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Digital Transformation, Green Innovation, and Pollution Abatement: Evidence from China

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Abstract: The advent of novel and potent digital technologies has substantially transformed ways enterprises undertake their production. How digital transformation will reshape the production model of enterprises and have an impact on pollution emissions is a crucial problem in existing research. In this paper, we construct a theoretical framework to illuminate the theoretical mechanism of firms employing digital technology to bring out pollution abatement effect. Using a series of firm-level datasets from China, this paper introduces fixed-effect specification to empirically examine the environmental effects triggered by digital transformation. We find a negative effect of digital transformation on firms' pollution emissions. The results are robust when potential endogeneity and mismeasurement problems are controlled for. Factors related to green innovation and investments in pollution abatement are found to play an important role in shaping the nexus between digital transformation and firm-level pollution emissions. This paper provides supporting firm-level evidence for the pollution abatement effect of digital transformation, which is essential for accelerating the construction of the digital economy, promoting the synergistic effect of digital transformation and green development, and achieving a balanced development of economic growth and environmental governance.

Keywords: digital transformation; green innovation; abatement investment; pollution emissions

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1. Introduction

China's economy has expanded rapidly since the reform and opening-up due to extensive investment-driven development. The environment in which we live is facing enormous problems as a result of this extensive increase. China faces serious resource and environmental problems, particularly with regard to water and air pollution [1,2]. Among the 338 cities surveyed in 2016, nearly 75 percent failed to match the air quality standards set by China and approximately 60 percent were heavily polluted due to the low water quality [3]. Large freshwater lakes and urban lakes lack qualified water quality, and lake eutrophication is intensified. However, in recent years, China has made great efforts in environmental governance, implementing a series of innovative reforms on environmental legislation. With the perfection of the environmental legislation system, China's overall environmental quality has effectively improved. In 14th Five-Year Plan, the Chinese government clearly stated that it would "ameliorate the environmental quality, accelerate the green transformation development, and comprehensively promote the efficiency of resource utilization". The Chinese government urgently needs to transform the traditional environmental governance paradigm and integrate environmental concerns with cutting-edge technological disciplines in order to address the persistent environmental difficulties in China. As a result, supporting corporate digital transformation and achieving the integration of the digital and real economies has emerged as the primary impetus behind China's present green upgradation and high-quality economic development.

With the rise of the fourth wave of scientific and technological revolution, new digital technologies such as artificial intelligence, big data, and blockchain continue to emerge.

The rapid ascent of digital enterprises has now established itself as a significant factor in the high-quality development of China's economy. According to the "China Digital Economy Development Report (2022)" released by the China Academy of Information and Communications Technology, the scale of China's digital economy has reached 45.5 trillion yuan in 2021, accounting for 39.8% of GDP. The development of the digital economy has got off to a strong start due to the proliferation of numerous digital enterprises. Digital enterprises enable manufacturing industries to undergo digital transformation by offering pertinent digital services and enhancing industries' access to technology [4]. For digital transformation, this paper refers to existing research and defines it as a process in which enterprises reconstruct production and operation activities and organizational structure through digital technology to improve production and operation efficiency and organizational management efficiency, and convert digitalization into core competitiveness [4,5]. Meanwhile, digital transformation is gradually being reflected in the enterprise's specific production behavior. By implementing digital technology, enterprises can restructure their organizational structure, manufacturing processes, and operational activities to increase production and management efficiency [6]. It is clear that the digital transformation of enterprises is not only a microscopic transformation brought about by the deep integration of digital technology and production behavior, but also an innovative symbol of the enterprises' transition from conventional to digital production systems.

The production behavior of Chinese firms is significantly impacted by the rapid expansion in the adoption of digital technologies. This has a significant and ongoing impact on China's pollution emissions, which are intimately linked to industrial production. Firms are the primary source of pollution emissions as a micro-subject of economic activity, and more than 80% of the pollutants are derived from the production activities of enterprises [3]. How digital transformation will affect firms' pollution emissions in China is thus a crucial and pressing issue related to these backgrounds. How can China's environmental governance be strengthened by fully releasing the productivity of the domestic digital economy and the scientific and technological power supplied by the explosive growth in digital enterprises? The analysis on these issues is particularly crucial for promoting the synergistic effect of digital transformation and green development and achieving a balanced development of economic growth and environmental governance. The existing literature generally demonstrates that technological advancement can increase firms' productivity and accelerate their green upgrading [7,8]. As an important driving force for the transformation of production behavior, the adoption of digital technology can effectively lead to the advancement of firms' technology and productivity [9,10]. However, owing to the limitation of micro-level data, existing research on digital transformation and environmental pollution is mainly conducted at the region and industry level [11,12]. We, therefore, employ a number of firm-level disaggregate datasets from China to study the micro-environmental effects of digital transformation, which is of great importance.

To investigate the effect of digital transformation on firms' pollution emissions, this paper constructs a theoretical model that contains digital technology, abatement, and firm pollution to shed light on the theoretical mechanism of firms using digital technology to bring about the pollution abatement effect. Specifically, we propose a detailed mechanism for why the adoption of digital transformation may have a lower emission intensity. Our model weaves together elements of the workhorse model from the heterogeneous firms [13] and environmental pollution [14] literature. The model consists of firms endogenously choosing factor inputs and investments in pollution abatement to avoid a tax on pollution emissions. Production behavior and pollution abatement selections are conditional on the adoption of digital technology, production factor input, and environmental cost including emission tax and abatement expense. Our model demonstrates that digital transformation enables firms to achieve green innovation and increase green investment specific to digital to optimize the structure of the factor input. The adoption of digital technology and clean inputs may switch the production mode matching the dirty inputs of polluting manufacturing enterprises, thus reducing firms' pollution emissions. Furthermore, our

model also predicts that digital transformation may help firms to generate a cost-reduction effect, which enables firms to have more operating funds to invest in emission abatement facilities and further curb emission intensity.

