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# Does Digital Transformation Promote Green and Low-Carbon Synergistic Development in Enterprises? A Dynamic Analysis Based on the Perspective of Chinese Listed Enterprises in the Heavy Pollution Industry

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**Abstract:** Digital transformation has become essential in promoting and upgrading enterprise elements and reshaping the market's competitive landscape. However, whether digital transformation can further promote green and low-carbon synergistic development is still being determined. Using data from 2008 to 2014 matched between A-share listed enterprises in China's heavily polluting industries and China's industrial enterprise pollution emission database (robustness tests were used city panel data from 2013 to 2019 to overcome the timeliness of enterprise-level data), we measured the green total factor productivity, carbon emission efficiency, and joint emission reduction efficiency of heavily polluting listed companies. We examined the dynamic impact of corporate digital transformation on corporate pollution and carbon emission reduction. The empirical results show that (1) digital transformation inhibits the enterprise's all-green factor productivity, carbon emission efficiency, and joint emission reduction efficiency in the short term but promotes them in the long term. Digital transformation can improve these three efficiencies by enhancing the enterprise's green technology innovation ability and optimizing factor allocation efficiency. (2) A heterogeneity analysis found that, in the external environment, the increase in environmental regulation enhances the impact of digital transformation on these three efficiencies; in the internal environment, the improvement of the competitiveness of the enterprise's products strengthens the promotion of digital transformation on the three efficiencies of pollution emission reduction and carbon emission reduction. (3) Further research shows that, in the long run, digital transformation can improve the synergistic effect of the pollution reduction and carbon emission reduction of enterprises. This is instructive for Chinese enterprises to achieve the synergistic development of digital transformation and green, low-carbon production.

**Keywords:** digital transformation; dynamic analysis; green total factor productivity; carbon emission efficiency; United Emission Abatement Efficiency; Synergistic Development

**JEL Classification:** Q5; R38

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## 1. Introduction

China has made tremendous achievements after more than 40 years of rapid economic development. However, the current environmental situation is dire, seriously affecting the quality and sustainability of China's economic growth and threatening the healthy lives of its people. In response, the Chinese government decided to "vigorously promote the construction of an ecological civilization", which requires adherence to the basic state policy of conserving resources and protecting the environment. Later, the Chinese government also pointed out that building an ecological civilization is a thousand-year plan for the sustainable development of the Chinese nation, and to this end, it put forward four major initiatives to build a "beautiful China". The Chinese government also stressed that "the concept of green water and green hills is the silver mountain of gold must be

firmly established and practiced, and development must be planned at the height of the harmonious coexistence of man and nature, and the road of ecological priority and green development must be unswervingly followed". This shows that the Chinese government has raised the importance of ecological and environmental management to an unprecedented level. However, the reality is that digital transformation policies, introduced as a critical initiative to promote inclusive green economic development, often need to be better implemented by local governments in China, resulting in slow progress in resource and environmental management and persistent pollution problems. Against this backdrop, it has become an essential task for China to promote a comprehensive green transformation of the economy, led by the "Double carbon" target. Enterprises are an essential link in the prevention of pollution and the green and low-carbon transformation of the economy. Promoting pollution reduction and carbon emission reduction effects at the enterprise level is the basis for China to achieve this ambitious goal. Existing research also confirms that green technology innovation is essential for companies to improve their efficiency in reducing pollution and carbon emissions [1–3]. In the context of the new generation of technological revolution, whether digital transformation, as a new driving force for green technological innovation and factor structure innovation, can help Chinese enterprises to improve synergies between pollution reduction and carbon emission reduction is a critical question that dovetails with the "double carbon" objective at the macro level and has a bearing on whether the transformation and upgrading of enterprises can be achieved at the micro level. We need to study this issue in depth.

Digital transformation has important theoretical significance for enterprises' green, low-carbon synergistic development. Digital technology provides data-driven decision support and resource optimization mechanisms. Enterprises collect, analyze, and utilize big data in real-time through digital tools to achieve effective resource utilization and carbon emission reduction. Digital transformation promotes cooperation and collaboration among enterprises to optimize supply chains, product design, and production processes through data and information sharing. Digital transformation also promotes a new model of green and low-carbon collaborative development of enterprises in globalization and realizes the cross-border trading of carbon emissions and the construction of carbon markets. Digital transformation provides enterprises with innovative paths to promote the realization of resource efficiency, carbon emission reduction, and cross-border cooperation. It promotes sustainable development and the construction of an ecological civilization, providing new research directions for academia.

In recent years, with the development of digital technologies such as "Internet+", artificial intelligence, and big data, more and more enterprises have joined the wave of digitalization, to transform their organizational structure, technological innovation level, and business management model through information technology, promoting the upgrading of their elements, reshaping the market competition pattern, and bringing new opportunities. Digital transformation is a new opportunity for enterprises to reduce pollution and carbon emissions. This is because the technological advances and digital communication technology applications embedded in the digital transformation can not only improve the efficiency of enterprises' production factors and energy use [4,5], but also promote the automation of production processes through the upgrading of the automation of the production process, which can also facilitate the "refinement" of the processes of material input, product manufacturing, and sales, enabling enterprises to accurately control the production process while monitoring energy consumption in real-time at each stage, reducing the rate of energy consumption and waste in production, which in turn has positive feedback on the reduction in pollution and carbon emissions [6–9]. However, the current academic debate on the pollution and carbon reduction effects of the digital transformation is also controversial, with some scholars arguing that the digital transformation can only deliver limited energy savings and that the use of ICTs can cause a rebound effect leading to increased energy consumption [10,11]. Sadorsky [12] found a significant positive correla-

tion between ICT adoption and electricity consumption as measured by three indicators: the number of personal computer users, Internet users, and mobile phone users.

It can be seen that, given the more mature digital transformation technology in developed countries, more studies have analyzed the pollution reduction and carbon emission reduction effects of digital transformation based on data from developed countries. However, the conclusions reached are not consistent, which may be because the pollution reduction and carbon emission reduction effects of digital transformation require a certain degree of support from the internal and external environments, e.g., enterprise digitization requires a certain degree of policy guidance in order to bring about the enhancement of pollution reduction and carbon emission reduction efficiency [13,14]. Due to the new opportunities for digital transformation to reduce pollution and carbon emissions in enterprises and the current academic controversy over its pollution and carbon reduction effects, especially in the Chinese context, there is an urgent need to investigate whether digital transformation in China can synergistically improve the efficiency of pollution and carbon emission reduction and to explore the mechanisms and conditions necessary for it, in order to fill the research gaps in this area and provide targeted guidance for digital transformation in China. The research will fill the research gaps in this area and provide targeted guidance for China's digital transformation.

An overview of the existing literature shows that although more and more scholars have focused on the relationship between China's digital transformation and the achievement of the "double carbon" goal, most of them have conducted static analyses based on provincial and municipal level data, lacking the micro-enterprise level and dynamic perspective [15–17]. However, in the process of pollution prevention and green development, enterprises are the final link in the implementation of green transformation, and clarifying the factors influencing the pollution reduction and carbon emission reduction of enterprises is the basis for scientific decision-making [18–21]. At the same time, it takes time for digital transformation to drive enterprises to complete clean technology iterations, and ignoring the lag in the overall effect of digital transformation in enterprises may underestimate the beneficial impact of digital transformation on enterprises' cleaner production. Distinguishing from existing research, and based on theoretical analysis, we adopt an empirical approach to investigate the dynamic impact and mechanism of action of digital transformation on the pollution reduction and carbon emission reduction of Chinese enterprises and explore the internal and external factors of digital transformation that affect the effect of pollution reduction and carbon emission reduction to provide more comprehensive empirical evidence for studying the cleaner production effect of the digital transformation of Chinese enterprises from a micro-dynamic perspective.

