion to CNY 3481.6 billion, at an average annual growth rate of 26.4%; the integrated part of the digital economy increased from CNY 26.1 billion to CNY 13,501.8 billion, at an average annual growth rate of 34.7%. The proportion of the basic part to the total scale of the digital economy showed an upward trend from 49.2% in 1997 to 50.9% in 2005, then decreased to 20.5% in 2018. The proportion of the integrated part to the total scale of the digital economy showed the opposite trend.

Table 1. The scale and structure of China's digital economy from 1997 to 2018 (1997 = 100) (1997 = 100 indicates that the price index was based on 1997).

Year	Basic Part Scale (Billion CNY)	Proportion of the Basic Part in the Digital Economy (%)	Integrated Part Scale (Billion CNY)	Proportion of the Integrated Part in the Digital Economy (%)	Digital Economy Scale (Billion CNY)	Proportion of the Digital Economy of GDP (%)
1997	25.3	49.2	26.1	50.8	51.4	0.6
1998	47.7	49.4	48.8	50.6	96.4	1.1
1999	89.8	49.7	91.0	50.3	180.8	2.0
2000	170.3	49.9	171.2	50.1	341.4	3.4
2001	322.3	50.1	321.3	49.9	643.6	5.9
2002	614.6	50.3	607.4	49.7	1222.1	10.3
2003	738.3	50.5	723.4	49.5	1461.7	11.2
2004	889.2	50.7	863.9	49.3	1753.1	12.2
2005	1157.9	50.9	1115.2	49.1	2273.1	14.2
2006	1251.2	47.8	1364.7	52.2	2615.9	14.5
2007	1360.2	44.9	1668.4	55.1	3028.5	14.7
2008	1448.7	42.2	1986.6	57.8	3435.3	15.2
2009	1706.4	38.1	2768.9	61.9	4475.2	18.1
2010	1810.0	34.5	3440.4	65.5	5250.4	19.2
2011	1896.4	31.2	4187.7	68.8	6084.1	20.3
2012	2070.0	29.4	4979.9	70.6	7049.9	21.8
2013	2285.2	27.7	5976.9	72.3	8262.1	23.7
2014	2546.1	26.1	7226.0	73.9	9772.1	26.1
2015	2831.4	25.7	8185.6	74.3	11,017.0	27.5
2016	2981.8	23.0	9982.4	77.0	12,964.2	30.3
2017	3400.8	22.6	11,647.1	77.4	15,047.9	32.9
2018	3481.6	20.5	13,501.8	79.5	16,983.3	34.8

4.1.2. Digital Economy Scale in Different Industries

This chapter distributed the basic and integrated digital economy components of each year based on the scale distribution structure of the digital economy in various industries under the BEA (Barefoot et al., 2018) accounting framework and the value-added distribution structure of each industry's ICT capital services. This resulted in a digital economy scale for 20 industries from 1997 to 2018 (Because of space limitations, this paper combined the data of 97 industry divisions into 20 industry sections, and only shows the data of 20 industry sections) (Figure 1).

Looking at the absolute value of the digital economy scale, manufacturing (Manuf) (limiting the space for images, we used the abbreviation instead of the full name of each industry; the abbreviation is the first three or four letters of the full name. Abbreviations and full names are presented in Table A1 of Appendix A) has remained at a high level, reaching CNY 3168.2 billion in 2018, accounting for 18.7% of the total digital economy scale that year. Other industries with large digital economy scales included construction (Const) and financial intermediation (Finan), both of which had a scale of over CNY 2000 billion in 2018. Excluding international organizations (Inter), the industry with the smallest digital economy scale was management of water conservancy, environment, and public facilities (Manag), with a digital economy scale of CNY 2.2 billion in 2018, accounting for 0.01% of the total digital economy scale that year.

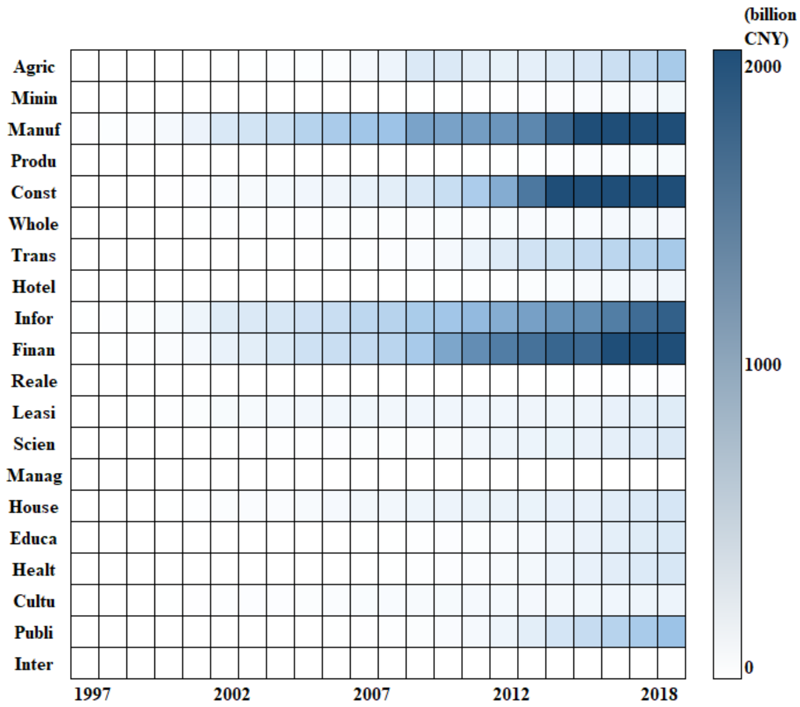

Figure 1. China's industry value added to the digital economy from 1997 to 2018 (The full names of the 20 industry sections and 97 industry divisions are shown in Table A1 of Appendix A) (1997 = 100).

Looking at digital economy scale growth rates, the digital economy scale growth rate of each industry was rapid, with the annual growth rate between 20% and 60% from 1997 to 2018. The national digital economy scale's average annual growth rate was 31.8%, with 14 of the 20 industries having an average annual growth rate above this level. The industry with the fastest digital economy scale growth rate was the real estate industry (RealE), with an average annual growth rate of 55.6%. Other industries experiencing rapid growth in digital economy scale included international organization (Inter); public management, social security, and social organization (Publi); and health and social services (Healt), all with average annual growth rates above 50%. Industries with relatively slower annual growth rates included leasing and business services (Leasi) and culture, sports, and entertainment (Cultu), with annual growth rates below 25%.

4.2. Carbon Emissions Induced by the Digital Economy

With the help of the carbon emission extended Ghosh input–output model, this paper calculated the carbon emissions induced by the digital economy in various industries (referred to as DCE) from 1997 to 2018 (Figure 2) (because of space limitations, we placed the carbon emissions induced by the digital economy of 97 industries in the Supplementary Materials). Financial (Finan) and manufacturing (Manuf) have consistently maintained high levels of DCE. In 2018, the DCE in the financial (Finan) and manufacturing (Manuf) industries accounted for 32.9% and 20.7% of all industries' digital carbon emissions, respectively. Transport, storage, and post (Trans) was also relatively high, with DCE exceeding 300 million tons of CO_2 in 2018, accounting for 11.8% of all industries. From 1990 to 2018, the DCE in all industries maintained high-speed growth, with an average annual growth rate of 40.2%. Among them, the real estate industry (RealE) had the fastest average annual growth rate, reaching 64.5%.