Based on the theoretical model predictions, this paper employs a series of firm-level datasets from the Annual Survey of Industrial Firms database (ASIF) and the Chinese Environmental Statistics database (CESD) to empirically identify the effect of digital transformation on firms' pollution emissions. The estimation results suggest that digital transformation has a significant negative effect on firms' pollution emissions. This confirms that firms can improve their environmental performance by adopting digital technologies. Moreover, we further introduce green innovation and investments in pollution abatement as two mechanism variables to explore the underlying mechanism of digital transformation on firms' pollution emissions. The results show that digital transformation has a positive and statistically significant effect on green innovation and investments in pollution abatement, which verifies the theoretical propositions discussed above.

This paper departs from the literature in three primary ways. Firstly, this paper provides fresh insights into the effect of digital transformation. The extensive existing literature is dedicated to exploring the effects of digital transformation on enterprise's performance. Some studies demonstrate that digital transformation can effectively increase the business performance and operating profits of enterprises [15]. Specifically, digital transformation enables firms to improve their productivity [16,17], innovation performance [18,19], and resources allocation efficiency [6]. In terms of the impact mechanism of digital transformation, the extant literature generally suggests that digital transformation mainly affects enterprise's performance by reducing operating costs, promoting R&D innovation, and improving production flexibility [20,21]. However, some studies show that there is no direct relationship between digital transformation and enterprise's performance; only a few parts of enterprise can benefit from digital technology due to the costly expenditure involved in the process of digital transformation [22]. As a whole, the extant literature mainly concentrates on the effects of digital transformation on various operating performances of enterprises, while the literature on the relationship between digital transformation and environmental performance is relatively limited. We, therefore, construct a comprehensively theoretical framework and empirical specification to investigate the effects of digital transformation on firms' pollution emissions, with a view to filling the gaps in the existing literature.

A second contribution of this paper is to enrich the understanding of firm-level pollution emissions. A large proportion of the existing literature investigates the influence factors of firms' pollution emissions. Regarding external factors, a disproportionate number of studies explore the effect of government environmental governance on pollution emissions in terms of environmental regulations or policies [23,24]. As the government imposes environmental tax on enterprises, stricter environmental regulations will weaken their willingness to emit pollutants, thereby reducing enterprises' pollution emissions [25,26]. This proves that law enforcement and supervision by local governments shape a decisive role in environmental governance, but achieving long-term environmental stability still depends on institutionalized mechanisms of law-enforcement and supervision [27,28]. As for internal factors, some studies find that the promotion of production efficiency and productivity can effectively reduce firms' pollution emissions through the adoption of production technology [8,29], while research into clarifying the mechanisms of production technology is quite sparse. In addition, considering the data limitations, a large number of studies are limited to identifying the environmental effects at the industry and prefecture levels [30–32]. Benefited from firm-level data availability, this paper uses the pollution data of industrial firms in China to investigate the effects of digital transformation on firms' pollution emissions. This detailed data allows us to extend previous analyses to look within firms and not merely within industries.

Lastly, this paper develops a tractable and flexible approach to investigating the micro-level environmental effects. Some existing research is dedicated to investigating the impacts

of a series of specific environmental policies based on quasi-natural experiments [33–35]. Although quasi-natural experiments are able to adopt difference-in-differences (DID) specifications to investigate the effect of individual environmental policies, governments have implemented dozens of overlapping environmental policies over the last decade, many of which have not been distinctly identified due to assorted policy effects and have no natural comparison group [8]. Our methodology builds on tools from a recent pollution emissions framework containing heterogeneous firms proposed by the trade literature. The nascent literature investigates the environmental effects of the heterogeneous firm model, but these studies emphasize the linkages between trade, especially trade liberalization, and environmental issues [36–38]. Research using the heterogeneous firm model to explore the nexus between digital transformation and environmental pollution emissions are quite sparse. Therefore, we innovatively introduce digital technology into the heterogeneous firm model consisting of emission behavior and deeply investigate the effect of digital transformation on firms' pollution emissions, which extends to extant studies on environmental issues.

The remainder of this paper is structured as follows: Section 2 introduces our theoretical model. Section 3 describes our dataset, identification strategy, and variable measurement. Section 4 reports our baseline results and a series of robustness results. Section 5 explores the underlying mechanism of our paper. Section 6 discusses our research findings, implications for theory and practitioners, and future research opportunities. Section 7 concludes our study.

2. Theoretical Model

We develop a model considering digital technology, abatement, and firm pollution, which is designed to fully investigate how digital transformation affects firm-level pollution emissions in Chinese industrial firms. In the model, firms produce differentiated goods under increasing returns and the production entails environmental emissions. We employ this theoretical framework to shed light on potential sources of environmental consequence under digital transformation conditions. The detailed setting and analysis of the model are described in the next five subsections.

2.1. Preferences

The representative agent has CES preferences over a continuum of horizontally differentiated manufactured goods:

$$U = \left(\int_{i\in\Omega} x_i^{\frac{\sigma-1}{\sigma}} di\right)^{\frac{\sigma}{\sigma-1}} \quad (1)$$

where x_i denotes the consumption of varieties of goods i and $\sigma = 1/1-\rho > 1$ is the elasticity of substitution between any two varieties. Utility maximization generates a residual demand curve for varieties of goods i:

$$x_i = \Phi p_i^{-\sigma} \quad (2)$$

where $\Phi = RP^{1-\sigma}$ captures market size, R measures total manufacturing revenue on all varieties, p_i denotes the price of varieties of goods i, P is the manufacturing price index.

2.2. Production

As in Shapiro and Walker [8] and Forslid et al. [39], we assume firms use two production factors to carry out production activities. One is manufacturing intermediate input m_i with pollution attributes; the other is digital-specific green input s_i, denoting the green and clean input embedded with digital technology features, which can more effectively reduce the pollution emissions in the production process of enterprises compared to ordinary clean inputs. The industrial activity in firms entails pollution in terms of environmental emissions. These pollution emissions are subject to environmental regulation and a firm thus has an incentive to reduce emissions. For the sake of simplicity, we shall assume that

environmental regulation is characterized in the form of taxation and the government levies a tax with a rate of t per unit of emissions from firms. To capture the pollution emissions, we follow Copeland and Taylor [14] and assume that each firm produces two outputs: an industrial good x_i and emissions e_i. In order to abate pollution, a firm can divert a fraction θ_i of the productive input away from the production of x_i. We consider the parameter θ_i as a variable abatement cost that is chosen by each firm to maximize profits. The joint production of industrial goods and emissions is given by:

