

<https://doi.org/10.63894/2024122503>

Low-Carbon Transformation and Enterprise Digitalization: Evidence from China's Manufacturing Industry

Fu Ming ^{1*}

¹Guangzhou Institute of Science and Technology

*Corresponding Email: 15796734137@163.com

Abstract

With the swift growth of the digital economy and rising concerns about the environment, the digital transformation of businesses and the shift toward low-carbon practices have become essential for economic vitality and growth potential. Existing research has mainly focused on how digitalization influences low-carbon development. However, the impact of low-carbon transformation on business digitalization has not been thoroughly explored. This paper introduces a theoretical model to examine the internal dynamics of how low-carbon city pilot programs affect digitalization. Using data from manufacturing companies listed on the Shanghai and Shenzhen A-shares from 2007 to 2022, a multi-period double difference model is developed. This model treats the low-carbon city pilot policy as a quasi-natural experiment to analyze the effects of low-carbon transformation on business digital transformation and its mechanisms. The findings indicate that low-carbon transformation significantly promotes enterprise digitalization. Additionally, easing financing constraints and boosting R&D investments are effective strategies for enhancing digital transformation. The low-carbon transformation of state-owned enterprises, less polluting industries, and businesses in central China shows a more substantial impact on digitalization. These results support the hypothesis that low-carbon transformation can provide a dual benefit of environmental protection and economic development from a digital perspective. Furthermore, this research offers insights for policy development aimed at promoting the synergistic growth of low-carbon transformation and digitalization.

Keywords: Low-carbon transformation, digitalization, development

This is an open access article. Published by MC Global Eduinfo Sdn. Bhd.

DOI: 10.63894/2024122503

ISSN: 3030-6272 eISSN: 3030-6779

1.0 Introduction

As the world's largest carbon emitter, China faces the dual imperative of mitigating environmental degradation and fostering high-quality economic transformation. In response, the Chinese government has enacted ambitious policies, including the "Dual Carbon" goals (peaking emissions by 2030 and achieving neutrality by 2060) and multiple batches of low-carbon city pilot programs (Zheng, 2023; Hou et al., 2023). Concurrently, the digital economy, characterized by technologies such as big data, cloud computing, and the Internet of Things, has emerged as a pivotal force for enhancing resource allocation efficiency and driving innovation (Lyu et al., 2023; Sun & Chen, 2023). This confluence raises a critical yet underexplored question: does the policy-driven low-carbon transition actively spur corporate digital transformation, and if so, through what mechanisms?

The existing literature provides robust but largely parallel insights into these two domains. On one hand, studies confirm that low-carbon policies, like the city pilots, significantly reshape corporate decision-making, prompting strategic realignment, green technology adoption, and adjustments in resource allocation to comply with environmental regulations (He, 2016; Chen et al., 2016; Xu et al., 2023). Some view this transition as a potential cost burden (Chen et al., 2023), while others, aligning with the spirit of the Porter Hypothesis (Porter & van der Linde, 1995), suggest it can stimulate innovation that improves competitiveness (Li et al., 2021). On the other hand, a separate stream of research highlights digitalization as a key enabler for low-carbon goals, demonstrating how digital technologies optimize production processes, reduce waste, and enhance supply chain transparency (Mondejar et al., 2021; Zhang & Li, 2020; Ebinger & Omondi, 2020). Numerous studies have empirically examined the impact of the digital economy on reducing urban carbon emissions (Zhu et al., 2022; Liu et al., 2022; Yu et al., 2022).

However, a significant theoretical and empirical gap persists. First, the causal direction has been predominantly examined in one direction—from digitalization to low-carbon outcomes. The reverse causality, i.e., whether and how low-carbon transition policies act as an institutional driver for enterprise digitalization, remains insufficiently theorized and empirically tested (Yang et al., 2023; Liu et al., 2023). Second, while the synergy is often asserted, the specific internal mechanisms bridging this causal link are unclear. Preliminary evidence suggests low-carbon policies may alleviate financing constraints or incentivize R&D (Yu et al., 2023; Chernenko et al., 2022), but these pathways lack comprehensive examination within a unified framework linking policy shock to digital outcomes. Third, existing research often overlooks the heterogeneous effects across firms with differing ownership structures, pollution intensities, and regional contexts, which is crucial for understanding the boundary conditions of this relationship (Wang & Li, 2023).