The trends of DCE varied from industry to industry. The DCE of agriculture, forestry, animal husbandry, and fishery (Agric) fell in 2010, probably because 2010 was a key year for achieving the Eleventh Five-Year Plan's energy conservation and emission reduction goals, and agriculture, forestry, animal husbandry, and fishery (Agric), as a key industry for carbon emissions, vigorously promoted digital transformation, eliminated poor general production capacity, actively promoted the development and promotion of energy-saving technologies, and reduced the growth rate of DCE.

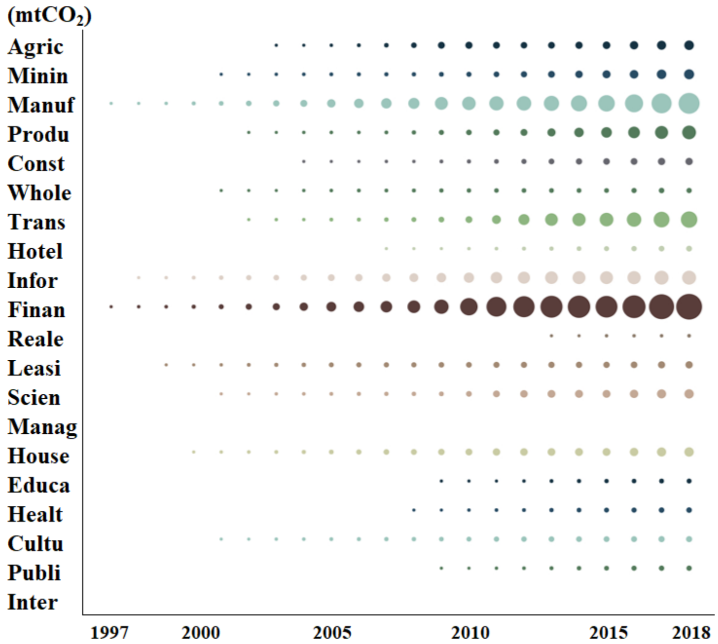

Figure 2. Carbon emissions induced by the digital economy of 20 industries in China from 1997 to 2018. $mtCO_2$ denotes one million tons of CO_2. (Different colors indicate different industries, and larger circles indicate larger values).

The DCE of the second industry, mining (Minin) and production and supply of electricity, heat, gas, and water (Produ) is increasing year by year. On the one hand, the energy consumption of secondary industry is relatively high, and some enterprises have insufficient motivation for energy conservation and emissions reduction or have been unable to bear the cost of the surge in digital transformation for energy conservation and emissions reduction [91]. On the other hand, because of China's immature digital transformation, it is difficult to transform traditional technologies into digital emissions reduction technologies, and there are obstacles such as insufficient innovation and low efficiency. The ability to achieve digital carbon emissions reduction needs to be further improved [92].

The DCE of tertiary industry, represented by leasing and business services (Leasi), scientific research and technical services (Scien); household services, repair, and other services (House); and culture, sports, and entertainment (Cultu), showed a decreasing trend from 2011 to 2015. This may have been because during the Twelfth Five-Year Plan period, China vigorously developed the service industry and strategic emerging industries, took energy conservation and emissions reduction as the starting point for transforming the mode of economic development, and implemented a number of energy conservation and emissions reduction measures, such as actively promoting residential electricity and water ladder prices and implementing heat metering and charging; strengthening energy conservation and emissions reductions in agricultural and rural, commercial and civil, and public institutions; and encouraging financial institutions to provide credit support for energy conservation, emissions reduction, and low-carbon projects.

Figure 3 displays the induced rate of digital economy carbon emissions (IR) for 20 industries using a heat map, where darker colors indicate a higher IR. The IR refers to the amount of carbon emissions per unit of DV and can be used to analyze the reasons for different DCE values in each industry.

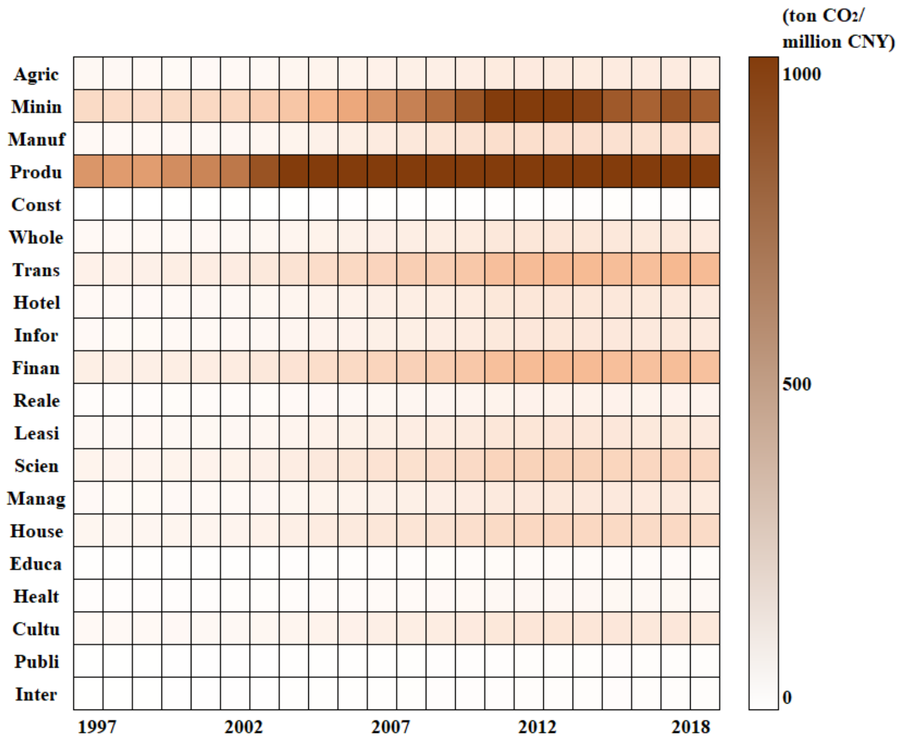

Figure 3. Induced rate of digital economy carbon emissions for 20 industries in China from 1997 to 2018.

The IR for production and supply of electricity, heat, gas, and water (Produ) remains high, followed by mining (Minin) and transport, storage, and post (Trans). In 2018, the IR values for production and supply of electricity, heat, gas, and water (Produ); mining (Minin); and transport, storage, and post (Trans) were 2552.3, 856.6, and 432.0 tons CO_2 per million CNY, respectively. The IR for the construction (Const), which had the lowest value, was only 11.8 tons CO_2 per million CNY. The three industries with high IR values were all of the energy consumption type. Therefore, to achieve the goals of carbon peaking and carbon neutrality, we must focus on the IR of energy consumption type industries. This could be achieved through considering three aspects: First, clean energy using digital technologies, such as big data, artificial intelligence, and cloud computing, should be developed, and it should be applied to industry energy conservation and emissions reductions [93]. Second, a mining environmental supply chain network using digital technologies, such as big data and blockchain, should be designed, reducing carbon emissions throughout the supply chain process [94]. Third, energy consumption structures should be adjusted by formulating policies that encourage the use of clean energy. Research and development of renewable energy power generation technology, energy storage technology, etc., should be conducted to substantially increase the proportion of nonfossil energy use, and a new type of renewable energy-based power system should be built as early as possible [95].