$$x_i = (1 - \theta_i)\varphi_i m_i^{\alpha} s_i^{1-\alpha} \tag{3}$$

$$e_i = \phi(\theta_i, s_i, f_{Ai})\varphi_i m_i^{\alpha} s_i^{1-\alpha} \tag{4}$$

with $0 < \theta_i < 1$ indicating that firms only adopt limited production input for pollution abatement. φ_i denotes the firm-level productivity. Equations (3) and (4) indicate that emissions depend on the industrial activities as well as the firms' abatement efforts. We, therefore, extend the abatement function:

$$\phi(\theta_i, s_i, f_{Ai}) = \frac{\left[(1 - \theta_i)/(\mu_i s_i)^{\lambda}\right]^{1/\gamma}}{h(f_{Ai})} \tag{5}$$

with $0 < \gamma < 1$ f_{Ai} denoting the investment in pollution abatement activity. Equation satisfies $f_{Ai} \geq 0$, $h'(f_{Ai}) > 0$, $h(0) = 1$ and $\partial\phi/\partial f_{Ai} < 0$ means that more investment in pollution abatement can effectively reduce pollution emissions. s_i measures digital-specific green inputs containing clean technology and digital knowledge. A unit of green input in production requires the joint adoption of clean intermediates and digital technologies. Hence, we can derive the price of green inputs as:

$$p_s = \int_0^1 [\tau \cdot p_g(\omega) + (1 - \tau)p_{\mu}(\omega)]d\omega \tag{6}$$

where p_g and p_{μ}, respectively, denote the price of green intermediate and digital technology; we regard them as exogenous factors to simplify the model setting. Equation satisfies ${p_s}'(\mu) < 0$ and determines the activeness of digital transformation activities. In the process of manufacturing industry, digital-specific green inputs can optimize the factor input structure and promote green upgrading to curb pollution discharge. μ and λ are the degree of digital transformation and digital-specific optimization parameter introduced in abatement function for emissions, respectively. We depart from the abatement function in the literature by assuming that abatement activity does not only depend on abatement investment f_{Ai}, but also green intermediate input and digital-specific technology. The abatement function reflects the fact that firms may reduce their pollution emissions through three different types of abatement efforts. A given reduction in pollution emissions may be reached either through increased abatement investment f_{Ai}, through increased green input s_i, or through firms' digital transformation degree μ.

We proceed by using Equation (5) to substitute for ϕ in (4), which can further be solved for $1 - \theta_i$. Combining (3) and (4), we can rewrite output as a Cobb–Douglas function of pollution emissions and productive factor inputs:

$$x_i = [h(f_{Ai})e_i]^{\gamma}\left[\varphi_i \mu_i^{\lambda/1-\gamma} m_i^{\alpha} s_i^{(1-\alpha)+\lambda/1-\gamma}\right]^{1-\gamma} \tag{7}$$

2.3. Firm Optimization Problem

Based on Equation (7), we obtain an integrated expression for the joint production function, which exploits the fact that although pollution is an output, it can equivalently also be treated as an input. This Cobb–Douglas production function indicates that productive inputs have an imperfect substitutability with pollution emissions. The parameter γ

governs the input intensity. Given the production function and factor price, each firm solves the cost minimization problem. Then, we can derive firms' total cost function:

$$C_i = f_{Ai} + \kappa[t/h(f_{Ai})]^{\gamma} p_m^{(1-\gamma)\alpha} p_s^{(1-\gamma)[(1-\alpha)+\lambda/1-\gamma]} \varphi_i^{\gamma-1} \mu_i^{-\lambda} \overline{x}_i \tag{8}$$

where $\kappa = \gamma^{-\gamma}[(1-\gamma)\alpha]^{-(1-\gamma)\alpha}\{(1-\gamma)[(1-\alpha)+\lambda/1-\gamma]\}^{(1-\gamma)[(1-\alpha)+\lambda/1-\gamma]} > 0$ collects model constants. Each firm operates under a monopolistic competition market and sets a price equal to a markup over marginal costs. Solving the profit maximization problem yields an optimal pricing rule for each firm:

$$p_i = \frac{\sigma}{\sigma-1}\kappa[t/h(f_{Ai})]^{\gamma} p_m^{(1-\gamma)\alpha} p_s^{(1-\gamma)[(1-\alpha)+\lambda/1-\gamma]} \varphi_i^{\gamma-1} \mu_i^{-\lambda} \tag{9}$$

using Equations (2) and (9), we can formulate the expression for firms' profits:

$$\pi_i = p_i x_i = p_i^{1-\sigma} R P^{\sigma-1} = \Xi \cdot \{[t/h(f_{Ai})]^{\gamma} p_m^{(1-\gamma)\alpha} p_s^{(1-\gamma)[(1-\alpha)+\lambda/1-\gamma]} \varphi_i^{\gamma-1} \mu_i^{-\lambda}\}^{1-\sigma} - f_{Ai} \tag{10}$$

with $\Xi \equiv \kappa^{1-\sigma}\sigma^{-\sigma}(\sigma-1)^{\sigma-1} R/P^{1-\sigma} > 0$ as an index of the market potential. Equation (10) indicates that the lower price of digital-specific green inputs and higher degree of digital transformation may lead to higher profit.

2.4. Abatement Investment

In order to derive the specific expression of abatement investment, we follow Forslid et al. [39] and assume the function form of abatement investment is $h(f_{Ai}) = f_{Ai}^{\rho}(\rho > 0)$. Maximizing firms' profit, we can calculate the optimal abatement investment:

$$f_{Ai}^{*} = [(1-\beta)B]^{\frac{1}{\beta}} t^{\frac{-\gamma(\sigma-1)}{\beta}} p_m^{\frac{-(1-\gamma)\alpha(\sigma-1)}{\beta}} p_s^{\frac{-(1-\gamma)[(1-\alpha)+\lambda/\gamma-1](\sigma-1)}{\beta}} \varphi_i^{\frac{(1-\gamma)(\sigma-1)}{\beta}} \mu_i^{\frac{\lambda(\sigma-1)}{\beta}} \tag{11}$$

with $\beta = 1-\gamma\rho(\sigma-1)$. Equation (11) reflects that the optimal abatement investment has a negative relationship with the price of digital-specific green inputs. The decline in p_s may reduce firms' production costs and firms are able to allocate more operating funds for abatement investment due to cost reductions.