Compared to existing research, this paper has marginal contributions in the following three areas. First, compared with the international literature that has focused on the impact of digital transformation on pollution reduction and carbon emission reduction efficiency, the corresponding research in China is still in its infancy. It focuses on static analysis at the macro level. To differentiate from existing research, we integrate "digital transformation-pollution reduction and carbon emission reduction efficiency" into a unified analytical framework from the perspective of the micro-dynamic analysis of enterprises, using data from Chinese listed enterprises and matched data from a database of pollution emissions of Chinese industrial enterprises, and measure "pollution reduction and carbon emission reduction efficiency" based on a Luenberger productivity index with a relaxed directional distance function. We measured green total factor productivity, carbon emission efficiency (*CEE*), and United Emission Abatement Efficiency (*UEAE*) for Chinese listed enterprises in the heavily polluting industries listed in the List of Listed Enterprises on Environmental Verification and Governance (2008) from 2008 to 2014, and then used these three efficiencies to denote enterprise pollution abatement and carbon abatement efficiency, and combined them with data on the digital transformation of Chinese listed enterprises to test the causal relationship between digital transformation and Chinese enterprise pollution abatement and carbon abatement. In addition, we measured the efficiency of pollution abatement and

carbon reduction at the city level in China from 2010 to 2019 for robustness testing. These enrich the research on the economic impact of digital transformation in China. Second, this paper verifies the transmission mechanism of the digital transformation of enterprises to enhance the efficiency of pollution emission reduction and the internal and external environmental influencing factors of enterprises. We reveal the internal logic of the effect of the digital transformation of enterprises to promote pollution emission reduction from two perspectives: the green technology innovation effect and the factor allocation optimization effect. We also explore and analyze the internal and external factors that support the impact of digital transformation on pollution and carbon emission reduction from the perspectives of urban environmental regulation intensity and enterprise product competitiveness. We provide explanatory ideas for the existing literature on the transmission paths and heterogeneous findings of digital transformation's impact on pollution and enterprises' carbon emission reduction. Third, we further measure the Synergies between Pollution Abatement and Carbon Emission Abatement in enterprises from the perspective of marginal abatement costs and explore the impact of digital transformation on the Synergies between Pollution Abatement and Carbon Emission Abatement (SPACA) in enterprises. We provide theoretical support and a scientific basis for the coordinated development of digital transformation and the green low-carbon upgrading of Chinese enterprises under the "double carbon" target. We expand and improve the relevant research on the synergistic relationship between digital transformation and enterprises' pollution and carbon emission reduction.

## 2. Theoretical Analysis and Research Hypothesis

### *2.1. Direct Impact of Digital Transformation on the Pollution Abatement and Carbon Abatement Efficiency of Enterprises*

Digital transformation refers to upgrading an enterprise's organizational structure and business model through information technology. Under conditions of complementarity with other production technologies, enterprises introduce digital transformation into their production and operation processes, which is conducive to improving production paradigms and promoting business process reengineering [13,14]. However, the impact of digital transformation on enterprises' clean production differs at different stages. In the early stage of digital transformation, enterprises need to invest money in digital infrastructure construction, platform construction, and the introduction of technical personnel [17]. At this time, economies of scale have yet to be formed, information sharing among users is difficult to achieve, and the digital transformation process is slow [10]. In addition, at the early stage of digital transformation, enterprises usually prioritize transforming low-energy-consuming aspects such as R&D, sales, and management and pay insufficient attention to traditional high-energy-consuming aspects [3]. At the same time, enterprises with more sunken redundant resources need help to obtain healthy cash flow. They cannot dispatch the internal and external resources required by the enterprise in the digital transformation process in real-time.

In contrast, such resources' idle and depreciation rates will delay the positive impact of early digital transformation on the enterprise's pollution abatement and carbon abatement efficiency [1]. As a result, more energy will be consumed in the initial digital transformation process, making it difficult for the effects of digital transformation on cleaner production to be fully realized. However, as digital transformation progresses, enterprises can highly integrate resources, constantly update, and use new technologies and equipment to improve their production processes and eliminate outdated and polluting old equipment, thus reducing direct pollutant emissions and promoting cleaner production in enterprises.

On this basis, we propose the following hypotheses:

**Hypothesis 1:** *In the short term, digital transformation will reduce enterprises' pollution abatement and carbon abatement efficiency; in the long term, digital transformation will increase enterprises' pollution abatement and carbon abatement efficiency.*

### *2.2. The Transmission Mechanism of Digital Transformation on the Pollution Abatement and Carbon Abatement Efficiency of Enterprises*

From the perspective of the transmission mechanism of digital transformation, the optimization of enterprises' organizational structure and business model brought about by digital transformation will further affect enterprises' pollution abatement and carbon abatement efficiency through the following two channels.

#### 2.2.1. Green Technological Innovation Mechanism of Digital Transformation

Digital transformation in the production and operation process of enterprises can promote green technology innovation in two ways: first, digital transformation in enterprises is the transformation of the original production and operation model through the application of advanced information and communication technologies, and this advanced digital communication technology, when applied, has the inherent quality of technological progress [22]. Chen et al. [23] found that introducing digital technology into various business operations, such as manufacturing and organizational management, through digital transformation would directly improve enterprises' production technology innovation capability. Second, digital communication technology can complement other production factors to improve enterprises' green technology innovation capacity. According to Schumpeter's innovation theory, innovation in enterprises involves the recombination of production factors, such as adding a new combination of production factors and production conditions to the production system that has never been used before [2,13]. Specifically, the integration of digital communication technology with other production factors, which embodies technological progress, can promote changes and effective linkages in enterprises' production, supply chain, and sales, which can more directly optimize the allocation of production factors, accelerate the flow of information, and improve enterprises' green technological innovation capabilities [24].

On this basis, in the face of the enormous challenge of environmental issues, technological innovation with digital information technology and intelligence is an essential way for enterprises to achieve green and low-carbon upgrading [4,25]. Such technological innovation resulting from digital transformation will not only improve the efficiency of production equipment and resource use but also help to identify and adjust wasteful aspects of production operations, improve energy consumption patterns, and promote pollution abatement and carbon abatement efficiency [26].

#### 2.2.2. Factor Allocation Optimization Mechanism of Digital Transformation

The improvement in pollution abatement and carbon abatement efficiency is driven by technological progress [27] and the increasing attention paid by scholars to the critical role of resource allocation efficiency in improving productivity [28,29]. The Chinese government attaches great importance to efficient factor allocation, and optimizing resource allocation efficiency can effectively support pollution abatement and carbon abatement efficiency [30,31]. Compared with the cost effect and innovation compensation effect that affect pollution abatement and carbon abatement efficiency, less attention has been paid to the impact of factor allocation efficiency, especially energy allocation efficiency, which is closely related to economic development and environmental quality. As energy is the lifeblood of economic development and the primary source of unwanted production, there is no doubt that efficient energy factor allocation can improve pollution abatement and carbon abatement efficiency [32].