4.3. Driving Factors of Carbon Emission Changes

In this paper, the SDA method was used to decompose carbon emission changes into four factors: digital economic labor productivity (DP), employment number, production technology level, and carbon emission intensity (Figure 4). Among them, the product of DP and employment number was the DV, and the industry level employment data in each year were from Wang et al. [96].

The change in carbon emissions caused by DP was found to be basically positive; the change in carbon emissions caused by employment number was negative after 2016; the change in carbon emissions caused by the production technology level was basically negative, and the change in carbon emissions caused by carbon emission intensity was basically negative after 2013. For the factor of DP, one of the important reasons for the gradual improvement in carbon emissions was the introduction of a large amount of automation equipment (i.e., industrial robots), which increased energy consumption and pollutant emissions which, in turn, led to an increase in carbon emissions [97–99].

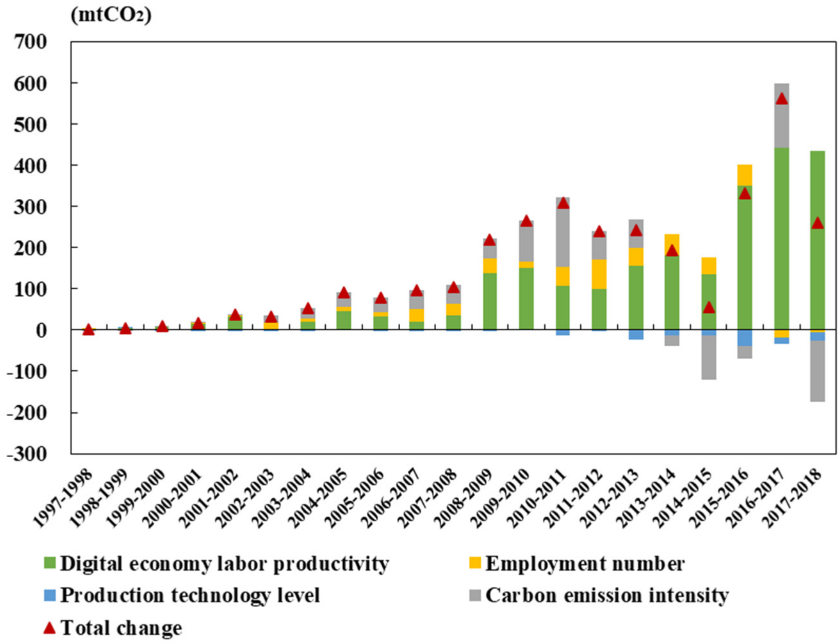

Figure 4. Structural decomposition analysis of carbon emissions induced by the digital economy.

For the factor of employment number, the commuting of employees [100,101], production process [102,103], and consumption [104,105], among other links, produce carbon emissions, but with the decline in employment in recent years, the rise of online offices, the rise of paperless offices, etc., the change in carbon emissions caused by the employment number has changed from positive to negative. For the factor of the production technology level, the improvement in the production technology level can promote carbon emission reductions while comprehensively improving productivity, indicating that China is persistently promoting ecological priorities, conservation, and intensification and green and low-carbon development. For the factor of carbon emission intensity, its impact on carbon emission changes has been negative since 2013, indicating that carbon emissions caused by the unit digital economy have begun to decrease. China has undertaken a series of measures towards low-carbon development commitments, launched the 2010 China Information and Communication Industry to Promote Low-Carbon Economic Development Summit Forum, and announced the adoption of low-carbon development measures for the information and communication industry.

From the above analysis, it is clear that DP is a major driver of carbon emissions. Therefore, further analysis was conducted on the carbon emissions induced by DP in different industries (Figure 5).

The carbon emissions induced by DP in manufacturing (Manuf) and financial intermediation (Finan) were found to be relatively high. In 2018, the carbon emissions induced by DP in manufacturing (Manuf) and financial intermediation (Finan) were 152.2 and 91.8 mt, accounting for 35.0% and 21.1% of all industries, respectively. The relatively high levels of carbon emissions induced by DP in manufacturing (Manuf) were because of the substitution of human workers with machines [106,107]; an increasing amount of machinery and equipment will lead to increasing energy consumption and pollutant emissions. For financial intermediation (Finan), most of the carbon emissions induced by DP came from indirect carbon emissions. Indirect carbon emissions from the financial intermediation (Finan) flow from financial intermediation (Finan) to other industries through the industrial chain and supply chain, such as investment and financing businesses [108], carbon market trading, and carbon financial derivatives [109]. From 2014 to 2015, the carbon emissions induced by DP in financial intermediation (Finan) were negative, which may have been because carbon finance began to develop in 2014; 2015 was the first year of carbon finance, when several carbon financial products involving asset management entered the market one after another. These products can effectively help enterprises scientifically manage carbon assets and achieve reasonable financing, leading to carbon emission reductions while improving DP.

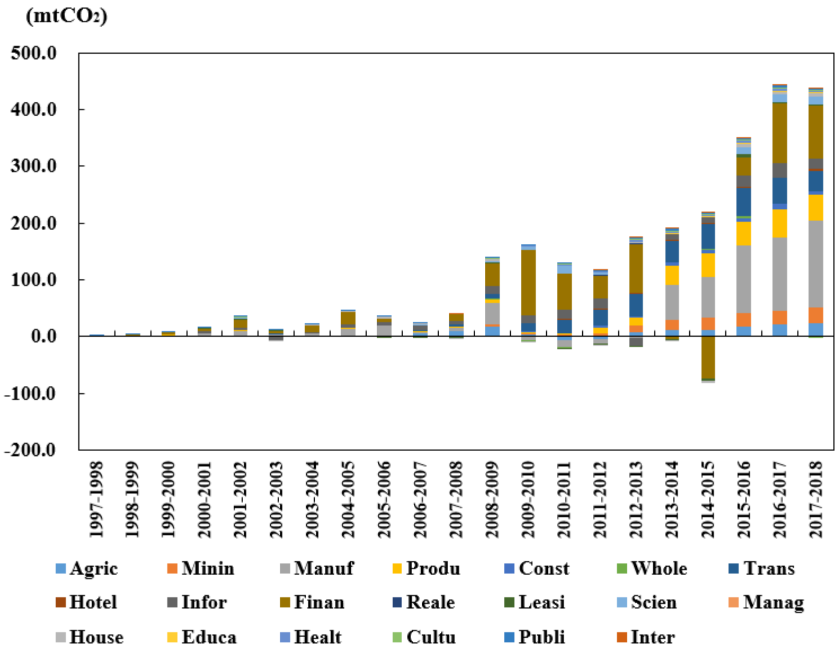

Figure 5. Carbon emissions induced by digital economy labor productivity (mtCO_2).

5. Conclusions

The 20th Communist Party of China National Congress Report highlighted the need to actively and steadily promote carbon peaking and carbon neutrality. As a new engine for high-quality development, digital transformation has brought about wide-ranging economic and social changes and has become a crucial means of promoting low-carbon transformation across all industries by balancing industrial and economic development with carbon peaking and carbon neutrality. This paper calculated the induced effects of China's industry digital transformation on carbon emissions from 1997 to 2018 and explored the driving factors behind carbon emissions.