This study aims to fill these gaps by investigating the causal effect of low-carbon city pilot policies on the digital transformation of manufacturing enterprises and elucidating the underlying mechanisms. Grounding our analysis in institutional theory (DiMaggio & Powell, 1983) and the resource-based view (Barney, 1991), we posit that low-carbon policies create coercive pressure and alter resource environments, thereby fostering digital capability building. Specifically, we treat the phased rollout of low-carbon city pilots as a quasi-natural experiment and employ a multi-period difference-in-differences (DID) model on a panel of Chinese A-share listed manufacturing firms from 2007 to 2022 (Hou et al., 2023; Zhang et al., 2023).

Our contributions are threefold. Theoretically, we extend the application of institutional theory by examining how environmental regulation, as a coercive force, drives a specific form of organizational change—digital transformation. We also contribute to the resource-based view by testing how policy-induced changes in resource access (financing) and allocation (R&D) mediate this process. Empirically, we provide robust causal evidence on a previously underexplored relationship and unpack the “black box” through mechanism tests on financing constraints and R&D investment. Practically, our heterogeneity analysis offers nuanced insights for policymakers to design targeted strategies that promote the synergistic development of low-carbon and digital transitions across different types of enterprises and regions (Zhang et al., 2022).

The remainder of this paper is structured as follows: Section 2 develops the theoretical framework and research hypotheses. Section 3 details the research design, model, and data. Section 4 presents the empirical results, including baseline estimates, robustness checks, mechanism, and heterogeneity analyses. Section 5 concludes with a discussion of findings, implications, and limitations.

2.0 Theoretical Analysis and Research Hypothesis

2.1. Institutional Context and Identification Strategy

To empirically test the theoretical linkage between low-carbon transition and enterprise digitalization, this study leverages the phased implementation of China's Low-Carbon City (LCC) pilot policy as a quasi-natural experiment. Initiated in three batches (2010, 2012, and 2017), this policy designated selected cities as pilots, requiring them to establish concrete low-carbon development plans and emission reduction targets (Wang et al., 2015; Li et al., 2018). The progressive expansion from the first batch (5 provinces and 8 cities) to subsequent batches reflects a deepening national commitment to low-carbon transformation, creating a staggered “treatment” across time and space (Li et al., 2018).

This policy context provides a critical identification advantage. For individual

manufacturing firms, the timing and location of this regulatory shock are largely exogenous, as the selection of pilot cities was based on city-level administrative characteristics and development readiness rather than the specific attributes or initiatives of individual firms within them. This spatial-temporal variation allows us to isolate the impact of low-carbon transition pressure from other confounding factors. Concurrently, the national strategic emphasis on the digital economy, as reiterated in key policy documents (Zhang et al., 2023), sets a broader backdrop where digital solutions are both available and incentivized. The LCC pilot policy, therefore, does not operate in a vacuum but within a policy ecosystem that simultaneously pushes firms toward low-carbon practices and pulls them toward digital means. This unique intersection offers a robust setting to examine whether and how the coercive pressure of low-carbon transition (the push) catalyzes digital transformation within firms, amidst the enabling environment for digitalization (the pull).

2.2. Theoretical Mechanisms and Research Hypotheses

Scholarly inquiry into the relationship between low-carbon transition and digitalization has converged along two primary, yet often parallel, trajectories: one examining the impact of low-carbon transition on corporate behavior, and another investigating the role of digitalization in enabling low-carbon goals (He, 2016; Chen et al., 2016; Mondejar et al., 2021). A critical synthesis of these streams reveals a significant gap concerning the causal mechanisms through which policy-driven low-carbon transition proactively stimulates enterprise digitalization.