Digital transformation can facilitate the digitization and intelligent upgrading of organizational structures and business models and correct distortions in factor allocation [33]. Digitalization can be used to strengthen and improve the efficiency of enterprises through the enabling effect of new technologies, which in turn can give rise to new business models and modes, open new channels for factor mobility, and improve factor allocation efficiency [17]. Second, using digital technologies in enterprises can effectively reduce search, transaction, matching, and replication costs by reducing information asymmetries [34].

As a result, transaction barriers can be lowered, breaking down market boundaries and expanding market scope, facilitating factor mobility in a larger space, optimizing factor allocation, and increasing pollution abatement and carbon abatement efficiency [35]. At the same time, optimizing factor allocation through digital transformation can also improve the quality and efficiency of enterprises' products and services, significantly reduce the production cost of products, shorten the product development cycle, and reduce the number of rework and product scrap, thereby promoting pollution abatement and carbon abatement efficiency [36,37].

Through the above analysis, this paper argues that the digital transformation of enterprises can improve pollution abatement and carbon abatement efficiency by promoting green technological innovation and optimizing factor allocation. Based on this, this paper proposes the following hypotheses:

**Hypothesis 2a:** *Digital transformation facilitates green technological innovation in enterprises, promoting pollution abatement and carbon abatement efficiency.*

**Hypothesis 2b:** *Digital transformation facilitates the optimization of enterprises' factor allocation, promoting pollution abatement and carbon abatement efficiency.*

### *2.3. The Heterogeneous Influences of the Internal and External Environment of the Enterprise*

However, we argue that these digital transformation mechanisms and their ultimate pollution abatement and carbon abatement efficiency effects also depend on the internal and external environment in which the firm operates, where the external environment is the intensity of environmental regulation in the region in which it operates. The internal environment is the competitiveness of the firm's products.

#### 2.3.1. The Heterogeneous Influences of the Intensity of Environmental Regulation

In terms of the external urban environment, for the digital economy to better serve the "dual carbon" goal, it is necessary to develop relevant information disclosure policies and mandatory measures through administrative means to guide digital technologies towards pollution abatement and carbon abatement efficiency [38,39]. In the case of enterprises, the degree to which the local government attaches importance to environmental protection affects the incentive for enterprises to increase pollution abatement and carbon abatement efficiency [40,41]. Accordingly, we argue that the intensity of urban environmental regulation, which is an essential indicator of the importance the local government, attaches to environmental protection and affects the pollution abatement and carbon abatement efficiency effect of enterprises' digital transformation [42,43], especially for enterprises in areas with environmental solid regulation.

This is because digital transformation has an innovation compensation effect. Under environmental regulation, enterprises improve their long-term competitiveness by improving their technological level to smooth out short-term costs [44,45]. Therefore, under stronger environmental regulation, enterprises are more environmentally conscious and focus more on green and sustainable development at the production and operation level, when digital transformation plays a more significant role in improving enterprises' green technological innovation, which in turn can better contribute to enterprises' pollution abatement and carbon abatement efficiency [46,47]. In contrast, in regions with weaker environmental regulations, enterprises tend to spend less on environmental protection when undergoing digital transformation in pursuit of higher profits, resulting in less incentive for digital transformation to green their production and operational processes, which in turn has a limited impact on pollution abatement and carbon abatement efficiency [48,49].

On this basis, we propose the following hypothesis:

**Hypothesis 3a:** *The higher the intensity of environmental regulations in an enterprise's region, the more pronounced the impact of digital transformation on pollution and carbon abatement efficiency.*

2.3.2. The Heterogeneous Influences of Product Competitiveness

In terms of the internal environment, i.e., the characteristics of the firm itself as a market player, the survival and growth of an enterprise depends on the competitiveness of its products in the market [50,51]. Enterprises with more competitive products have higher market adaptability and lower path dependence and transfer costs for product innovation. They are more willing to drive technological innovation and factor allocation optimization for digital transformation, thus improving pollution and carbon abatement efficiency [52,53]. On the other hand, enterprises with less competitive products struggle to gain significant market share and establish a competitive advantage, which in turn makes it more challenging to invest in frontier technologies and sustain innovation in production structures [54,55]. Even when these enterprises undergo digital transformation, the transformation's technological innovation and factor allocation optimization effects are significantly reduced [56,57].

On this basis, we propose the following hypothesis:

**Hypothesis 3b:** *The more competitive an enterprise's product is, the more significant the contribution of digital transformation to pollution and carbon abatement efficiency.*

The diagram of the impact mechanisms in this study is shown in Figure 1.

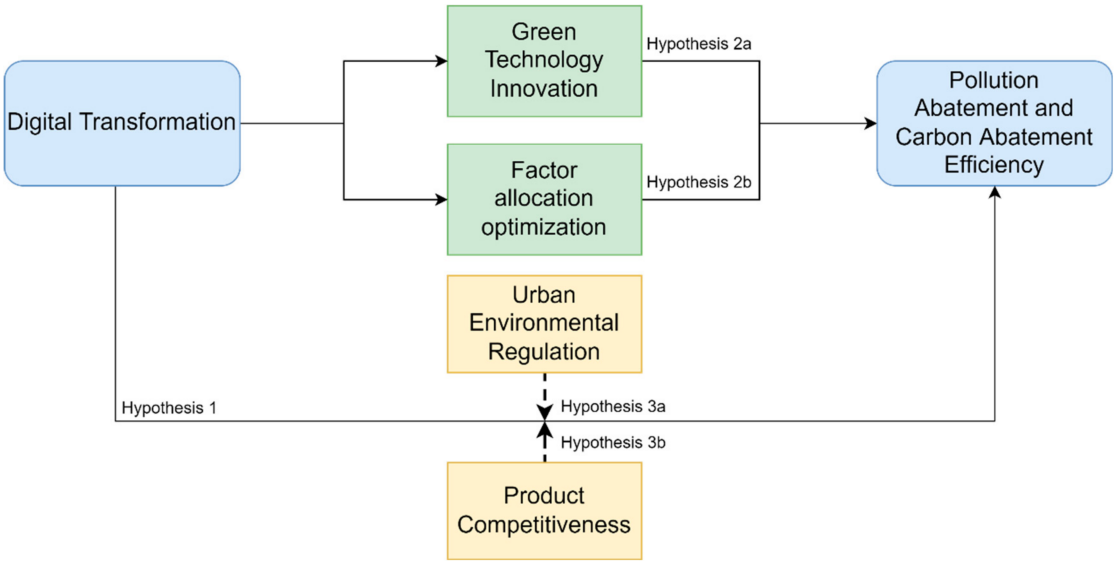


**Figure 1.** Influence mechanism diagram.

## 3. Study Design

### *3.1. Sample Selection and Processing*

Unlike most of the literature that focuses on pollution abatement and carbon abatement efficiency at the provincial, municipal, or industry level [15], we use data from listed enterprises and matched data from the China Industrial Emissions Database to calculate pollution abatement and carbon abatement efficiency at the enterprise level to fill a research gap in the existing literature. There are three reasons for choosing listed enterprises in the heavily polluting industries listed in the Environmental Protection Verification Industry Classification Management List of Listed Enterprises (2008) in the China Industrial Enterprises Pollution Emission Database as the research target. First, in terms of total emissions, the primary pollutants emitted by the critical enterprises surveyed in the China Industrial Enterprises Pollution Emission Database account for more than 85% of the total annual emissions in each region. Second, the database is the most detailed and comprehensive in terms of statistics on the types of energy consumption and pollutant emissions of enterprises, recording the number of energy resources such as coal, oil, natural gas, and water

consumed by polluting enterprises, as well as industrial wastewater emissions, ammonia nitrogen emissions, chemical oxygen demand emissions, nitrogen oxide emissions, sulfur dioxide emissions, smoke emissions, industrial dust emissions, and other pollutant emission quantities, which makes the calculated total green factor productivity of enterprises more accurate. Finally, in terms of the impact of digital transformation, the 'compliance cost' and 'crowding out effect' are more direct and higher in the current period than in the general enterprises, forcing them to make green technological innovations later. The pollution abatement and carbon abatement efficiency effect of digital transformation is also more pronounced, which fits well with the purpose of this study. Although the data on industrial emissions in China is more comprehensive, there is a severe lag, which only goes up to 2014. Given the objective limitation of the period of the data, we use city-level pollution abatement and carbon abatement efficiency from 2015 to 2019 in the robustness check, clustering the data at the city level for empirical testing [58].