This paper presents the following four findings. First, between 1997 and 2018, the DV in manufacturing (Manuf), construction (Const), and financial intermediation (Finan) remained at a high level, with the average annual growth rate of DV in all industries ranging from 20% to 60%. Second, from 1997 to 2018, the trend in DCE in different industries varied. Among them, the DCE of primary industry decreased in 2010, those from secondary industry showed an increasing trend year by year, and those from tertiary industry showed a decreasing trend from 2011 to 2015. Third, the induced rate of digital economy carbon emissions (IR) for energy consumption industries was found to be relatively high, which could be addressed by developing clean energy, designing environmentally friendly supply chain networks, and adjusting energy consumption structures. Fourth, the decomposition of carbon emission drivers showed that the digital economy labor productivity (DP) has not yet shown a promoting effect on carbon emission reductions.

Based on the results of this paper, the following policy recommendations are proposed. First, different carbon reduction policies and objectives should be formulated for different types of industries. As can be seen from the above results, there were years when DCE began to decline and the IR also varied among different types of industries. Therefore, it is crucial to issue relevant policies to achieve the goals of carbon peaking and carbon neutrality quickly and effectively. Second, China should strengthen the construction of a digital platform for ecological environment governance, unify data standards and technical specifications across industries, break down technical barriers caused by monopolistic behavior of data platforms, and lay out a digital green technology ecosystem around existing key core technologies. Third, we should build a green and low-carbon industrial chain and supply chain. Under the "chain era", all departments are closely interrelated; therefore, carbon emission accounting standards, labeling systems, and traceability mechanisms should be established along the industrial chain and supply chain, and a mechanism for sharing responsibility for emission reductions between departments should be formed on this basis to strengthen the coordinated emission reductions of multiple departments.

This study had some limitations. First, because of space constraints, we were unable to display the complete charts for all 97 industry divisions in the main text. Second, because of the availability of carbon emissions data, our research only covered the years 1997–2018. We included the complete data for the DCE of all 97 industry divisions in the Supplementary Materials and hope that future research will update the time span of the study.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su151612170/s1, Table S1: Carbon emissions induced by the digital economy of 97 industry divisions in China from 1997 to 2018 (mtCO_2).

Author Contributions: Conceptualization, X.J.; methodology, X.J.; data curation, J.F.; software, J.F.; writing—original draft, Q.L.; writing—review and editing, X.J.; visualization, Y.L.; supervision, L.Z.; project administration, L.Z. All authors have read and agreed to the published version of the manuscript.

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Appendix A

Table A1. Industry sections and names of 97 industry divisions.

Code	Abbr.	Industry Section	Code	Industry Division
A	Agric	Agriculture, Forestry, Animal Husbandry, and Fishery	1	Agriculture
			2	Forestry
			3	Animal Husbandry
			4	Fishery
			5	Agricultural, Forestry, Animal Husbandry, Fishery Specialized and Support Activities
B	Minin	Mining	6	Coal Mining, Washing Industry
			7	Petroleum, and Natural Gas Extraction Industry
			8	Ferrous Metal Ore Mining and Dressing Industry
			9	Nonferrous Metal Ore Mining and Dressing Industry
			10	Nonmetal Mining and Dressing Industry
			11	Mining Specialized and Support Activities
			12	Other Mining Industries

Table A1. *Cont.*

Code	Abbr.	Industry Section	Code	Industry Division
C	Manuf	Manufacturing	13	Agricultural and Sideline Food Processing Industry
			14	Food Manufacturing Industry
			15	Wine, Beverage and Refined Tea Manufacturing Industry
			16	Tobacco Products Industry
			17	Textile Industry
			18	Textile, Clothing and Apparel Industry
			19	Leather, Fur, Feather and Their Product, and Shoe Manufacturing Industry
			20	Wood Processing and Bamboo, Rattan, Palm, Grass, and Straw Products Industry
			21	Furniture Manufacturing Industry
			22	Paper and Paper Products Industry
			23	Printing and Recordable Media Reproduction Industry
			24	Cultural, Educational, and Sporting Goods Manufacturing Industry
			25	Petroleum, Coal, and Other Fuel Processing Industry
			26	Chemical Materials and Chemical Product Manufacturing Industry
			27	Pharmaceutical manufacturing
			28	Chemical Fiber Manufacturing Industry
			29	Rubber and Plastic Products Industry
			30	Nonmetal Mineral Products Industry
			31	Ferrous Metal Smelting and Pressing Industry
			32	Nonferrous Metal Smelting and Pressing Industry
			33	Metal Product Industry
			34	General Equipment Manufacturing Industry
			35	Specialized Equipment Manufacturing Industry
C	Manuf	Manufacturing	36	Automobile Manufacturing Industry
			37	Railway, Shipbuilding, Aerospace, and Other Transportation Equipment Manufacturing Industry
			38	Electrical Machinery and Equipment Manufacturing Industry
			39	Computer, Communication, and Other Electronic Equipment Manufacturing Industry
			40	Instrumentation Manufacturing Industry
			41	Other Manufacturing Industries
			42	Comprehensive Utilization of Waste Resources Industry
			43	Metal Product, Machinery, and Equipment Repair Industry
D	Produ	Production and Supply of Electricity, Heat, Gas and Water	44	Electricity, Heat Production, and Supply Industry
			45	Gas Production and Supply Industry
			46	Water Production and Supply Industry
E	Const	Construction	47	House Construction Industry
			48	Civil Engineering Construction Industry
			49	Construction Installation Industry
			50	Building Decoration, Finishing, and Other Building Industries

Table A1. *Cont.*

Code	Abbr.	Industry Section	Code	Industry Division
F	Whole	Wholesale and Retail Trades	51	Wholesale Industry
			52	Retail Industry
G	Trans	Transport, Storage, and Post	53	Railway Transportation Industry
			54	Road Transportation Industry
			55	Water Transportation Industry
			56	Aviation Transportation Industry
			57	Pipeline Transportation Industry
			58	Multimodal Transportation and Transportation Agency Industry
			59	Loading and Unloading, Handling, and Storage Industry
			60	Postal Industry
H	Hotel	Hotels and Catering Services	61	Accommodation Industry
			62	Catering Industry
I	Infor	Information Transmission, Software, and Information Technology	63	Telecommunications, Broadcasting, Television, and Satellite Transmission Services
			64	Internet and Related Services
			65	Software and Information Technology Services Industry
J	Finan	Financial Intermediation	66	Currency and Financial Services
			67	Capital Market Services
			68	Insurance Industry
			69	Other Financial Industries
K	RealE	Real Estate Industry	70	Real Estate Industry
L	Leasi	Leasing and Business Services	71	Leasing Industry
			72	Business Service Industry
M	Scien	Scientific Research and Technical Services	73	Research and Experimental Development
			74	Professional Technical Services
			75	Science and Technology Promotion and Application Services
N	Manag	Management of Water Conservancy, Environment and Public Facilities	76	Water Conservancy Management Industry
			77	Ecological Protection and Environmental Governance Industry
			78	Public Facility Management Industry
			79	Land Management Industry
O	House	Household Services, Repair and Other Services	80	Residential Service Industry
			81	Motor Vehicle, Electronic Product, and Daily Product Repair Industry
			82	Other Services Industry
P	Educa	Education	83	Education
Q	Healt	Health and Social Service	84	Healthcare
			85	Social Assistance
R	Cultu	Culture, Sports, and Entertainment	86	News and Publishing Industry
			87	Radio, Television, Film, and Video Production Industry
			88	Culture and Art Industry
			89	Sports Industry
			90	Entertainment Industry