2.2.1. Low-Carbon Transition as an Impetus for Strategic and Operational Change

Confronted with stringent carbon emission policies and the national “Dual Carbon” targets, firms are compelled to fundamentally reassess their business strategies and resource utilization models (He, 2016). This transition imposes significant pressure, potentially increasing short-term production costs and creating financial burdens as firms may need to curtail polluting activities and invest in environmentally friendly technologies (Chen et al., 2023; Xu et al., 2023). However, this pressure also acts as a catalyst for strategic innovation. To achieve emission reduction and efficiency gains, firms are driven to seek transformative solutions, with digital technologies emerging as a pivotal tool. The adoption of technologies such as the Internet of Things and big data analytics facilitates real-time production monitoring and precise energy management, directly enhancing resource efficiency and reducing waste (Chen et al., 2016; Tyfield et al., 2015). Consequently, the regulatory pressure of low-carbon transition creates a compelling context for firms to explore and integrate digital tools into their operations, not merely for compliance but as a

means to rebuild competitive advantage (Xu et al., 2023; Li et al., 2021). Furthermore, rising societal expectations for environmental transparency and governance increase the necessity for firms to demonstrate sustainable performance, potentially accelerating the adoption of digital systems for data management and reporting.

2.2.2. Digitalization as a Facilitator for Low-Carbon Objectives

Conversely, a robust body of literature establishes digitalization as a powerful enabler of low-carbon development. Digital technologies optimize resource allocation, enhance production process control, and improve supply chain transparency, thereby contributing significantly to energy conservation and emission reduction (Mondejar et al., 2021; Zhang & Li, 2020; Chen, 2022). For instance, intelligent systems powered by real-time data can minimize resource input and reduce overproduction, lowering the carbon footprint across the value chain (Mondejar et al., 2021). Digitalization also fosters innovative business models, allowing firms to launch green products and services that meet evolving market demands for sustainability (Parida et al., 2019; Yu et al., 2023). This synergy suggests a mutually reinforcing relationship where digital and green transformations can advance together (Yu et al., 2023; Rogetzer et al., 2018).

2.2.3. Integrating the Pathways: From Policy Shock to Digital Response

Despite these insights, the extant literature exhibits a notable asymmetry. While the facilitating role of digitalization in achieving low-carbon goals is well-documented, the reverse causal pathway—whether and how the exogenous shock of a low-carbon transition policy actively drives enterprise digitalization—remains underexplored and theoretically underdeveloped (Yang et al., 2023; Liu et al., 2023). There is no consensus on the precise mechanisms through which environmental policy impacts digital investment at the firm level (Chernenko et al., 2022; Wang et al., 2022). Some preliminary evidence suggests that low-carbon city pilots may ease financing constraints for firms (Yu et al., 2023), yet a comprehensive framework detailing the transmission channels from policy pressure to digital outcomes is lacking. Most studies focus on supply-side effects, neglecting how policy alters internal firm conditions and investment incentives on the demand side.

To address this gap, this paper proposes an integrated mechanism centered on resource reallocation. We argue that the low-carbon city pilot policy, as a salient regulatory shock, can promote enterprise digitalization primarily by reshaping two critical internal resource conditions: alleviating financing constraints and stimulating R&D investment. First, the policy and its associated supportive measures (e.g., green credit, fiscal subsidies) can improve firms' access to capital, providing the necessary financial resources

for costly digital investments. Second, the imperative for low-carbon innovation inherently boosts R&D expenditures, which often encompass digital technology development and adoption, thereby enhancing the firm's absorptive capacity for digital transformation. Moreover, the strength of these effects is likely to be heterogeneous, varying with firm ownership, industry pollution intensity, and regional development context due to differences in resource endowments, regulatory sensitivity, and market pressures (Wang & Li, 2023).

Based on the foregoing analysis, we posit the following hypotheses:

H1: The low-carbon transition has a significant promoting effect on enterprise digitalization.

H2: The low-carbon transition promotes enterprise digitalization by alleviating financing constraints and increasing R&D investment.

H3: The promoting effect of the low-carbon transition on enterprise digitalization is more pronounced in state-owned enterprises, non-polluting industries, and enterprises located in China's central region.

3.0 Study Design and Model Construction

This research examines the effects of low-carbon transformation on enterprise digitalization within publicly listed manufacturing firms in the Shanghai and Shenzhen A-share markets from 2007 to 2022. The study utilizes a combination of low-carbon city pilot programs established in three phases to investigate this relationship. The processing of company data is conducted as follows: (1) firms classified as ST and *ST are excluded from the analysis; (2) to mitigate the influence of extreme values and outliers on the regression results, all continuous variables are trimmed by 1% both before and after the analysis. This study utilizes data obtained from the China Securities Market and Research Database (CSMAR) along with the China Research Data Service Platform (CNRDS).