2.5. Comparative Static Analysis

Further, to investigate the potential impact of digital transformation on the firm-level pollution emissions, we employ Shepard's lemma based on cost equation to derive the emission intensity function of firm *i*:

$$e_i = [(1-\beta)B]^{\frac{-\rho\gamma}{\beta}} \gamma\kappa t^{\frac{\gamma-\beta}{\beta}} p_m^{\frac{(1-\gamma)\alpha}{\beta}} p_s^{\frac{(1-\gamma)[(1-\alpha)+\lambda/\gamma-1]}{\beta}} \varphi_i^{\frac{\gamma-1}{\beta}} \mu_i^{\frac{-\lambda}{\beta}} \tag{12}$$

Taking the first-order partial derivative of Equation (12) with regard to the degree of digital transformation of firm *i* can be written:

$$\begin{aligned} \frac{\partial e_i}{\partial \mu_i} = & \underbrace{\xi[(1-\beta)B]^{\frac{-\rho\gamma}{\beta}} \gamma\kappa t^{\frac{\gamma-\beta}{\beta}} p_m^{\frac{(1-\gamma)\alpha}{\beta}} p_s^{\frac{\xi-1}{\beta}} \varphi_i^{\frac{\gamma-1}{\beta}} \mu_i^{\frac{-\lambda}{\beta}} p_s'(\mu)}_{(-)} \\ & + \underbrace{(-\lambda/\beta)[(1-\beta)B]^{\frac{-\rho\gamma}{\beta}} \gamma\kappa t^{\frac{\gamma-\beta}{\beta}} p_m^{\frac{(1-\gamma)\alpha}{\beta}} p_s^{\frac{(1-\gamma)[(1-\alpha)+\lambda/\gamma-1]}{\beta}} \varphi_i^{\frac{\gamma-1}{\beta}} \mu_i^{\frac{-(\lambda+\beta)}{\beta}}}_{(-)} \end{aligned} \tag{13}$$

with $\xi = (1-\gamma)[(1-\alpha)+\lambda/\gamma-1]$, $p'_s(\mu) < 0$ implying that $\partial e_i/\partial \mu_i < 0$. The FOC provides an important implication for firms' optimal emissions intensity in the equilibrium. That is, firms implementing a higher degree of digital transformation may reduce the price of green inputs and further effectively reduce firm-level pollution emissions. The result is summarized as Proposition 1:

Proposition 1. *The increase in digital transformation degree can effectively reduce firm-level pollution emissions.*

Based on the theoretical analysis above, we adopt the chain rule to subdivide the path through which digital transformation affects pollution emissions into the following two mechanisms:

$$\frac{\partial e_i}{\partial \mu_i} = \underbrace{\underbrace{\frac{\partial e_i}{\partial \phi_i}}_{(+)}\underbrace{\frac{\partial \phi_i}{\partial s_i}}_{(-)}\underbrace{\frac{\partial s_i}{\partial p_s}}_{(-)}\underbrace{\frac{\partial p_s}{\partial \mu_i}}_{(-)}}_{Green\ \ innovation\ \ effect} + \underbrace{\underbrace{\frac{\partial e_i}{\partial \phi_i}}_{(+)}\underbrace{\frac{\partial \phi_i}{\partial f_{Ai}}}_{(-)}\underbrace{\frac{\partial f_{Ai}}{\partial p_s}}_{(-)}\underbrace{\frac{\partial p_s}{\partial \mu_i}}_{(-)}}_{Abatement\ \ investment\ \ effect} \tag{14}$$

Given Equation (14), it can be obviously seen that the increase in digital transformation degree reduces the price of digital-specific green inputs, forming a pollution abatement mechanism with two effects: (1) Green innovation effect. Digital transformation enables firms to realize green innovation through digital technology and increase digital-specific green inputs to optimize the factor input structure. The adoption of digital technology and clean input may alter the production pattern that matches the dirty input of polluting manufacturing firms, thereby reducing the intensity of firm-level pollution emissions. (2) Abatement investment effect. Digital transformation may help firms to generate a cost-reduction effect, which enables firms to have more operating funds to invest in emission abatement facilities. As a key way to reduce pollution emissions, the increase in abatement investment may directly curb emission intensity. Therefore, we present theoretical Propositions 2 and 3 as follows:

Proposition 2. *Digital transformation enables firms to realize green innovation and further reduce firm-level pollution emissions.*

Proposition 3. *Digital transformation enables firms to increase abatement investment and further reduce firm-level pollution emissions.*

3. Data and Methodology

3.1. Data and Sample

Our analysis contains three databases, including the Annual Survey of Industrial Firms database (ASIF), Chinese Environmental Statistics Database (CESD), and China City Statistical Yearbook (CSY). We merge these three databases and construct a panel dataset from 2000 to 2012 to examine the effect of digital transformation on pollution emissions.

Firm-level pollution data are compiled from Chinese Environmental Statistics Database (CESD) which is directly collected by the Ministry of Environment Protection of China and updated annually. The database contains detailed pollution emission information over 60 variables such as wastewater emissions, chemical oxygen demand (COD), flue gas, sulfur dioxide emissions (SO_2), nitrogen oxide, and other pollutant emissions. The database is a unique firm-level environmental information database covering around 85% heavily polluting firms of the major pollutants. We adopt this database to obtain firm-level pollution emission information about several pollutants.

Information regarding digital transformation used in the article comes from China City Statistical Yearbook published by the National Bureau of Statistics of China, which comprehensively reflects the socio-economic development and urban construction of each prefecture-level city in China. We collect the prefecture-level digital information as well as the prefecture-level control variables from China City Statistical Yearbook.