Table A1. *Cont.*

Code	Abbr.	Industry Section	Code	Industry Division
S	Publi	Public Management, Social Security, and Social Organization	91	Organs of the Communist Party of China
			92	National Institutions
			93	People's Political Consultative Conference and Democratic Parties
			94	Social Security
			95	Mass Organizations, Social Organizations, and Other Member Organizations
			96	Grassroots Mass Self-Government Organizations and Other Organizations
T	Inter	International Organization	97	International Organizations

References

1. Chen, M.; Cui, Y.; Jiang, S.; Forsell, N. Toward Carbon Neutrality Before 2060: Trajectory and Technical Mitigation Potential of Non-CO_2 Greenhouse Gas Emissions from Chinese Agriculture. *J. Clean. Prod.* **2022**, *368*, 133186. [CrossRef]
2. Lin, J.; Nie, J.; Wang, T.; Yue, X.; Cai, W.; Liu, Y.; Zhang, Q. Towards Carbon-Neutral Sustainable Development of China. *Environ. Res. Lett.* **2023**, *18*, 060201. [CrossRef]
3. Huo, T.; Du, Q.; Xu, L.; Shi, Q.; Cong, X.; Cai, W. Timetable and Roadmap for Achieving Carbon Peak and Carbon Neutrality of China's Building Sector. *Energy* **2023**, *274*, 127330. [CrossRef]
4. Yu, Y.; Shi, C.; Guo, J.; Pang, Q.; Deng, M.; Na, X. To What Extent Can Clean Energy Development Advance the Carbon Peaking Process of China? *J. Clean. Prod.* **2023**, *412*, 137424. [CrossRef]
5. Yan, Y.; Li, J.; Xu, Y.; Zhang, Y. Research on Industry Difference and Convergence of Green Innovation Efficiency of Manufacturing Industry in China Based on Super-Sbm and Convergence Models. *Math. Probl. Eng.* **2021**, *2021*, 4013468. [CrossRef]
6. Zheng, H.; Gao, X.; Sun, Q.; Han, X.; Wang, Z. The Impact of Regional Industrial Structure Differences on Carbon Emission Differences in China: An Evolutionary Perspective. *J. Clean. Prod.* **2020**, *257*, 120506. [CrossRef]
7. Yang, J.; Zou, R.; Cheng, J.; Geng, Z.; Li, Q. Environmental Technical Efficiency and its Dynamic Evolution in China's Industry: A Resource Endowment Perspective. *Resour. Policy* **2023**, *82*, 103451. [CrossRef]
8. Chen, C.; Ye, F.; Xiao, H.; Xie, W.; Liu, B.; Wang, L. The Digital Economy, Spatial Spillovers and Forestry Green Total Factor Productivity. *J. Clean. Prod.* **2023**, *405*, 136890. [CrossRef]
9. Lv, Z. The Impact of Digital Economy on Middle-Income Groups: An Empirical Study in China. *Int. Bus. Econ. Stud.* **2023**, *5*, 70. [CrossRef]
10. Wang, L.; Chen, L. Impacts of Digital Economy Agglomeration on Carbon Emission: A Two-Tier Stochastic Frontier and Spatial Decomposition Analysis of China. *Sustain. Cities Soc.* **2023**, *95*, 104624. [CrossRef]
11. Wu, J.; Zhao, R.; Sun, J. What Role Does Digital Finance Play in Low-Carbon Development? Evidence From Five Major Urban Agglomerations in China. *J. Environ. Manag.* **2023**, *341*, 118060. [CrossRef] [PubMed]
12. *GB/T 4754-2017*; National Economic Industry Classification. National Bureau of Statistics; China National Institute of Standardization: Beijing, China, 2017.
13. Ghosh, A. Input-Output Approach in an Allocation System. *Economica* **1958**, *25*, 58–64. [CrossRef]
14. Meng, F.; Zhao, Y. How Does Digital Economy Affect Green Total Factor Productivity at the Industry Level in China: From a Perspective of Global Value Chain. *Environ. Sci. Pollut. Res.* **2022**, *29*, 79497–79515. [CrossRef]
15. Ran, Q.; Yang, X.; Yan, H.; Xu, Y.; Cao, J. Natural Resource Consumption and Industrial Green Transformation: Does the Digital Economy Matter? Resour. *Policy* **2023**, *81*, 103396. [CrossRef]
16. Wang, F.; Shackman, J.; Liu, X. Carbon Emission Flow in the Power Industry and Provincial CO_2 Emissions: Evidence from Cross-Provincial Secondary Energy Trading in China. *J. Clean. Prod.* **2017**, *159*, 397–409. [CrossRef]
17. Xian, Y.; Wang, K.; Shi, X.; Zhang, C.; Wei, Y.; Huang, Z. Carbon Emissions Intensity Reduction Target for China's Power Industry: An Efficiency and Productivity Perspective. *J. Clean. Prod.* **2018**, *197*, 1022–1034. [CrossRef]
18. Yu, S.; Hu, X.; Fan, J.; Cheng, J. Convergence of Carbon Emissions Intensity Across Chinese Industrial Sectors. *J. Clean. Prod.* **2018**, *194*, 179–192. [CrossRef]
19. Ling, Y.; Xia, S.; Cao, M.; He, K.; Lim, M.K.; Sukumar, A.; Yi, H.; Qian, X. Carbon Emissions in China's Thermal Electricity and Heating Industry: An Input-Output Structural Decomposition Analysis. *J. Clean. Prod.* **2021**, *329*, 129608. [CrossRef]
20. Xin, H.; Wang, S.; Chun, T.; Xue, X.; Long, W.; Xue, R.; Zhang, R. Effective Pathways for Energy Conservation and Emission Reduction in Iron and Steel Industry Towards Peaking Carbon Emissions in China: Case Study of Henan. *J. Clean. Prod.* **2023**, *399*, 136637. [CrossRef]