3.1 Model Setting

An artificial experiment is used to construct an inter-period double-difference model to examine the impact of low-carbon transformation on the digitisation of firms. A low-carbon city pilot project established in three phases is used as the basis for the model. The model has the following structure:

$$DCG_{it} = \alpha_0 + \alpha_1 LC_{it} + \alpha_2 X_{it} + IdFE + YearFE + \varepsilon_{it} \quad (1)$$

In this context, DCG_{it} represents the variable of digital transformation of enterprises, while LC_{it} signifies low-carbon transformation. X_{it} is the control variable, $IdFE$ are the individual fixed effects, $YearFE$ are the time fixed

effects. ε_{it} is the random disturbance term.

3.2 Sample Selection

3.2.1. Dependent Variable

To measure enterprise digitalization (*DCG*), we employ a text-analysis-based proxy validated in prior literature as an effective indicator of strategic focus on digital transformation (Wu et al., 2021). Building upon the findings of that study, keywords were identified from five distinct domains: artificial intelligence technology, big data technology, cloud computing technology, blockchain technology, and digital technology applications. Subsequently, we computed the frequency of each keyword's occurrence. To assess the degree of digital transformation within organizations, we incremented the frequency of the term “digital transformation” by one.

3.2.2. Core Explanatory Variable

The phased low-carbon city pilot policy serves as a quasi-natural experiment to capture the exogenous shock of low-carbon transition pressure on firms (Ma & Sun, 2024). According to their research, the low-carbon city pilot programs initiated in three distinct phases in 2010, 2012, and 2017 are utilized as quasi-natural experiments to analyze the process of low-carbon transformation. In instances where a firm is situated in a city designated as a pilot city during a specific year, that year and all subsequent years are assigned a value of 1; otherwise, a value of 0 is assigned. The second cohort of low-carbon city pilots was announced in December 2012, making 2013 the designated year of policy shock for this particular group of pilots.

3.2.3. Control Variables

Firm Size-It is measured by the natural logarithm of total assets. Leverage: the ratio of total liabilities to total equity and liabilities. ROA-It is computed as the net profit as a ratio to total assets. Growth of Company- Growth rate in operating profit in the current year compared to last year, % change. The Enterprise Cash Flow is calculated by the cash flows from operations divided by total assets. It can be considered that the size of the board of directors by the natural logarithm of number of directors. The proportion of shares owned by the largest shareholder measures the stake of the largest shareholder. Last of all, the age of the firm is measured by the natural logarithm of the difference between the current year and the year in which the firm was established, offset by adding one.

3.2.4. Measurement Validity and Discussion

The construction of our core variables follows established practices in the

literature to ensure conceptual validity. For the dependent variable, the text-based measure of digital transformation (*DCG*) is justified as it directly captures a firm's strategic emphasis and disclosed commitments to digital technologies, which is a valid proxy for its digitalization orientation and has been widely adopted in recent studies on corporate digitalization (Wu et al., 2021). While alternative proxies exist, such as IT investment intensity or the count of digital patents, they often capture only one input or output facet of digitalization. The text-based measure offers a more holistic view of the firm's overall strategic engagement with the digital paradigm, aligning with our research objective.

For the core explanatory variable, the use of the low-carbon city pilot policy dummy (*LC*) as a proxy for low-carbon transition pressure is well-grounded. This policy represents a clear, exogenous regulatory shock that mandates a systemic shift towards low-carbon development at the city level, thereby creating a strong and measurable treatment effect on firms located within pilot areas. This operationalization is standard in policy evaluation studies utilizing quasi-natural experiments (Ma & Sun, 2024). The staggered implementation across three batches provides the temporal variation required for a robust multi-period DID design.

3.3. Descriptive Statistics

Summary statistics for the variables analyzed in this study are shown in Table 1 below. The degree of enterprise digitalization varies between the maximum value of 6.140 and the minimum value of 0.000, indicating that the level of digitalization among enterprises in the manufacturing sector differs significantly. In general, it is relatively low, as represented by the mean of 1.196. Also, about 54.2% of the enterprises in the sample are influenced by the low-carbon city pilot policy, as reflected by the mean value of 0.542 for low-carbon transition. The existing literature also predominantly supports the rest of the tested control variables.