Information regarding firm-level production information is derived from Annual Survey of Industrial Firms database (ASIF) which is conducted by the National Bureau of Statistics of China for the 1998–2012 period. The database is the most comprehensive and representative firm-level dataset in China, covering all state-owned firms (SOEs)

and non-state-owned firms of over 5 million yuan, containing more than 100 variables related to production and financial information. We collect firm-level basic characteristics as our control variables from ASIF and process the data sample in accordance with the suggestions of Brandt et al. [40]. Specifically, we eliminate the nonmanufacturing firms, adjust the industry codes into unified codes, and delete the sample of firms with total assets less than fixed assets, total assets less than current assets, negative value added, employment and sales, and fewer than eight employees to ensure the reliability of the data sample. After merging ASIF database, CESD database, and the prefecture-level data from China City Statistical Yearbook, we obtain the panel data from 2000 to 2012, including 117,769 firms and 394,962 sample information.

3.2. Identification Strategy

To examine the relationship between digital transformation and firm-level pollution emissions, we estimate the following baseline specification using the fixed effect model:

$$Pollution_{ict} = \alpha + \beta_1 Digital_{ct} + X'_{it}\gamma_1 + X'_{ct}\gamma_2 + \lambda_i + \lambda_c + \lambda_t + \varepsilon_{ict} \quad (15)$$

where i denotes firm, c denotes prefecture, and t denotes year. The dependent variable measures pollution emissions for firm i in prefecture c at year t, while the key explanatory variable $Digital_{ct}$ is the level of digital economy development in prefecture c at year t. The X'_{it} and X'_{ct} refers to a set of firm-level and prefecture-level control variables, respectively. In addition, we introduce firm-specific, prefecture-specific, and year-specific fixed effects $\lambda_i, \lambda_c, \lambda_t$ in model equation to capture factors that alter at the firm, prefecture, and year level. ε_{ict} is an idiosyncratic error term, controlling for other unspecified factors. We focus on the coefficients β_1, which indicate the effects of digital transformation on firms' pollution emissions.

3.3. Variable Measurement

3.3.1. Measurement of Pollution Emissions

Using data from CESD, we employ several pollutants to gauge firm-level pollution emissions. CESD reports detailed information on conventional pollution emissions produced by manufacturing firms, such as wastewater emissions, chemical oxygen demand (COD), flue gas, soot, sulfur dioxide emissions (SO_2), nitrogen oxide, and other pollutant emissions. Specifically, we adopt wastewater emissions as our dependent variable in baseline regression. In the section of robustness checks, we further adopt alternative measures to capture firm-level pollution emissions.

3.3.2. Measurement of Digital Transformation

A key issue of this paper is the measurement of digital transformation. As in Huang et al. [41], we adopt the principal component analysis (PCA) method to construct a comprehensive digital transformation index with four digital indicators including the penetration rate of internet, internet-related practitioners, internet-related output, and the number of mobile internet users. Since digital technology is developed through basic internet technology and information and communication technology (ICT), this comprehensive index based on the internet or ICT has been widely used by a large amount of the existing literature as a proxy for the degree of digital transformation [42–44]. Specifically, the penetration rate of internet is represented by the number of internet users per 100 people and the internet-related output is a proxy of the total amount of telecommunication services per capita. We collect these digital variables from China City Statistical Yearbook and various public information and adopt the PCA method to synthesize a comprehensive digital indicator to reflect the degree of digital transformation.

3.3.3. Control Variable

We collect a set of firm-level and prefecture-level variables to be used as controls in our empirical model to mitigate the problem of omitted variables. The control variables are

constructed as follows: (1) size is the natural logarithm of the number of firm employees; (2) age is the firm age; (3) KL is defined as capital–labor ratio; (4) manage is the natural logarithm of firm management expenses; (5) SOE indicates the ownership of firm which equals one for state-owned enterprises and zero otherwise; (6) Pgdp is the natural logarithm of prefecture-level GDP per capita; (7) indstr is defined as industry structure, measured by the proportion of added value of the 2nd industry to GDP; (8) fiscal is the natural logarithm of prefecture-level government fiscal expenditure. The description and data sources of variables are listed in Table 1 and the summary statistics of the main variables used in this paper are presented in Table 2. According to the descriptive results, we find that there are large differences in the level of pollution emissions across enterprises. Further, the average degree of digital transformation in the prefecture level is already at a relatively high level, which reflects the vigorous development of digital technology.

Table 1. Description and data sources of variables.

Variable	Definition	Data Sources
Pollution	The logarithm of the amount of wastewater emissions	CESD database
Digital	A comprehensive index constructed by PCA method	China CSY
Size	The natural logarithm of the number of employees	ASIF database
Age	Enterprise establishment period	ASIF database
KL	The ratio of the fixed capital stock to the number of employees	ASIF database
Manage	Enterprise management expense	ASIF database
SOE	Indicate whether the state-owned enterprises	ASIF database
Pgdp	Prefecture-level GDP per capita	China CSY
Indstr	The ratio of industrial value added to GDP	China CSY
Fiscal	The natural logarithm of the fiscal expenditure	China CSY

Table 2. Summary statistics.

Variable	Obs	Mean	Std. Dev	Min	Max
Pollution	394,962	10.83	2.996	0	22.291
Digital	394,962	4.082	1.029	0.465	6.238
Size	394,962	5.442	1.165	0	12.145
Age	394,962	2.276	0.809	0	4.727
KL	394,962	1.725	0.339	0	16.059
Manage	394,962	7.84	1.689	0	16.326
SOE	394,962	0.08	0.271	0	1
Pgdp	394,962	10.163	0.917	7.401	13.018
Indstr	394,962	0.507	0.086	0.157	0.91
Fiscal	394,962	13.954	1.026	9.705	16.842

4. Empirical Results

4.1. Baseline Results

In order to investigate the effect of digital transformation on firms' pollution emissions, we control a series of firm-level and prefecture-level variables in a stepwise manner and adopt a fixed-effects model to estimate Equation (15) as our baseline regression. We further consider the robust standard errors of clustered prefectures to address the serial correlation and heteroskedasticity problem on the estimation results. Table 3 reports the baseline results.