21. Liu, J.; Li, S.; Ji, Q. Regional Differences and Driving Factors Analysis of Carbon Emission Intensity from Transport Sector in China. *Energy* **2021**, *224*, 120178. [CrossRef]
22. Heinonen, J.; Junnila, S. Implications of Urban Structure on Carbon Consumption in Metropolitan Areas. *Environ. Res. Lett.* **2011**, *6*, 014018. [CrossRef]
23. Wang, R.; Wen, X.; Wang, X.; Fu, Y.; Zhang, Y. Low Carbon Optimal Operation of Integrated Energy System Based on Carbon Capture Technology, Lca Carbon Emissions and Ladder-Type Carbon Trading. *Appl. Energy* **2022**, *311*, 118664. [CrossRef]
24. Deng, Z.; Kang, P.; Wang, Z.; Zhang, X.; Deng, Z. The Impact of Urbanization and Consumption Patterns on China's Black Carbon Emissions Based on Input-Output Analysis and Structural Decomposition Analysis. *Environ. Sci. Pollut. Res.* **2021**, *28*, 2914–2922. [CrossRef] [PubMed]
25. Lenzen, M. Primary Energy and Greenhouse Gases Embodied in Australian Final Consumption: An Input–Output Analysis. *Energy Policy* **1998**, *26*, 495–506. [CrossRef]
26. Li, Y.L.; Chen, B.; Chen, G.Q. Carbon Network Embodied in International Trade: Global Structural Evolution and its Policy Implications. *Energy Policy* **2020**, *139*, 111316. [CrossRef]
27. Wang, S.; Zhao, Y.; Wiedmann, T. Carbon Emissions Embodied in China–Australia Trade: A Scenario Analysis Based on Input–Output Analysis and Panel Regression Models. *J. Clean. Prod.* **2019**, *220*, 721–731. [CrossRef]
28. Zhu, Q.; Peng, X.; Wu, K. Calculation and Decomposition of Indirect Carbon Emissions from Residential Consumption in China Based on the Input–Output Model. *Energy Policy* **2012**, *48*, 618–626. [CrossRef]
29. Bai, D.; Dong, Q.; Khan, S.A.R.; Li, J.; Wang, D.; Chen, Y.; Wu, J. Spatio-Temporal Heterogeneity of Logistics CO_2 Emissions and their Influencing Factors in China: An Analysis Based on Spatial Error Model and Geographically and Temporally Weighted Regression Model. *Environ. Technol. Innov.* **2022**, *28*, 102791. [CrossRef]
30. Huang, J.; Li, X.; Wang, Y.; Lei, H. The Effect of Energy Patents on China's Carbon Emissions: Evidence from the Stirpat Model. *Technol. Forecast. Soc. Change* **2021**, *173*, 121110. [CrossRef]
31. Li, Z.; Wu, H.; Wu, F. Impacts of Urban Forms and Socioeconomic Factors on CO_2 Emissions: A Spatial Econometric Analysis. *J. Clean. Prod.* **2022**, *372*, 133722. [CrossRef]
32. Wang, J.; Rickman, D.S.; Yu, Y. Dynamics Between Global Value Chain Participation, CO_2 Emissions, and Economic Growth: Evidence from a Panel Vector Autoregression Model. *Energy Econ.* **2022**, *109*, 105965. [CrossRef]
33. Gao, C.; Tao, S.; He, Y.; Su, B.; Sun, M.; Mensah, I.A. Effect of Population Migration on Spatial Carbon Emission Transfers in China. *Energy Policy* **2021**, *156*, 112450. [CrossRef]
34. Shi, K.; Liu, G.; Cui, Y.; Wu, Y. What Urban Spatial Structure is More Conducive to Reducing Carbon Emissions? A Conditional Effect of Population Size. *Appl. Geogr.* **2023**, *151*, 102855. [CrossRef]
35. Cai, W.; Song, X.; Zhang, P.; Xin, Z.; Zhou, Y.; Wang, Y.; Wei, W. Carbon Emissions and Driving Forces of an Island Economy: A Case Study of Chongming Island, China. *J. Clean. Prod.* **2020**, *254*, 120028. [CrossRef]
36. Wang, Z.; Chen, S.; Cui, C.; Liu, Q.; Deng, L. Industry Relocation or Emission Relocation? Visualizing and Decomposing the Dislocation Between China's Economy and Carbon Emissions. *J. Clean. Prod.* **2019**, *208*, 1109–1119. [CrossRef]
37. Wu, S.; Hu, S.; Frazier, A.E. Spatiotemporal Variation and Driving Factors of Carbon Emissions in Three Industrial Land Spaces in China From 1997 to 2016. Technol. *Forecast. Soc. Chang.* **2021**, *169*, 120837. [CrossRef]
38. Cao, Q.; Kang, W.; Xu, S.; Sajid, M.J.; Cao, M. Estimation and Decomposition Analysis of Carbon Emissions from the Entire Production Cycle for Chinese Household Consumption. *J. Environ. Manag.* **2019**, *247*, 525–537. [CrossRef]
39. Luo, J.; Gong, Y. Air Pollutant Prediction Based on Arima-Woa-Lstm Model. *Atmos. Pollut. Res.* **2023**, *14*, 101761. [CrossRef]
40. Fang, H.; Jiang, C.; Hussain, T.; Zhang, X.; Huo, Q. Input Digitization of the Manufacturing Industry and Carbon Emission Intensity Based on Testing the World and Developing Countries. *Int. J. Environ. Res. Public Health* **2022**, *19*, 12855. [CrossRef]
41. Li, G.; Liao, F. Input Digitalization and Green Total Factor Productivity Under the Constraint of Carbon Emissions. *J. Clean. Prod.* **2022**, *377*, 134403. [CrossRef]
42. Liu, M.; Wen, J.; Meng, Y.; Yang, X.; Wang, J.; Wu, J.; Chen, H. Carbon Emission Structure Decomposition Analysis of Manufacturing Industry from the Perspective of Input-Output Subsystem: A Case Study of China. *Environ. Sci. Pollut. Res.* **2022**, *30*, 19012–19029. [CrossRef] [PubMed]
43. Wang, J.; Dong, X.; Dong, K. How Digital Industries Affect China's Carbon Emissions? Analysis of the Direct and Indirect Structural Effects. *Technol. Soc.* **2022**, *68*, 101911. [CrossRef]
44. Lenzen, M.; Murray, J. Conceptualising Environmental Responsibility. *Ecol. Econ.* **2010**, *70*, 261–270. [CrossRef]
45. Rodrigues, J.F.D.; Domingos, T.M.D.; Marques, A.P.S. *Carbon Responsibility and Embodied Emissions*; Routledge: Abingdon, UK, 2010.
46. Rodrigues, J.; Domingos, T. Consumer and Producer Environmental Responsibility: Comparing Two Approaches. *Ecol. Econ.* **2008**, *66*, 533–546. [CrossRef]
47. Xu, L.; Chen, G.; Wiedmann, T.; Wang, Y.; Geschke, A.; Shi, L. Supply-Side Carbon Accounting and Mitigation Analysis for Beijing-Tianjin-Hebei Urban Agglomeration in China. *J. Environ. Manag.* **2019**, *248*, 109243. [CrossRef]
48. Moyer, J.D.; Hughes, B.B. Icts: Do they Contribute to Increased Carbon Emissions? Technol. *Forecast. Soc. Chang.* **2012**, *79*, 919–931. [CrossRef]