This paper firstly matches the data of critical industrial pollution source survey enterprises with the data of listed enterprises in China's heavy pollution industry using the keyword "enterprise organization code + year". At the same time, concerning the existing literature, the matched data were processed as follows: samples with apparent errors in the data, such as industrial output value, total assets, fixed assets, interest expenses, administrative expenses, etc., were deleted; samples with missing key indicators were deleted; samples with average annual employment of less than eight people were deleted; and variables involving price factors, such as total assets and fixed assets, were deflated by fixed assets, for example, the investment price index deflated total assets and fixed assets, and industrial output value and sales revenue were deflated by the ex-factory product price index, resulting in a total of 3045 samples from 435 listed enterprises in the heavy pollution industry from 2008 to 2014. A panel of Chinese cities was also constructed based on the China City Statistical Yearbook, and 3045 samples from 281 cities from 2013 to 2019 were obtained for robustness testing.

### *3.2. Choice of Method for Measuring Pollution Abatement and Carbon Abatement Efficiency*

Since the data envelopment analysis (DEA) method does not require a priori functional forms and distributional assumptions and can incorporate both energy inputs and pollutant emissions into the analytical framework, it effectively overcomes many of the shortcomings of traditional TFP measurement methods and has been widely used in pollution abatement and carbon abatement efficiency measurement in recent years [59,60]. Currently, the primary methods for calculating pollution abatement and carbon abatement efficiency using data envelopment analysis include the earlier Malmquist productivity index based on Shepherd's output distance function, the Malmquist-Luenberger productivity index based on the directional distance function, and the Luenberger productivity index based on the relaxed directional distance function. Of these, the Luenberger productivity index not only considers 'bad' output but also addresses the 'radial' and 'angular' issues and is currently the most general method for calculating pollution abatement and carbon abatement efficiency [61]. Therefore, we use the Luenberger productivity index based on a relaxed directional distance function to measure *GTFP*, *CEE*, and *UEAE* and use these three efficiencies to measure enterprises' pollution abatement and carbon abatement efficiency indices. Therefore, we use the Luenberger productivity index based on a relaxed directional distance function to measure enterprises' pollution abatement and carbon abatement efficiency indexes. Due to space limitations, this article will not go into detail.

Based on the Luenberger productivity index principle, we construct the optimal production frontier for each Chinese firm for each year by treating each firm as an independent production decision unit. The value of the enterprise's output is defined as "good" output, and the emissions from the enterprise's production are defined as "bad" output [62]. Capital input is measured by the total fixed assets of the firm; labor input is measured by the number of employees of the firm, and 'good' output is measured by the value of the gross industrial output of the firm, all of which are obtained from the database of

Chinese industrial enterprises. Due to the different products produced by different types of enterprises or the different production technologies and techniques used by the same type of enterprise, the main types of energy inputs and pollutant emissions vary widely between enterprises. To incorporate these differences into a unified calculation standard, we standardize enterprises' energy inputs and pollutant emissions separately to achieve uniformity and comparability of measurement.

The energy standard currently adopted in China is the standard coal, used as a standard amount for converting various energy sources. In this paper, according to the General Rules for Calculation of Comprehensive Energy Consumption, the different types of energy inputs of enterprises are converted into a unified standard coal consumption as an energy input, along with capital input and labor input, which form the three inputs in measuring the pollution abatement and carbon abatement efficiency of enterprises. The previous "single factor charge for exceeding wastewater and exhaust gas standards" model was changed to a "multi-factor charge for total emissions in terms of pollution equivalents" model, i.e., a flat fee is charged for each "pollution equivalent" [63]. In this paper, the emissions of various pollutants are converted into a uniform number of pollution equivalents based on the pollution equivalents of various pollutants as determined by the Administrative Measures on Emission Charges and included in the measurement of total green factor productivity as a measure of "bad" output. The Measures for the Administration of Wastewater Charge Standards stipulate that the wastewater charge standard is RMB 0.7 per pollutant equivalent and the exhaust gas charge standard is RMB 0.6 per pollutant equivalent, so in this paper, when adding the number of pollutant equivalents of industrial wastewater and industrial exhaust gas, the weights of the two are adjusted according to the ratio of the charges per pollutant equivalent. The above fundamental indicators used to calculate energy inputs and pollutant emissions were obtained from the database of enterprises surveyed for primary industrial pollutant sources in the "Environment Statistics Reporting System". Combining the above three inputs of capital, labor, and energy, and two outputs of enterprise output and pollutant emissions, we measure the growth of pollution abatement and carbon abatement efficiency of listed enterprises in heavily polluting industries from 2008 to 2014, considering energy inputs and pollutant emissions.

We used the carbon emission factor method to calculate $CO_2$ emissions from energy consumption at the enterprise level, considering the study by Wang et al. [35] for the primary energy standard coal conversion factor and $CO_2$ emission factor. The calculation formula is as follows:

$$Q_{CO_2} = \sum_{i=1}^{n} K_i E_i$$

where $Qco_2$ is the carbon dioxide emissions of an enterprise, $E_i$ is the consumption of $i$ energy sources, and $K_i$ is the carbon dioxide emission factor of $i$ energy source. Given that coal, natural gas, and fuel oil account for more than 80% of the total energy consumption, this paper uses these three types of energy as examples to estimate enterprises' overall carbon dioxide emissions.

Combining the three inputs of capital, labor, and energy and the two outputs of output value and pollutant emissions, this paper measures the growth of green total factor productivity, carbon emission efficiency, and joint emission reduction efficiency of listed enterprises in the heavy pollution industry from 2008 to 2014, considering energy inputs and pollutant emissions. This paper also uses data on wastewater, waste gas, and soot emissions; urban industrial electricity consumption; and urban industrial output from the 2013–2019 China Urban Statistical Yearbook and scales the urban data to the enterprise level by using the proportional method and combines the carbon emission data of CSMAR listed enterprises to form a panel of enterprise data from 2013 to 2019 to measure green total factor productivity, carbon emission efficiency, and joint emission reduction efficiency. The joint emission reduction efficiency is tested for robustness. Descriptive statistics are shown in Table 1.