We start with a simple fixed-effect specification that contains only the key explanatory variable, digital transformation, and fixed effects in Column 1. The coefficient estimates on pollution emissions are negative and statistically significant, suggesting a disincentive effect of digital transformation on pollution emissions. In Columns 2 and 3, we, respectively, control for some firm-specific and prefecture-specific control variables that may correlate with pollution emissions or digital transformation. We find that there is no significant variation in the estimation coefficient and significance of digital transformation. In Column 4, we further introduce all the controls and fixed effects used in our paper to investigate the

effect of digital transformation on pollution emissions. The results show that our estimates of interest remain negative and statistically significant at the 1% level, and magnitude also barely changes. Overall, the baseline results in Table 3 demonstrate that digital transformation significantly inhibits firms' pollution emissions and is found to effectively prove the theoretical proposition 1.

Table 3. Baseline results.

	Dependent Variable: Pollution Emissions			
	(1)	**(2)**	**(3)**	**(4)**
Digital	−0.243 ***	−0.250 ***	−0.222 ***	−0.256 ***
	(0.069)	(0.068)	(0.072)	(0.071)
Size		0.229 ***		0.229 ***
		(0.011)		(0.011)
Age		0.078 ***		0.077 ***
		(0.009)		(0.009)
KL		0.212 ***		0.210 ***
		(0.022)		(0.022)
Manage		0.076 ***		0.076 ***
		(0.005)		(0.005)
SOE		0.113 ***		0.117 ***
		(0.032)		(0.032)
Pgdp			−0.227 ***	−0.238 ***
			(0.044)	(0.044)
Indstr			0.348 ***	0.138
			(0.128)	(0.128)
Fiscal			0.250 ***	0.246 ***
			(0.031)	(0.030)
Firm FE	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	394,962	394,962	394,962	394,962
Adj. R	0.794	0.796	0.794	0.796

Note: *** indicates significance at 1%. Standard errors in parentheses are robust and clustered.

4.2. Robustness Checks

In baseline estimation, we have preliminarily tested the effect of digital transformation on firms' pollution emissions. In this section, we conduct a large number of robustness checks to ensure whether our findings are robust to these tests. Specifically, we undertake several extra robustness tests to tackle the potential identification bias originated from mismeasurement and endogeneity problems caused by reverse causality.

4.2.1. Alternative Measures of Pollution Emissions

In baseline regression, we employ wastewater emissions as a proxy variable of firms' pollution emissions. However, the adoption of a single variable may lead to the measurement bias of pollution emissions. To address the potential mismeasurement problem of pollution emissions, we thus employ alternative measures for robustness analysis. Table 4 presents the corresponding results. In Columns 1–4, we, respectively, consider four different pollutants as alternative proxy variables of pollution emissions: waste gas emissions, chemical oxygen demand (COD), industrial dust emissions, and sulfur dioxide emissions (SO_2). The estimation results indicate that the coefficients of digital transformation are negative and statistically significant at the 1% level. In addition, digital transformation has a greater inhibitory effect on COD in terms of estimation magnitude, while the effect on SO_2 is relatively smaller. These findings provide further supporting evidence consistent with the baseline results.

Table 4. Robustness checks: alternative measures of pollution emissions.

	Dependent Variable: Pollution Emissions			
	(1)	**(2)**	**(3)**	**(4)**
	Waste Gas	**COD**	**Dust**	**SO_2**
Digital	−0.565 ***	−0.918 ***	−0.381 ***	−0.310 ***
	(0.072)	(0.100)	(0.101)	(0.116)
Control variables	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	394,962	355,068	301,924	289,188
Adj. R	0.769	0.809	0.806	0.813

Note: *** indicates significance at 1%. Standard errors in parentheses are robust and clustered.

4.2.2. Alternative Measures of Digital Transformation

In baseline regression, we adopt the PCA method to construct a prefecture-level digital transformation index of key explanatory variables. However, the comprehensive index obtained from PCA method may lead to measurement bias due to the selection of component variables. We, therefore, remeasure digital transformation by separating the comprehensive index into four component variables to address the potential estimation deviation problem. Table 5 reports the results of the robustness check. Concretely, we, respectively, introduce the penetration rate of internet, internet-related practitioners, internet-related output, and the number of mobile internet users as the proxy variable of digital transformation in Columns 1–4. The estimation results show that the effects of digital transformation on firms' pollution emissions are all negative and statistically significant, which is consistent with our baseline results. These robustness tests suggest that our main estimates are robust to the potential mismeasurement problem.

Table 5. Robustness checks: alternative measures of digital transformation.

	Dependent Variable: Pollution Emissions			
	(1)	**(2)**	**(3)**	**(4)**
Digital	−0.440 **	−0.259 **	−0.252 ***	−0.117 ***
	(0.175)	(0.111)	(0.071)	(0.045)
Control variables	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	394,962	394,962	394,962	394,962
Adj. R	0.796	0.796	0.796	0.796

Note: **, *** indicates significance at 5%, and 1%. Standard errors in parentheses are robust and clustered.

4.2.3. Endogenous Test

Since manufacturing firms with higher pollution emissions may often be firms with a lower degree of digital transformation, our estimation strategy may be disturbed by reverse causality. This paper alleviates the endogenous problems by adopting the instrumental variable method. We draw on the method of Huang et al. [41] to employ the number of post offices in prefecture level in 1984 as an instrumental variable for digital transformation.

Considering the number of post offices in 1984 as a historical variable, which is difficult to be affected by digital transformation in the current period. Therefore, this variable conforms to the exogenous hypothesis of instrumental variable. On the other hand, throughout the development history of internet technology in China, the internet entered the public's view mainly from telephone dial-up PSTN access, then ISDN, ADSL access to the current fiber-optical broadband access technology [41]. In the early stage of the popularization of fixed telephones, the distribution of post offices, as the executive department for laying fixed telephones, may affect the distribution of fixed telephones to a certain extent and further affect the early access to the internet. Therefore, the number of the prefecture-level

post offices in 1984 is a suitable instrumental variable for digital transformation due to its satisfaction of the correlation requirements and the exogenous hypothesis of instrumental variable. In addition, given this variable does not change over time, it is unable to directly apply to panel data. Referring to the Nunn and Qian [45], we, respectively, employ the number of national internet users and interfaces in the previous year to interact with the number of post offices in 1984. Finally, we employ the two interaction terms to reflect time-varying characteristics and conduct an instrumental variable test.