49. Horner, N.C.; Shehabi, A.; Azevedo, I.L. Known Unknowns: Indirect Energy Effects of Information and Communication Technology. *Environ. Res. Lett.* **2016**, *11*, 103001. [CrossRef]
50. Jiang, D. Transformation and Development of the Coal-Based Energy Industry Under the Goals of Carbon Peaking and Carbon Neutrality. *Chin. J. Urban Environ. Stud.* **2022**, *10*, 2250008. [CrossRef]
51. Xu, Q.; Zhong, M.; Li, X. How Does Digitalization Affect Energy? International Evidence. *Energy Econ.* **2022**, *107*, 105879. [CrossRef]
52. Gelenbe, E.; Caseau, Y. The Impact of Information Technology on Energy Consumption and Carbon Emissions. *Ubiquity* **2015**, *2015*, 1–15. [CrossRef]
53. Andrae, A.; Edler, T. On Global Electricity Usage of Communication Technology: Trends to 2030. *Challenges* **2015**, *6*, 117–157. [CrossRef]
54. Zhou, X.; Zhou, D.; Wang, Q.; Su, B. How Information and Communication Technology Drives Carbon Emissions: A Sector-Level Analysis for China. *Energy Econ.* **2019**, *81*, 380–392. [CrossRef]
55. Belkhir, L.; Elmeligi, A. Assessing Ict Global Emissions Footprint: Trends to 2040 & Recommendations. *J. Clean. Prod.* **2018**, *177*, 448–463.
56. Berkhout, F.; Hertin, J. De-Materialising and Re-Materialising: Digital Technologies and the Environment. *Futures* **2004**, *36*, 903–920. [CrossRef]
57. Meng, C.; Du, X.; Zhu, M.; Ren, Y.; Fang, K. The Static and Dynamic Carbon Emission Efficiency of Transport Industry in China. *Energy* **2023**, *274*, 127297. [CrossRef]
58. Añón Higón, D.; Gholami, R.; Shirazi, F. Ict and Environmental Sustainability: A Global Perspective. *Telemat. Inform.* **2017**, *34*, 85–95. [CrossRef]
59. Yang, Z.; Gao, W.; Han, Q.; Qi, L.; Cui, Y.; Chen, Y. Digitalization and Carbon Emissions: How Does Digital City Construction Affect China's Carbon Emission Reduction? Sustain. *Cities Soc.* **2022**, *87*, 104201.
60. Zhang, Q.; Wang, Q. Digitalization, Electricity Consumption and Carbon Emissions—Evidence from Manufacturing Industries in China. *Int. J. Environ. Res. Public Health* **2023**, *20*, 3938. [CrossRef]
61. Zhang, W.; Li, H.; Wang, S.; Zhang, T. Impact of Digital Infrastructure Inputs on Industrial Carbon Emission Intensity: Evidence from China'S Manufacturing Panel Data. *Environ. Sci. Pollut. Res.* **2023**, *30*, 65296–65313. [CrossRef]
62. Husaini, D.H.; Lean, H.H. Digitalization and Energy Sustainability in Asean. *Resour. Conserv. Recycl.* **2022**, *184*, 106377. [CrossRef]
63. Hoang, A.Q.; Tue, N.M.; Tu, M.B.; Suzuki, G.; Matsukami, H.; Tuyen, L.H.; Viet, P.H.; Kunisue, T.; Sakai, S.; Takahashi, S. A Review on Management Practices, Environmental Impacts, and Human Exposure Risks Related to Electrical and Electronic Waste in Vietnam: Findings from Case Studies in Informal E-Waste Recycling Areas. *Environ. Geochem. Health* **2022**, *45*, 2705–2728. [CrossRef]
64. Tran, M.; Brand, C. Smart Urban Mobility for Mitigating Carbon Emissions, Reducing Health Impacts and Avoiding Environmental Damage Costs. *Environ. Res. Lett.* **2021**, *16*, 114023. [CrossRef]
65. Chen, X.; Mao, S.; Lv, S.; Fang, Z. A Study on the Non-Linear Impact of Digital Technology Innovation on Carbon Emissions in the Transportation Industry. *Int. J. Environ. Res. Public Health* **2022**, *19*, 12432. [CrossRef]
66. Dorahaki, S.; Rashidinejad, M.; Abdollahi, A.; Mollahassani-pour, M. A Novel Two-Stage Structure for Coordination of Energy Efficiency and Demand Response in the Smart Grid Environment. *Int. J. Electr. Power Energy Syst.* **2018**, *97*, 353–362. [CrossRef]
67. Zhang, R.; Fu, W.; Kuang, Y. Can Digital Economy Promote Energy Conservation and Emission Reduction in Heavily Polluting Enterprises? Empirical Evidence from China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 9812. [CrossRef] [PubMed]
68. Ang, B.W. Monitoring Changes in Economy-Wide Energy Efficiency: From Energy–Gdp Ratio to Composite Efficiency Index. *Energy Policy* **2006**, *34*, 574–582. [CrossRef]
69. Ang, B.W.; Mu, A.R.; Zhou, P. Accounting Frameworks for Tracking Energy Efficiency Trends. *Energy Econ.* **2010**, *32*, 1209–1219. [CrossRef]
70. Zeng, L.; Xu, M.; Liang, S.; Zeng, S.; Zhang, T. Revisiting Drivers of Energy Intensity in China During 1997–2007: A Structural Decomposition Analysis. *Energy Policy* **2014**, *67*, 640–647. [CrossRef]
71. Su, B.; Ang, B.W. Multiplicative Decomposition of Aggregate Carbon Intensity Change Using Input–Output Analysis. *Appl. Energy* **2015**, *154*, 13–20. [CrossRef]
72. Zhang, Y. Supply-Side Structural Effect on Carbon Emissions in China. *Energy Econ.* **2010**, *32*, 186–193. [CrossRef]
73. Ali, Y.; Ciaschini, M.; Socci, C.; Pretaroli, R.; Sabir, M. Identifying the Sources of Structural Changes in CO_2 Emissions in Italy. *Econ. Politica* **2019**, *36*, 509–526. [CrossRef]
74. Fan, J.; Cao, Z.; Zhang, X.; Wang, J.; Zhang, M. Comparative Study on the Influence of Final Use Structure on Carbon Emissions in the Beijing-Tianjin-Hebei Region. *Sci. Total Environ.* **2019**, *668*, 271–282. [CrossRef] [PubMed]
75. Lu, Q.; Fang, K.; Heijungs, R.; Feng, K.; Li, J.; Wen, Q.; Li, Y.; Huang, X. Imbalance and Drivers of Carbon Emissions Embodied in Trade Along the Belt and Road Initiative. *Appl. Energy* **2020**, *280*, 115934. [CrossRef]
76. Wang, Y.; Sun, M.; Xie, R.; Chen, X. Multiplicative Structural Decomposition Analysis of Spatial Differences in Energy Intensity Among G20 Countries. *Appl. Sci.* **2020**, *10*, 2832. [CrossRef]
77. Ali, Y.; Pretaroli, R.; Sabir, M.; Socci, C.; Severini, F. Structural Changes in Carbon Dioxide (CO_2) Emissions in the United Kingdom (UK): An Emission Multiplier Product Matrix (EMPM) Approach. *Mitig. Adapt. Strateg. Glob. Chang.* **2020**, *25*, 1545–1564. [CrossRef]