Table 1: Presents the Descriptive Statistics

Variable	Mean	SD	Max	Min
DCG	1.196	1.272	6.140	0.000
LC	0.542	0.498	1.000	0.000
size	22.035	1.164	26.452	19.317
lev	0.398	0.190	0.908	0.027
roa	0.045	0.065	0.257	-0.373
growth	0.171	0.374	4.024	-0.658
cashflow	0.050	0.067	0.283	-0.223
board	2.116	0.192	2.708	1.609
top1	0.338	0.140	0.758	0.080
firmage	2.867	0.348	3.611	0.693

4.0 Empirical Results Analysis

4.1 Correlation Analysis

To test the correlation between variables before regression and avoid the impact of multicollinearity on the estimation results, this study uses the Pearson correlation coefficient. As shown in the correlation analysis results in Table 2, a correlation coefficient of 0.256 is found between low-carbon transformation and enterprise digitalisation, which passes the 1% significance test. This result suggests a significant positive correlation between low-carbon transformation and enterprise digitalisation, providing preliminary evidence that low-carbon transformation can promote enterprise digitalisation. Additionally, since the correlation coefficients between the selected explanatory variables are all below the empirical threshold of 0.8, there is no serious multicollinearity, meaning the regression results are not significantly affected by multicollinearity.

Table 2: Correlation Analysis

Variable	DCG	LC	size	lev	roa	growth	cashflow
DCG	1.000						
LC	0.256* **	1.000					
size	0.131* **	0.050** *	1.000				
lev	-0.017 **	-0.036* **	0.459** *	1.000			
roa	-0.011	-0.020* **	0.032** *	-0.368* **	1.000		
growth	0.017* **	0.016**	0.065** *	0.044** *	0.291** *	1.000	
cashflow	-0.010	-0.021* **	0.089** *	-0.167* **	0.450** *	0.034* **	1.000
board	-0.109 ***	-0.101* **	0.229** *	0.151** *	0.010	-0.006	0.013**
top1	-0.061 ***	-0.014* *	0.099** *	-0.003	0.140** *	0.013*	0.090***
firmage	0.145* **	0.143** *	0.227** *	0.101** *	-0.071* **	-0.075 ***	0.057***
	board	top1	firmage				
board	1.000						
top1	-0.013 *	1.000					
firmage	-0.002	-0.118* **	1.000				

Note: *, **, and *** indicate a significance level of 10%, 5%, and 1%, respectively.

4.2 Baseline Regression Analyses

Regression estimation for multi-period double-difference model is conducted to explore the effect of low-carbon transformation on enterprise digitalization. It can be seen from the benchmark regression results in Table 3 that, prior to the addition of control variables in column, the low-carbon transition coefficient regarding enterprise digitalization is 0.068, statistically significant at a significance level of 1%. In column, by adding control variables, including firm size in attempting to control for potential firm-specific characteristics, the regression coefficient of low-carbon transformation and firm digitalization was reduced to -0.070, yet still statistically significant at 1%. The above results show that the low-carbon transformation significantly promotes the digital transformation of enterprises, whether or not adding the control variables.

Table 3: Results of the Baseline regression

	(1)	(2)
Variable	DCG	DCG
LC	0.068***	0.070***
	(0.024)	(0.023)
size		0.218***
		(0.015)
lev		0.027
		(0.059)
roa		-0.179
		(0.118)
growth		0.022
		(0.016)
cashflow		-0.033
		(0.096)
board		0.201***
		(0.049)
top1		-0.471***
		(0.094)
firmage		0.022
		(0.091)
Constant	1.159***	-3.986***
	(0.014)	(0.404)
Individual fixed	Yes	Yes
Time fixed	Yes	Yes
Observations	22,603	22,603
R-squared	0.760	0.765

Note: *, **, and *** indicate a significance level of 10%, 5%, and 1%, respectively. The values in parentheses are robust standard errors, as in the table below.