**Table 1.** Descriptive statistics.

| Variable | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| GTFP | 3045 | 0.036 | 0.048 | −0.381 | 0.539 |
| CEE | 3045 | 0.003 | 0.069 | −0.615 | 0.621 |
| UEAE | 3045 | 0.012 | 0.053 | −0.542 | 0.577 |
| DI | 3045 | 5.477 | 14.738 | 0.000 | 151.452 |
| Scale | 3045 | 22.288 | 1.298 | 19.541 | 26.465 |
| Age | 3045 | 7.661 | 9.413 | 0.069 | 163.302 |
| Profit | 3045 | 1.577 | 1.551 | 0.079 | 14.258 |
| Flow | 3045 | 8.555 | 1.043 | 5.590 | 11.557 |
| Debt | 3045 | 0.410 | 0.190 | 0.057 | 0.848 |
| HI | 3045 | 0.123 | 0.109 | 0.014 | 1 |

## 4. Model Setting and Empirical Results

### *4.1. Model Setting*

To test the dynamic effect of digital transformation on enterprises' pollution abatement and carbon abatement efficiency at the firm level, the transmission mechanism, and the analysis of the heterogeneity of the firm's internal and external environment, we construct the following dynamic model:

$$GTFP_{it}|CEE_{it}|UEAE_{it} = \alpha + \beta DI_{it} + \lambda DI_{iT} + \theta X_{it} + \phi_{\mathrm{i}} + \varphi_{\mathrm{t}} + \varepsilon_{\mathrm{it}} \quad (1)$$

$$M_{it} = \alpha + \beta DI_{it} + \lambda DI_{iT} + \theta X_{it} + \phi_{\mathrm{i}} + \varphi_{\mathrm{t}} + \varepsilon_{\mathrm{it}} \quad (2)$$

$$GTFP_{it}|CEE_{it}|UEAE_{it} = \alpha + \beta DI_{it} * T_{it} + \lambda DI_{iT} * T_{it} + \gamma T_{it} + \theta X_{it} + \phi_{\mathrm{i}} + \varphi_{\mathrm{t}} + \varepsilon_{\mathrm{it}} \quad (3)$$

where $GTFP_{it}$, $CEE_{it}$, or $UEAE_{it}$ is the pollution abatement and carbon abatement efficiency index of firm $i$ in year $t$, $DI_{it}$ is the degree of digital transformation of firm $i$ in year $t$, the vector $DI_{iT}$ denotes the degree of digital transformation of firm $i$ with five consecutive lags and is used to examine the lagged effect of digital transformation on $GTFP_{it}$, $CEE_{it}$ or $UEAE_{it}$, $M_{it}$ is a mechanism variable, $T_{it}$ is a moderating variable, the vector $X_{it}$ denotes firm-level and industry-level control variables, $\phi_i$ and $\varphi_t$ denote individual fixed effects and time fixed effects, respectively, and $\varepsilon_{it}$ is the error term.

### *4.2. Variable Settings*

#### 4.2.1. Explained Variables

The specific measurement and calculation of the pollution abatement and carbon abatement efficiency index for enterprises are described above under 'Options for measuring pollution abatement and carbon abatement efficiency'.

#### 4.2.2. Explanatory Variables

The degree of digital transformation (DI) of enterprises: In this paper, we first refer to the studies of [23,64] to summarize the keywords related to digital transformation and then use Python technology to keyword-match the textual content in the annual reports listed enterprises from 2003 to 2014, count the number of occurrences of related words, construct the enterprise year variables, and logarithmically process. The higher the number of occurrences of digital-transformation-related terms in the annual reports of enterprises, the higher the degree of digital transformation of the company. The digital transformation data of listed enterprises from 2013 to 2019 were also clustered at the city level for robustness testing.

4.2.3. Control Variables

The main firm-level control variables include: (1) firm size (scale), measured by total fixed assets, which reflects the difficulty of enterprises to undertake green technology transformation [65]; (2) firm age (age), which reflects the degree of path dependence of enterprises to conduct production and operation in the traditional mode [66]; (3) profit, measured by the ratio of operating profit to total assets, which reflects the amount of capital available for green technology innovation [67]; (4) flow, measured using the ratio of total current assets to the sum of total current assets and total fixed assets, reflecting the firm's ability to realize assets in the short term [68]; (5) debt, measured using the ratio of total liabilities to total assets, reflecting the difficulty of financing [69]; (6) financing constraint (Restri), measured using the ratio of interest expense to fixed assets, reflecting the cost of financing [70]; and (7) management level (manage), measured using the ratio of overhead expenses to main business, which reflects the level of management of the firm, with a higher value indicating a poorer level of management [71].

Industry-level control variables include (1) the total industry output size (Toutput), measured as the sum of the industrial sales output value of all enterprises in the four-digit code industry, reflecting the capacity of the product market; the more significant the value, the larger the potential market that enterprises may obtain after improving their green technology level, which is expected to have a positive impact on enterprises' pollution abatement and carbon abatement efficiency [72]; and (2) the degree of industry competition (HHI), calculated as the industrial sales value of enterprises in a four-digit code industry; the more competitive the industry (the smaller the HHI), the greater the pressure on enterprises to engage in technological innovation, and the more conducive to improving pollution abatement and carbon abatement efficiency [73].

4.2.4. Mediating Variables

The main ones are (1) green technological innovation (GTI), which is measured in this paper by the number of green patents of enterprises borrowing from [36] and (2) factor allocation optimization (FAO), where the decomposition method of [74] is borrowed to measure the level of factor allocation efficiency of enterprises.

4.2.5. Heterogeneous Grouping Variables

The main ones are (1) the intensity of environmental regulation (ER), which is measured in this paper using the city-level environmental regulation index constructed by [75], and (2) product competitiveness (PC), which is measured in this paper using the firm markup rate, following [76].

*4.3. Empirical Results*

4.3.1. Baseline Regression Results

Column (1) of Table 2 presents the regression results of model (1). The coefficients on digital transformation generally change from significantly negative to significantly positive from the current period to five lags, indicating temporal heterogeneity in the impact of digital transformation on *GTFP*, *CEE*, and *UEAE*.

From the results of the baseline regression analysis, our study finds that there is a difference from the findings of [18]. Using the current period data of digital transformation for regression, J. Wang et al. [18] obtain that, under the condition of mean reversion, digital transformation can promote enterprises' green and low-carbon transformation. However, by examining the lag period of enterprises' digital transformation, we find that the conclusion of this paper is only in the lag period the same as that of [18], i.e., the facilitating effect of digital transformation on enterprises' green and low-carbon development is only practical in the first and fourth period of the lag period of digital transformation, while it is ineffective or even inhibitory in the current period of digital transformation. This result is consistent with the conclusions of [77,78], who added the current and lagged terms of digital transformation in their empirical model and found that the current period of digital

transformation hurts productivity, while the lagged period of digital transformation has a positive impact on productivity. Through the dynamic analysis, we not only validate the conclusions of [77,78], but also provide additional insights and a more detailed description of the complexity of the green and low-carbon transition effect of digital transformation and the mechanisms behind it.

**Table 2.** Baseline regression tests.

| Variables | (1) GTFP | (2) CEE | (3) UEAE |
|---|---|---|---|
| DI | −0.007 *** | −0.021 *** | −0.011 *** |
| | (0.001) | (0.008) | (0.002) |
| DI_t-1 | 0.031 *** | 0.054 *** | 0.043 *** |
| | (0.009) | (0.023) | (0.016) |
| DI_t-2 | 0.003 | 0.021 | 0.010 |
| | (0.031) | (0.047) | (0.032) |
| DI_t-3 | 0.014 | 0.074 | 0.041 |
| | (0.025) | (0.082) | (0.060) |
| DI_t-4 | 0.015 *** | 0.063 *** | 0.036 *** |
| | (0.002) | (0.024) | (0.009) |
| DI_t-5 | 0.184 | 0.386 | 0.275 |
| | (0.325) | (0.525) | (0.487) |
| Control variables | Yes | Yes | Yes |
| City–firm FE | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes |
| Observations | 3045 | 3045 | 3045 |
| R-squared | 0.623 | 0.698 | 0.786 |

Note: *** denotes significance level of 1%, and all values in brackets denote robust standard errors of clustering at the city–firm level; the models all use two-way fixed effects models.