78. Zhang, B.; Zhai, G.; Sun, C.; Xu, S. Re-Calculation, Decomposition and Responsibility Sharing of Embodied Carbon Emissions in Sino-Korea Trade: A New Value-Added Perspective. *Emerg. Mark. Financ. Trade* **2021**, *57*, 1034–1049. [CrossRef]
79. Guevara, Z.; Henriques, S.; Sousa, T. Driving Factors of Differences in Primary Energy Intensities of 14 European Countries. *Energy Policy* **2021**, *149*, 112090. [CrossRef]
80. Yuan, R.; Zhao, T. Changes in CO_2 Emissions from China's Energy-Intensive Industries: A Subsystem Input–Output Decomposition Analysis. *J. Clean. Prod.* **2016**, *117*, 98–109. [CrossRef]
81. Wei, J.; Huang, K.; Yang, S.; Li, Y.; Hu, T.; Zhang, Y. Driving Forces Analysis of Energy-Related Carbon Dioxide (CO_2) Emissions in Beijing: An Input–Output Structural Decomposition Analysis. *J. Clean. Prod.* **2017**, *163*, 58–68. [CrossRef]
82. Xu, S.; Zhang, L.; Liu, Y.; Zhang, W.; He, Z.; Long, R.; Chen, H. Determination of the Factors that Influence Increments in CO_2 Emissions in Jiangsu, China Using the Sda Method. *J. Clean. Prod.* **2017**, *142*, 3061–3074. [CrossRef]
83. Yu, Y.; Hou, J.; Jahanger, A.; Cao, X.; Balsalobre-Lorente, D.; Radulescu, M.; Jiang, T. Decomposition Analysis of China's Chemical Sector Energy-Related CO_2 Emissions: From an Extended SDA Approach Perspective. *Energy Environ.* **2023**, 1–22. [CrossRef]
84. Wang, Y. An Industrial Ecology Virtual Framework for Policy Making in China. *Econ. Syst. Res.* **2017**, *29*, 252–274. [CrossRef]
85. Asni, A.E.; Muk, B.; Dumancic, K. Defining and Measuring the Digital Economy in Croatia. In Proceedings of the International Conference on the Economics of Decoupling (ICED), Zagreb, Croatia, 30 November–1 December 2019.
86. Wang, C.; Wang, Y. Accounting of ICT Capital Services at the Industry Level in China. *Stat. Res.* **2017**, *34*, 24–36. (In Chinese)
87. Guan, Y.; Shan, Y.; Huang, Q.; Chen, H.; Wang, D.; Hubacek, K. Assessment to China's Recent Emission Pattern Shifts. *Earth's Future* **2021**, *9*, e2021EF002241. [CrossRef]
88. Shan, Y.; Guan, D.; Zheng, H.; Ou, J.; Li, Y.; Meng, J.; Mi, Z.; Liu, Z.; Zhang, Q. China CO_2 Emission Accounts 1997–2015. *Sci. Data* **2018**, *5*, 170201. [CrossRef]
89. Shan, Y.; Huang, Q.; Guan, D.; Hubacek, K. China CO_2 Emission Accounts 2016–2017. *Sci. Data* **2020**, *7*, 54. [CrossRef] [PubMed]
90. *GB/T 4754-2011*; National Economic Industry Classification. National Bureau of Statistics; China National Institute of Standardization: Beijing, China, 2011.
91. Yu, J.; Xu, R.; Zhang, J.; Zheng, A. A Review on Reduction Technology of Air Pollutant in Current China's Iron and Steel Industry. *J. Clean. Prod.* **2023**, *414*, 137659. [CrossRef]
92. Ming, C.; Ke, W. The Combining and Cooperative Effects of Carbon Price and Technological Innovation on Carbon Emission Reduction: Evidence from China's Industrial Enterprises. *J. Environ. Manag.* **2023**, *343*, 118188.
93. Cao, Z.; Qian, L. Crowding Effect of Institutional Openness Based on the Big Data Algorithm on the Efficiency of New Energy Technology Innovation. *Front. Bioeng. Biotechnol.* **2023**, *11*, 1178737. [CrossRef]
94. Valderrama, C.V.; Santibañez-González, E.; Pimentel, B.; Candia-Véjar, A.; Canales-Bustos, L. Designing an Environmental Supply Chain Network in the Mining Industry to Reduce Carbon Emissions. *J. Clean. Prod.* **2020**, *254*, 119688. [CrossRef]
95. Tang, D. Evaluate the Sustainable Marketing Strategy to Optimal Online Leasing of New Energy Vehicles Under the Background Big Data Economy. *J. Enterp. Inf. Manag.* **2022**, *35*, 1409–1424.
96. Wang, Y.; Jia, X.; Wang, C. Research on Sectoral Employment Accounting of China. Statistical Research. *Stat. Res.* **2021**, *38*, 3–18. (In Chinese)
97. Wang, J.; Wang, W.; Liu, Y.; Wu, H. Can Industrial Robots Reduce Carbon Emissions? Based On the Perspective of Energy Rebound Effect and Labor Factor Flow in China. *Technol. Soc.* **2023**, *72*, 102208. [CrossRef]
98. Paul, D.; Dieudonné, T.; Guillaume, C. Method and Evaluations of the Effective Gain of Artificial Intelligence Models for Reducing CO_2 Emissions. *J. Environ. Manag.* **2023**, *331*, 117261.
99. Wang, E.Z.; Lee, C.C.; Li, Y. Assessing the Impact of Industrial Robots on Manufacturing Energy Intensity in 38 Countries. *Energy Econ.* **2022**, *105*, 105748. [CrossRef]
100. Yang, W. The Nonlinear Effects of Multi-Scale Built Environments on CO_2 Emissions from Commuting. *Transp. Res. D* **2023**, *118*, 103736. [CrossRef]
101. Yang, L.; Wang, Y.; Han, S.; Liu, Y. Urban Transport Carbon Dioxide (CO_2) Emissions by Commuters in Rapidly Developing Cities: The Comparative Study of Beijing and Xi'an in China. *Transp. Res. D Transp. Environ.* **2017**, *68*, 65–83. [CrossRef]
102. Segovia Hernández, J.G.; Gómez-Castro, F.I.; Romero-Izquierdo, A.G.; Conde-Mejía, C.; López-Molina, A. Partial Energy Integration Between Biofuels Production Processes: Effect on Costs, CO_2 Emissions and Process Safety. *Process Saf. Environ. Prot.* **2022**, *159*, 918–930. [CrossRef]
103. Wang, G.; Zhou, J. Multiobjective Optimization of Carbon Emission Reduction Responsibility Allocation in the Open-Pit Mine Production Process Against the Background of Peak Carbon Dioxide Emissions. *Sustainability* **2022**, *14*, 9514. [CrossRef]
104. Fan, J.; Wang, J.; Qiu, J.; Li, N. Stage Effects of Energy Consumption and Carbon Emissions in the Process of Urbanization: Evidence From 30 Provinces in China. *Energy* **2023**, *276*, 127655. [CrossRef]
105. Akan, T. Explaining and Modeling the Mediating Role of Energy Consumption Between Financial Development and Carbon Emissions. *Energy* **2023**, *274*, 127312. [CrossRef]
106. Damioli, G.; Van Roy, V.; Vertesy, D. The Impact of Artificial Intelligence on Labor Productivity. *Eurasian Bus. Rev.* **2021**, *11*, 1–25. [CrossRef]
107. Lei, C.; Farhad, T.; Muhammad, M. Role of Artificial Intelligence on Green Economic Development: Joint Determinates of Natural Resources and Green Total Factor Productivity. *Resour. Policy* **2023**, *82*, 103508.

108. Peng, W.; Lu, S.; Lu, W. Green Financing for the Establishment of Renewable Resources Under Carbon Emission Regulation. *Renew. Energy* **2022**, *199*, 103508. [CrossRef]
109. Yao, C. Carbon Derivatives-Directed International Supervision Laws and Regulations and Carbon Market Mechanism. *Sustainability* **2022**, *14*, 5976.