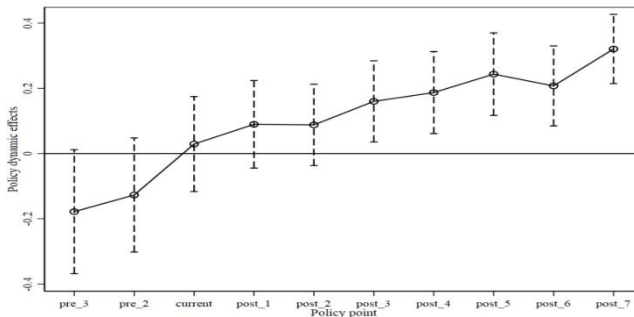
4.3. Robustness Test

4.3.1. Parallel Trend Test

To ensure that the level of digitization between firms in the treatment group and the control group does not differ significantly before the implementation of the carbon city pilot, the difference-in-differences (DID) model is used to test the impact of the carbon transition on firms' digitization. The event study method conducts the parallel trends test. The model is specified as follows:

$$DCG_{it} = \lambda_0 + \sum_{k=2}^3 \beta_{-k} \text{Before}_{kt} + \lambda_1 \text{Current}_t + \sum_{k=1}^7 \beta_k \text{After}_{kt} + \lambda_2 X_{it} + \text{IdFE} + \text{YearFE} + \varepsilon_{it} \quad (2)$$

The above result of the parallel trend test illustrates the insignificance of coefficients for the period before the low-carbon city pilot. That means no huge discrepancies in the level of digitalization had existed among firms beforehand. Hence, the DID model is appropriate to use in finding the causal relationship for the researchers (Colombo & Garrone, 1996; Gómez-Plana & Latorre, 2019). Obviously positive coefficients in the three post-pilot periods suggest that the low-carbon city pilot policy has significantly facilitated the digital transformation of firms.



4.3.2. Plac

Figure 1: Parallel trend test.

This paper can control for how the estimated effects of a given factor-or some alternative policy-change by randomly selecting 800 companies to be in the treatment group, while all other companies serve as the control group. The author create and analyze such a dummy policy interaction term using a baseline regression model. From Figure 2, most of the coefficients of the political dummy variables lie around zero, while the corresponding p-values are all above 0.1. This leads to the result that the estimates of the baseline regression are significant at 10% level. Hence, this leads to the result that the potential confounding factors have not affected the results of the earlier baseline regression, which justifies the robustness of those conclusions.

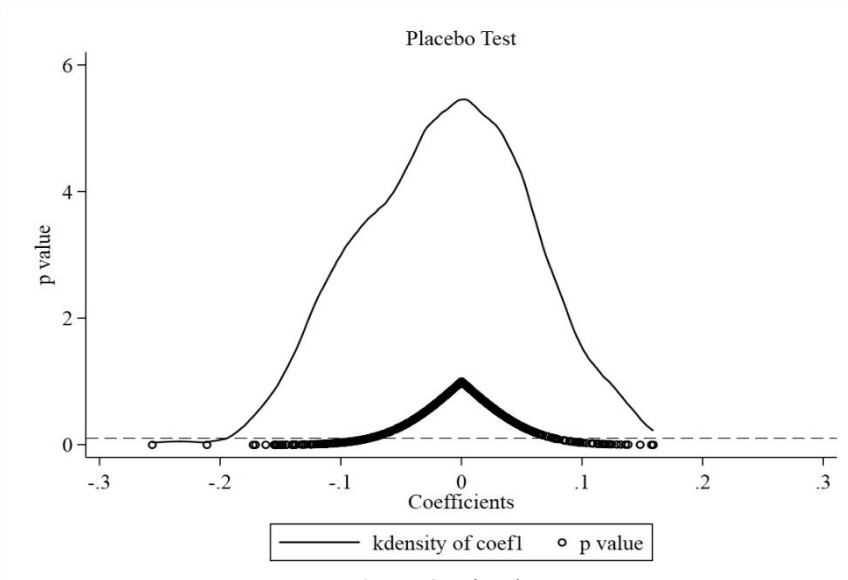


Figure 2: Placebo test

4.3.3. Propensity Score Matching

In order to limit sample self-selection bias, researchers usually use sample matching to reduce these biases in estimation. Particularly, sample matching relies on the PSM method (King & Nielsen, 2019). To this end, one first estimates a logistic regression model to conduct 1:1 nearest neighbor matching of samples. Then, one analyzes the matched samples using a benchmark regression model. Column (1) of Table 4 presents the regression coefficient of the low-carbon transition to firm digitalization, which is 0.110 at the 1% significance level. This result therefore reinforces the conclusion that the low-carbon transition promotes firm digitization, as suggested by the regression results using the approach of PSM-DID (Peduzzi et al., 1996; King & Nielsen, 2019).