The following relevant studies support the empirical results of this paper. The reason for generating such empirical results in this paper is that the "compliance cost" brought about by digital transformation is a one-off expenditure in the current year, which is immediate. Its negative impact on pollution reduction and carbon emission reduction efficiency is mainly reflected in the current period of digital transformation. In contrast, the crowding-out effect of the productive and profitable investment brought about by digital transformation has a marginal decreasing impact on pollution reduction and carbon emission reduction efficiency [79]. The negative impact on pollution abatement and carbon abatement efficiency is mainly reflected in the current period of digital transformation. In contrast, the crowding out of productive and profitable investments due to digital transformation has a marginal decreasing impact on pollution abatement and carbon abatement efficiency [80], and the combination of the two directly reduces pollution abatement and carbon abatement efficiency in the current period. The "innovation compensation" effect of digital transformation is weakest or even zero in the current period. However, it has a marginal increasing process over time [18], which is the opposite of the negative lag effect of crowding out investment. Not surprisingly, enterprises' investment in green technology comes precisely from reallocating otherwise productive, profitable investments. Therefore, over time, these two effects reinforce and offset each other so that the impact of digital transformation on enterprises' pollution abatement and carbon abatement efficiency is 'neutralized' [81]. In the empirical results of this paper, the coefficients of lag1, lag2, and lag3 digital transformation are statistically insignificant until the latter is greater than the former, increasing enterprises' *GTFP*, *CEE*, or *UEAE*, i.e., the coefficient of lag4 digital transformation is significantly positive, confirming Hypothesis 1 of this paper.

#### 4.3.2. Endogeneity Treatment and Robustness Tests

There are two potential endogeneity problems with the empirical evidence in this paper: First, there is a bidirectional causal relationship between digital transformation and

pollution abatement and carbon abatement efficiency, i.e., accelerating digital transformation may increase the pollution abatement and carbon abatement efficiency of enterprises, while an increase in the pollution abatement and carbon abatement efficiency of enterprises may also lead to a greater incentive and demand for enterprises to undertake a high level of digital transformation. Second, many factors affect enterprises' pollution abatement and carbon abatement efficiency, and the control variables included in the empirical evidence of this paper are limited, which may have the problem of omitted variables. Based on this, we adopt the following two approaches to deal with possible endogeneity problems in the empirical evidence.

Instrumental Variables Method

To mitigate potential endogeneity effects, we follow [82] and select the number of fixed telephones per 10,000 people in each city in 1985 as an instrumental variable for the digital transformation of enterprises. On the one hand, the digital transformation process of enterprises is assumed to have started with the diffusion of ICTs, led by the Internet, which started with the widespread diffusion of fixed telephones. On the other hand, the communication methods used in the past by the location of enterprises can influence the acceptance and application of information technology in many ways, such as the level of technology and social preferences. Therefore, we argue that if a region has a high penetration rate of fixed telephones, the degree of digital transformation of enterprises in that region will also be higher, in line with the correlation requirement. On the other hand, the primary users of fixed-line telephones are citizens, and enterprises' pollution abatement and carbon abatement efficiency situation does not affect them, which satisfies the exogeneity requirement. In addition, considering that the number of fixed-line telephones per 10,000 people in each city in 1985 is cross-sectional data and cannot be used directly as an instrumental variable in panel data, we follow [83] and treat the number of fixed-line telephones per 10,000 people in each city in 1985 as an interaction term with the number of people with nationwide Internet access in the lagged period, and use it as an instrumental variable for the degree of digital transformation in the current period, and the regression results are shown in columns (1) to (4) of Table 3 Panel A below. According to the results, the LM statistic is significant at the 1% level, rejecting the hypothesis of "under-identification of instrumental variables"; the F statistic is also more significant than the critical value for identifying weak instrumental variables in Stock-Yogo, rejecting the hypothesis of "weak instrumental variables". Therefore, the instrumental variables selected in this paper are appropriate and reliable. At the same time, according to the results of the second stage test in Table 2, the digital transformation variable is significantly negative at the 1% level, which is consistent with the previous findings and indicates that the conclusions of this paper are robust.

**Table 3.** Endogeneity treatment and robustness tests.

| **Panel A: Endogeneity Treatment** | | | | |
|---|---|---|---|---|
| **Variables** | | **2SLS** | | |
| | **(1)** **First Phase** | **(2)** **Second Phase: GTFP** | **(3)** **Second Phase: CEE** | **(4)** **Second Phase: UEAE** |
| DI | 0.021 *** | −0.011 *** | −0.024 *** | −0.018 *** |
| | (0.000) | (0.002) | (0.010) | (0.008) |
| DI_t-4 | 0.011 *** | 0.061 *** | 0.082 *** | 0.070 *** |
| | (0.002) | (0.014) | (0.032) | (0.022) |
| Kleibergen-Paap rk LM | 24.62 ** | | | |
| Cragg-Donald Wald F | 22.74 | | | |
| Control variables | Yes | Yes | Yes | Yes |
| City–firm FE | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Observations | 3045 | 3045 | 3045 | 3045 |
| R-squared | 0.859 | 0.726 | 0.837 | 0.763 |

**Table 3.** *Cont.*

| **Panel B: DID Model Robustness Tests** | | | | | | |
|---|---|---|---|---|---|---|
| **Variables** | **DID** | | | | | |
| | **Whether Digital Transformation** | | | **Degree of Digital Transformation** | | |
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| | **GTFP** | **CEE** | **UEAE** | **GTFP** | **CEE** | **UEAE** |
| duit*dtit | 0.071 *** | 0.087 *** | 0.079 *** | | | |
| | (0.021) | (0.034) | (0.029) | | | |
| duit*dtit*DI | | | | 0.008 *** | 0.016 *** | 0.013 *** |
| | | | | (0.002) | (0.006) | (0.005) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes |
| City–firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3045 | 3045 | 3045 | 3045 | 3045 | 3045 |
| R-squared | 0.704 | 0.846 | 0.726 | 0.757 | 0.637 | 0.598 |

| **Panel C: City Panel Robustness Tests** | | | |
|---|---|---|---|
| **Variables** | **City Panel Data 2013–2019** | | |
| | **(1)** | **(2)** | **(3)** |
| | **GTFP** | **CEE** | **UEAE** |
| DI | −0.010 *** | −0.024 *** | −0.015 *** |
| | (0.003) | (0.0013) | (0.006) |
| DI_t-4 | 0.020 *** | 0.074 *** | 0.043 *** |
| | (0.007) | (0.033) | (0.018) |
| Control variables | Yes | Yes | Yes |
| City–firm FE | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes |
| Observations | 3045 | 3045 | 3045 |
| R-squared | 0.547 | 0.747 | 0.811 |

Note: **, *** denote significance levels of 5%, and 1%, respectively; values in brackets denote robust standard errors of clustering at the city–firm level.