We employ the two-stage least squares method to estimate Equation (15). Table 6 presents the corresponding results. In Columns 1–2, IV_1 is composed of the interaction term of the number of prefecture-level post offices in 1984 and the number of national internet users in the previous year. We construct the other instrumental variable (IV_2) by replacing the number of national internet users with the number of national internet interfaces and reconstruct the interaction term. The first-stage regression results in Column 1 and 3 show that instrumental variable employed in this paper is significantly positively correlated with the endogenous variable. The estimation coefficient is 0.014 and 0.013, which passes the 5% significance test and satisfies the correlation hypothesis. The second-stage results demonstrate that the effect of digital transformation on firms' pollution emissions is significantly negative at the 1% significance level, which is consistent with the benchmark regression results and further proves Proposition 1. Moreover, we conduct an underidentication test and a weak identification test to check the rationality of the instrumental variables. Based on the test results, we find that the first-stage F values are all higher than 10 and the Kleibergen–Paap rk LM statistic is significant at the 1% level, rejecting the null hypothesis of the underidentification test. The test results also suggest that both the Cragg–Donald Wald F statistic and the Kleibergen–Paap rk Wald F statistic exceed the critical value of the Stock–Yogo weak identification F test. These results prove that our instrumental variables adopted in this paper are appropriate.

Table 6. Robustness checks: endogenous test.

	Dependent Variable: Pollution Emissions			
	(1)	**(2)**	**(3)**	**(4)**
	IV_1		**IV_2**	
	First Stage	**2SLS**	**First Stage**	**2SLS**
Digital	0.014 **		0.013 **	
	(0.000)		(0.000)	
IV_1		−1.364 ***		
		(0.282)		
IV_2				−1.964 ***
				(0.325)
K–P rk LM Stat	8767.306 ***	8767.306 ***	8234.918 ***	8234.918 ***
K–P rk Wald Stat	7192.376 ***	7192.376 ***	6878.968 ***	6878.968 ***
	(16.38)	(16.38)	(16.38)	(16.38)
Control variables	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	313,816	313,816	263,555	263,555

Note: **, *** indicates significance at 5%, and 1%. Standard errors in parentheses are robust and clustered.

5. Mechanism Test

In the baseline estimation, we have identified a negative and significant effect of digital transformation on firms' pollution emissions. Referring to the previous theoretical analysis, digital transformation affects firm-level pollution emissions mainly through green innovation effects and abatement investment effect. In this section, we tend to provide some further evidence to shed light on the underlying mechanism of digital transformation.

5.1. Mechanism of Green Innovation

Our theoretical model suggests that green innovation is a key mechanism that digital transformation can effectively reduce firms' pollution emissions. As the results of green innovation promoting pollution reduction have been strongly supported by the existing literature [46–49], we then examine whether digital transformation affects firms' green innovation. We estimate the following specification to explore the potential mechanism:

$$GTFP_{ict} = \alpha + \beta_1 Digital_{ct} + X'_{it}\gamma_1 + X'_{ct}\gamma_2 + \lambda_i + \lambda_c + \lambda_t + \varepsilon_{ict} \quad (16)$$

where i denotes firm, c denotes prefecture, and t denotes year. The mechanism variable $GTFP_{ict}$ measures green total factor productivity for firm i in prefecture c at year t, while the key explanatory variable $Digital_{ct}$ is the level of digital economy development in prefecture c at year t. The X'_{it} and X'_{ct} refers to a set of firm-level and prefecture-level control variables, respectively. In addition, we introduce firm-specific, prefecture-specific, and year-specific fixed effects $\lambda_i, \lambda_c, \lambda_t$ in the model equation to capture factors that alter at the firm, prefecture, and year level. ε_{ict} is an idiosyncratic error term, controlling for other unspecified factors.

In terms of the measurement of green innovation, we adopt green total factor productivity (GTFP) as the proxy variable of green innovation. Based on the nonradial and nonoriented SBM directional distance function, we construct a Malmquist–Luenberger (ML) productivity index to gauge GTFP [50]. In the process of measurement, we take labor, capital, and energy consumption as input variables and further take total production output and exhaust emissions as output variables and unexpected output variables. Columns 1–2 in Table 7 report the estimation results for green innovation. We add two different GTFP constructed by sequential-ML and global-ML productivity indexes in Column 1 and 2 to investigate the role of green innovation. The results show that digital transformation has a positive and statistically significant effect on green innovation. Since the increase in green innovation can reduce firms' pollution emissions [46,47], we can reasonably infer that the adoption of digital transformation enables firms to realize green innovation and ultimately reduce pollution emissions. The estimation results of Columns 1–2 in Table 7 provide empirically supporting evidence for theoretical proposition 2.

Table 7. Mechanism test.

	Dependent Variable: Pollution Emissions			
	(1)	**(2)**	**(3)**	**(4)**
	Green Innovation		**Abatement Investment**	
Digital	0.172 ***	0.229 ***	0.139 ***	0.189 **
	(0.055)	(0.060)	(0.014)	(0.083)
Control variables	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	183,407	183,407	312,171	292,707
Adj. R	0.807	0.855	0.725	0.822

Note: **, *** indicates significance at 5%, and 1%. Standard errors in parentheses are robust and clustered.

5.2. Mechanism of Abatement Investment

Based on the theoretical framework in this paper, abatement investment is also an important mechanism for diminishing pollution emissions in digital transformation. In this subsection, we employ two abatement variables collected from the CESD database, the number of wastewater treatment facilities and exhaust treatment facilities, to examine whether digital transformation increases the abatement investment and realizes the pollution-reduction effect. The estimation equation is as follows:

$$Abatement_{ict} = \alpha + \beta_1 Digital_{ct} + X'_{it}\gamma_1 + X'_{ct}\gamma_2 + \lambda_i + \lambda_c + \lambda_t + \varepsilon_{ict} \quad (17)$$

where i denotes firm, c denotes prefecture, and t denotes year. The mechanism variable $Abatement_{ict}$ measures abatement investment for firm i in prefecture c at year t. $Digital_{ct}$ is the level of digital economy development in prefecture c at year t. Firm-level and prefecture-level control variables and fixed effects are consistent with the Equation (16), ε_{ict} is an idiosyncratic error term.