Replacement of Differences-in-Differences Method

The phased and incremental approach to digital transformation by enterprises provides an appropriate quasi-natural experiment for this study. Therefore, following [23], we use a double-difference model to differentially score the control and experimental groups of listed enterprises undertaking digital transformation activities in order to minimize the estimation error caused by the intrinsic differences that exist between the individuals involved and the time trend that is unrelated to the experimental group and to obtain accurate results on the impact of digital transformation on enterprises' *GTFP*, *CEE*, or *UEAE*. In this paper, models (4) and (5) are constructed to test the impact of digital transformation on the *GTFP* of enterprises:

$$GTFP_{it}|CEE_{it}|UEAE_{it} = \alpha + \beta((du_{it} * dt_{it}) + \theta X_{it} + \phi_{\mathrm{i}} + \varphi_{\mathrm{t}} + \varepsilon_{\mathrm{it}} \quad (4)$$

$$GTFP_{it}|CEE_{it}|UEAE_{it} = \alpha + \beta((du_{it} * dt_{it} * DI_{it}) + \theta X_{it} + \phi_{\mathrm{i}} + \varphi_{\mathrm{t}} + \varepsilon_{\mathrm{it}} \quad (5)$$

where $du_{it}$ is an individual dummy variable that equals one if the firm underwent a digital transformation during the study period and 0 otherwise, and the $dt_{it}$ is a time dummy variable that equals 1 for the year the firm underwent digital transformation and subsequent years. The coefficients of the interaction term reflect the change in the effect on the firm's *GTFP*, *CEE*, or *UEAE* before and after digital transformation. Model (5) also introduces the degree of digital transformation (DI), and the interaction term coefficients reflect the effect of the intensity of transformation on the *GTFP*, *CEE*, or *UEAE* of an enterprise after digital transformation. The regression results are shown in columns (1) and (6) of Table 3 Panel B. The results show that the coefficients of the interaction terms, which are the focus of this paper, are all significantly negative, implying that digital transformation is still conducive to increasing enterprises' *GTFP*, *CEE*, or *UEAE* after mitigating the endogeneity problem using the double difference approach.

Replacement of City Sample Data

Considering the relatively severe statistical time lag of the pollution emission data of Chinese industrial enterprises and the objective limitation of the data period, we construct the *GTFP*, *CEE*, or *UEAE* at the city level from 2013 to 2019 and cluster the digital transformation data of enterprises at the city level for empirical testing [58]. The regression results are shown in columns (1) and (3) of Table 3 Panel C. The results show that the city sample data differ from the benchmark regression data only in the regression coefficients and the degree of fit, with no difference in positive or negative coefficients and significance, indicating that the empirical results from the benchmark regression data are still applicable to the current study, despite the lag in data years, and that the results are credible and valid.

4.3.3. Analysis of Impact Mechanisms

We empirically test the mechanisms of green technological innovation and factor allocation efficiency. The regression results in Table 4, columns (1) and (2), show that the coefficients of the mediating variables are significantly positive, indicating that digital transformation can positively contribute to enterprises' *GTFP*, *CEE*, or *UEAE* through the effect of green technological innovation and the effect of factor allocation optimization [23,67]. The empirical results confirm Hypothesis 2a and Hypothesis 2b, respectively.

**Table 4.** Conduction mechanism test.

| **Variables** | **(1) Green Technology Innovation Mediating Role** | **(2) Factor Allocation Optimization Mediating Role** |
|---|---|---|
| | GTI | FAO |
| DI | −0.013 *** | −0.011 *** |
| | (0.000) | (0.000) |
| DI_t-4 | 0.121 *** | 0.108 *** |
| | (0.050) | (0.047) |
| Control variables | Yes | Yes |
| City–firm FE | Yes | Yes |
| Time FE | Yes | Yes |
| Observations | 3045 | 3045 |
| $R^2$ | 0.659 | 0.926 |

Note: *** denotes significance levels of 1%; values in brackets denote robust standard errors of clustering at the city–firm level. The models all use two-way fixed effects models.

4.3.4. Examination of the Heterogeneity of an Enterprise's Internal and External Environment

We also empirically test for heterogeneity in the intensity of urban environmental regulation outside the firm and product competitiveness within the firm—columns (1) and (6) of Table 5 present the empirical results. The results show that the interaction term between the moderating variables and four-lagged digital transformation is significantly positive, indicating that environmental regulations and product competitiveness can positively moderate the contribution of the digital transformation to enterprises' *GTFP*, *CEE*, or *UEAE* in the long run in both internal and external environments. However, in the short run, only the increase in the intensity of environmental regulations can weaken the dampening effect of digital transformation on enterprises' *GTFP*, *CEE*, or *UEAE* [53,76,84]. The empirical results confirm Hypothesis 3a and Hypothesis 3b, respectively.

**Table 5.** Examination of the heterogeneity of an enterprise's internal and external environment.

| Variables | Heterogeneity of Urban Environmental Regulation | | | Heterogeneity of Enterprises' Product Competitiveness | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | GTFP | CEE | UEAE | GTFP | CEE | UEAE |
| DI | −0.002 *** | −0.012 *** | −0.012 *** | −0.008 *** | −0.022 *** | −0.012 *** |
| | (0.000) | (0.005) | (0.005) | (0.002) | (0.009) | (0.005) |
| DI_t-4 | 0.007 *** | 0.014 *** | 0.014 *** | 0.003 *** | 0.017 *** | 0.014 *** |
| | (0.000) | (0.005) | (0.005) | (0.001) | (0.006) | (0.005) |
| ER*DI | −0.071 *** | −0.089 *** | −0.078 *** | | | |
| | (0.021) | (0.043) | (0.030) | | | |
| ER*DI_t-4 | 0.047 *** | 0.063 *** | 0.051 *** | | | |
| | (0.013) | (0.021) | (0.018) | | | |
| PC*DI | | | | −0.004 *** | −0.013 *** | −0.010 *** |
| | | | | (0.001) | (0.005) | (0.003) |
| PC*DI_t-4 | | | | 0.003 *** | 0.016 *** | 0.012 *** |
| | | | | (0.001) | (0.007) | (0.005) |
| Control variables | Yes | Yes | Yes | Yes | Yes | Yes |
| City–firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3045 | 3045 | 3045 | 3045 | 3045 | 3045 |
| $R^2$ | 0.704 | 0.867 | 0.741 | 0.757 | 0.639 | 0.836 |

Note: *** denotes significance level of 1%; values in brackets denote robust standard errors of clustering at the city–firm level; the models all use two-way fixed effects models.

## 5. Further Research

We further explore the Synergies between Pollution Abatement and Carbon Emission Abatement in the digital transformation of enterprises from the perspective of marginal abatement costs. Firstly, this paper calculates the marginal abatement cost of pollution emissions or carbon emissions under separate abatement and the marginal abatement cost of pollution emissions or carbon emissions under joint abatement. Then, following the idea of [85], the synergistic effect is defined as the ratio of the change in marginal abatement cost under separate abatement to that under joint abatement to measure the synergistic effect of pollution reduction and carbon abatement. Finally, enterprises' digital transformation impact on the SPACEA is tested.

### *5.1. Measuring the Synergies between Pollution Abatement and Carbon Emission Abatement of Enterprises*

Referring to [86], the shadow prices of carbon emissions and industrial wastewater, industrial waste gas, and industrial soot of enterprises were estimated by Shephard's Lemma using the pairwise relationship between the non-radial directional distance function and the cost function, followed by linear programming, to find the marginal abatement cost $MAC$ of non-desired outputs.

As the units of both marginal abatement cost and marginal carbon reduction cost do not coincide, dimensionless treatment was first performed before measuring the synergistic effect:

$$\Delta C_{PL} = \frac{MACB_{PL} - MACT_{PL}}{MACB_{PL}} \tag{6}$$

$$\Delta C_{CO_2} = \frac{MACB_{CO_2} - MACT_{CO_2}}{MACB_{CO_2}} \tag{7}$$

where $MACB_{PL}$ is the marginal abatement cost of enterprise pollution emissions when pollution alone was reduced, $MACT_{PL}$ is the marginal abatement cost of enterprise pollution emissions when reduced together with carbon emissions, and $\Delta C_{PL}$ represents the percent-

age of reduction in the marginal abatement cost of pollution emissions when abatement was combined compared to abatement alone, i.e., the pollution abatement effect. $MACB_{CO_2}$ is the marginal abatement cost of enterprise carbon emissions when reducing carbon alone, $MACT_{CO_2}$ is the marginal abatement cost of enterprise carbon emissions when reduced together with pollution emissions, and $\Delta C_{CO_2}$ represents the percentage of reduction in the marginal abatement cost of carbon emissions when abatement is combined compared to abatement alone, i.e., the carbon abatement effect. On this basis, the SPACEA is defined as $T = \alpha * \Delta C_{PL} + \beta * \Delta C_{CO_2}$ when pollution reduction and carbon reduction are equally significant, $\alpha = \beta = 0.5$.

### *5.2. The Impact of the Digital Transformation of Enterprises on the Synergies between Pollution Abatement and Carbon Emission Abatement Test*

The results in column (1) of Table 5 show that the coefficient for the current period of digital transformation is significantly negative, indicating that in the short term, digital transformation has a dampening effect on the SPACEA. In contrast, the coefficient for the lagged four periods of digital transformation is significantly positive, indicating that digital transformation positively affects the SPACEA in the long run. The results in columns (2)–(3) of Table 6 show that the coefficients for the four lags of digital transformation are significantly positive and have a more significant impact on the carbon reduction effect, indicating that the pollution abatement and carbon emission abatement effects of digital transformation are slightly more favorable than the carbon abatement effects.

**Table 6.** The impact of digital transformation of enterprises on the Synergies between Pollution Abatement and Carbon Emission Abatement test.

| Variables | (1) SPACE | (2) Pollution Abatement Effect | (3) Carbon Abatement Effect |
|---|---|---|---|
| DI | −0.043 *** | −0.029 *** | −0.049 *** |
| | (0.020) | (0.012) | (0.017) |
| DI_t-4 | 0.047 *** | 0.034 *** | 0.060 *** |
| | (0.019) | (0.011) | (0.027) |
| Control variables | Yes | Yes | Yes |
| City–firm FE | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes |
| Observations | 3045 | 3045 | 3045 |
| R-squared | 0.591 | 0.712 | 0.693 |

Note: *** denotes significance level of 1%; values in brackets denote robust standard errors of clustering at the city–firm level; the models all use two-way fixed effects models.

## 6. Conclusions and Policy Recommendations

Promoting enterprise pollution reduction and carbon emission reduction is a necessary foundation and key handle for China to achieve the "double carbon" target and green economic transformation. Based on the development of new-generation information technology, this study advances the literature by examining the impact of digital transformation on enterprise pollution reduction and carbon emission reduction in China. This paper uses data from 2008 to 2014 matched between A-share listed enterprises in China's heavily polluting industries and China's industrial enterprise pollution emission database, as well as panel data constructed by combining the data of heavily polluting listed enterprises from 2013 to 2019 and the China City Statistical Yearbook, to analyze the impact of Chinese enterprises' digital transformation. The main findings are as follows: First, digital transformation has a suppressive effect on enterprises' green total factor productivity, carbon emission efficiency, and United Emission Abatement Efficiency in the short term, but it can significantly promote these three types of efficiency in the long term. Digital transformation can improve enterprises' resource use efficiency by promoting green technology innovation capability and optimizing their factor allocation efficiency, thereby improving these three

types of pollution and carbon emission abatement efficiencies. Second, the effect of digital transformation on green total factor productivity, carbon emission efficiency, and United Emission Abatement Efficiency is influenced by the internal and external environment in which the enterprise is located. In the external environment, the greater the intensity of environmental regulations in the region where an enterprise is located, the more significant the effect of digital transformation on green total factor productivity, carbon emission efficiency, and United Emission Abatement Efficiency; in the internal environment, that is, the enterprise's characteristics, the competitiveness of its products can enhance the effect of digital transformation on green total factor productivity, carbon emission efficiency, and United Emission Abatement Efficiency. Third, our further research from the perspective of marginal abatement costs found that digital transformation can promote Synergies between Pollution Abatement and Carbon Emission Abatement in the long run, achieving a green and low-carbon synergistic development.

The policy implications of this study for promoting the synergistic development of digital transformation and green low-carbon production in Chinese enterprises are as follows: First, they further strengthen the construction of digital infrastructure and related public services. Local governments can set up funds to support the digital transformation of enterprises according to the development of the local economy and the digital economy and strengthen the capacity building of public services such as enterprise digital transformation promotion centers to help enterprises solve the problems of "not knowing how to transform, not being able to transform, and not daring to transform", strengthen and promote the will and process of enterprise digital transformation, and provide a favorable external environment for enterprises to improve their efficiency in pollution reduction and carbon emission reduction. Second, enterprises should take advantage of digitalization to tap new dynamic energy. Enterprises should empower technological innovation with digital transformation and make use of the organic integration of digital technology and core business to transform enterprises in all aspects and across the chain, reduce their production energy consumption, improve their flexible production capacity and resource use efficiency, and smooth the transmission mechanism of digital transformation to enterprise pollution abatement and carbon emission abatement production. Third, to give full play to the synergistic effect of digital transformation on pollution reduction and carbon emission reduction, we must pay attention to the supporting role of the external environment, further increase the intensity of environmental regulation, and enhance the environmental awareness of enterprises by carrying out activities to introduce environmental protection laws and regulations into enterprises. At the same time, it is also necessary to build an exchange platform for enterprises based on themselves, learn from each other, and work hand in hand to enhance the competitiveness of their products, reduce the coordination and reform costs of their digital transformation, and promote the synergistic development of their digital transformation and pollution reduction and low-carbon production. Fourth, the findings of this study have important implications for international audiences, researchers, and academics. This study provides valuable insights into the impact of digital transformation on the synergistic development of pollution and carbon reduction in Chinese enterprises. International audiences can compare these findings with their national contexts to understand the potential impacts of digital transformation on pollution and carbon reduction in different environments. They can learn from China's experience and apply it to their practices in addressing environmental challenges and promoting sustainable development.

## 7. Limitations and Prospects

Although this paper provides a detailed discussion of the intrinsic connection and influence mechanism of the synergistic development of digital transformation, enterprise pollution reduction, and carbon reduction, it still needs improvement. First, since the pollution data of Chinese industrial firms are only updated to 2014, we cannot use more time-sensitive data. Thus, the empirical sample needs to include the panel data of firms after 2014. Although we used city-level data to extend the sample year to 2019 to conduct

the robustness test, it is difficult for city data to reflect the actual situation of individual enterprises due to data limitations. Second, this paper mainly analyses the impact mechanism of digital transformation on the synergistic development of enterprises' pollution reduction and carbon reduction from the perspective of green innovation and market allocation, and future research can explore more micro-influence mechanisms.

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**Institutional Review Board Statement:** The work does not involve any hazards, such as the use of animal or human subjects.

**Informed Consent Statement:** All participants were aware of and agreed to participate in this study.

**Data Availability Statement:** The data presented in this study are available on request from the corresponding author.

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