The results are shown in Columns 3–4 in Table 7. We find that the adoption of digital transformation increases firms' abatement investment. Given that a large amount of the literature has confirmed that the increase in abatement investment can reduce firms' pollution emissions [8,38,51], we have grounds to consider that digital transformation can reduce firms' pollution emissions by increasing their abatement investment. Therefore, the results of Columns 3–4 in Table 7 effectively prove the theoretical proposition 3 in our article.

6. Discussion

Building on extant research, this study constructs a theoretical framework that contains digital technology, abatement, and firm pollution and introduces a fixed-effect specification to theoretically and empirically examine the association between digital transformation and firms' pollution emissions. We find that digital transformation is negatively associated with firms' pollution emissions. After considering the potential endogeneity and mismeasurement problems, the results are still stable. Besides investigating the baseline effects, we also examine the mechanism of green innovation and investments in pollution abatement in shaping the associations between digital transformation and firms' pollution emissions. The results suggest that significant mechanism roles of both green innovation and investments in pollution abatement. Tables 3–7 summarize our overall findings.

6.1. Theoretical Implications

Our study contributes to the literature by addressing the interface between digital transformation and firm-level pollution emissions by investigating how a firm adopts digital technologies to realize digital transformation and further abate its pollution emissions. The results for Proposition 1 illustrate that digital transformation can significantly reduce the pollution emissions of manufacturing enterprises. This finding is in agreement with the evidence in the literature showing that firms with a high degree of digital technology adoption can effectively inhibit pollution emissions and further enhance green development [52,53]. As a process of technological innovation and organizational transformation, digital transformation enables firms to apply digital technology to the enterprise production process, which is intelligent production. Through the production process, data analysis, and scientific decision making of the intelligent production model, enterprises can effectively achieve production scheduling, equipment service, and quality control, thus reducing pollution emissions [52]. In addition, enterprises can construct digital ecosystems through digital transformation to reduce the consumption of resources and the discharge of related wastes, thus achieving a sustainable manufacturing process [53].

Our study also provides evidence that the reduction effect of digital transformation in firms' pollution emissions mainly comes from two aspects: green innovation and investments in pollution abatement. On the one hand, the positive externalities formed by digital transformation promote the transformation of production links and realize the emergence of green production processes. It reduces the low efficiency and unnecessary loss of resources in the process of resource allocation and further promotes the green innovation of enterprises [54]. Green innovation enables firms to increase clean factor inputs to optimize the factor input structure. The adoption of digital technology and clean input may alter the production pattern that matches the dirty input of polluting manufacturing firms, thereby reducing the intensity of firm-level pollution emissions [47]. On the other hand, the adoption of digital transformation may enable firms to realize efficient resource allocation and generate a cost-reduction effect, which enables firms to have more operating

funds to invest in emission abatement facilities [8,39]. As a key way to reduce pollution emissions, the increase in abatement investment may directly curb emission intensity.

6.2. Practical Implications

Our study provides some meaningful practical implications. First, from the perspective of the integration of the digital economy and the real economy, we should notice that digital transformation of enterprises is a decisive requirement for the high-quality development of the real economy. Enterprises should take the new generation of digital technology and digital platform ecology as an opportunity to vigorously promote the digital transformation and give full play to the scope economic effect brought about by digital transformation in order to improve production efficiency and reduce production costs. Second, the government should actively guide firms to seize the opportunities of digital transformation and enhance the enthusiasm of enterprises for digital transformation by implementing preferential measures such as tax reduction and exemption and technical subsidies. Some private enterprises are limited by their own development conditions, making it difficult to achieve digital transformation; the government needs to provide more supportive policies for these enterprises.

Lastly, since digital transformation can improve environmental performance to a great extent, the government should recognize the importance of adopting digital transformation to address environmental problems. In the past, the government would restrict the production behavior of highly polluting enterprises by issuing environmental regulations. This was regarded as a way to mitigate the environmental pressure. However, these measures also lead to the sacrifice of the economic benefits [55]. We provide a fresh insight to solve these severe environmental problems, that is, we can effectively employ the inhibitory effects of digital transformation on firms' pollution emissions to improve environmental performance. This is of vital importance to balance the nexus between economic development and environmental protection.

6.3. Limitations and Directions for Future Research

While the insights found in our study are significant, we acknowledge that our study has limitations. Due to the data limitations of digital transformation at the firm level, we can only adopt the principal component analysis (PCA) method to construct a comprehensive index with four digital indicators as a proxy for prefecture-level digital transformation. Although firm-level information about digital transformation gradually appears in the annual reports of listed enterprises, the number of listed enterprises is relatively small, which cannot fully reflect the specific characteristics of overall manufacturing enterprises in China. Thus, future research should capture more firm-level information about digital transformation and conduct a more detailed analysis at the firm level based on the improvement of data availability.

Further, while we include green innovation and investments in pollution abatement as two key mechanisms, from theoretical and empirical standpoints, in shaping the nexus between digital transformation and firms' pollution emissions, there may be other important factors capturing the environmental effect of digital transformation. Future research should delve further into other aspects that may affect firms' pollution emissions through digital transformation and determine its primary influence mechanism through quantitative evaluation.

7. Conclusions

Enterprise production has gradually entered the era of digital technology, which has also brought a profound effect on the environmental performance. This paper constructs a theoretical model that contains digital technology, abatement, and firm pollution to clarify the theoretical mechanism of firms using digital technology to bring about the pollution abatement effect. In this model, production behavior and pollution abatement selections are conditional on the adoption of digital technology, production factor input,

and environmental cost including emission tax and abatement expense. Based on the model, with a unique firm-level pollution dataset from China, we introduce a fixed-effect specification to empirically examine the effect of digital transformation on firms' pollution emissions and further identify the mechanism of the green innovation and investments in pollution abatement. Our estimated results suggest that digital transformation has a significant negative effect on firms' pollution emissions. The results are robust when potential endogeneity and mismeasurement problems are controlled for. In addition, the results of this mechanism indicate that digital transformation has a positive and statistically significant effect on green innovation and investments in pollution abatement. Digital transformation enables firms not only to increase green input specific to digital to optimize the structure of factor input through the process of green innovation, but also to generate a cost-reduction effect, which enables firms to have more operating funds to invest in emission abatement facilities, thereby curbing pollution emissions of enterprises.

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