4.3.4. Heckman Two-Step Method

The author applied the Heckman two-step approach in order to take into consideration the problem of sample selection bias. To be more specific, in this case, the first step was estimating the IMR by using a probit model; at the second stage, the estimated IMR was introduced into the basic regression model. As was shown in column (2) of the following Table 4, the regression coefficient of the low-carbon transition to firm digitalization is 0.070, statistically significant at 1%. According to the Heckman two-step method, firm digitalization is still positively influenced by the transition to the low-carbon position, which further enhances the robustness of the above conclusions.

4.3.5 Excluding the Municipal Sample

To assess the strength of the results, it took out samples from the four municipalities of Beijing, Shanghai, Tianjin, and Chongqing. As can be seen from column in Table 4 below, the regression coefficient of low-carbon transition to enterprise digitalization is 0.085, and it passes the 1% significance level test. It means that excluding municipal samples, the low-carbon transition still promotes enterprise digitalization, hence enhancing the robustness of previous conclusions.

4.3.6 Control for Regional Characteristics

Given the regional influence, the researcher carried out a robustness check by adding a regional fixed effect in order to catch the regional characteristics. From the results shown in Table 4 below, column (4) provides the regression coefficient of low-carbon transition with enterprise digitalization as 0.058, statistically significant at the 5 percent significance level. The findings above tend to indicate that even considering regional features, low-carbon transition contributes significantly to enterprise digitization, hence reinforcement in the robustness of the previous conclusion.

Table 4: Robustness Test

	(1)	(2)	(3)	(4)
Variable	DCG	DCG	DCG	DCG
LC	0.110***	0.070***	0.085***	0.058**
	(0.038)	(0.023)	(0.026)	(0.023)
IMR		2.648		
		(3.456)		
size	0.212***	0.245***	0.220***	0.217***
	(0.023)	(0.038)	(0.016)	(0.015)
lev	0.002	-0.187	-0.026	0.024
	(0.088)	(0.287)	(0.064)	(0.059)
roa	-0.266	-0.580	-0.347***	-0.171
	(0.177)	(0.537)	(0.125)	(0.118)
growth	0.004	0.125	0.034*	0.022
	(0.025)	(0.137)	(0.018)	(0.016)
cashflow	0.080	-1.275	0.006	-0.032
	(0.148)	(1.624)	(0.102)	(0.096)
board	0.256***	-0.221	0.229***	0.204***
	(0.074)	(0.554)	(0.053)	(0.049)
top1	-0.275*	-0.039	-0.521***	-0.471***
	(0.142)	(0.572)	(0.098)	(0.094)
firmage	0.055	0.059	-0.018	0.019
	(0.137)	(0.104)	(0.097)	(0.091)
Constant	-4.212***	-5.315***	-3.948***	-3.952***
	(0.608)	(1.783)	(0.428)	(0.405)

	(1)	(2)	(3)	(4)
Individual fixed	Yes	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes	Yes
area fixed	No	No	No	Yes
Observations	11,017	22,603	19,375	22,603
R-squared	0.772	0.765	0.762	0.766

4.4. Mechanism Test

To examine the theoretical mechanisms proposed in Hypothesis 2, we test whether low-carbon transformation promotes digitalisation by alleviating resource constraints and stimulating innovation efforts. Specifically, we focus on two mediating channels: enterprise financing constraints and enterprise R&D investment. The SA index measures the firms' financing constraints (SA), and the amount of firms' R&D expenditure measures their R&D investment. Researchers constructed an empirical model, with reference to existing research (Jiang, 2022), to test the impact of low-carbon transformation on financing constraints and R&D investment.. The model is set as follows:

$$M_{it} = \alpha_0 + \alpha_1 LC_{it} + \alpha_2 X_{it} + IdFE + YearFE + \varepsilon_{it} \quad (3)$$

M_{it} is corporate financing constraints and R&D investment.

As shown in the following results of Table 5, the regression value of business financing bottlenecks on the low-carbon transition in column (1) is -0.006 and passes the 1% significance test. This indicates that business financing bottlenecks are significantly reduced by the low-carbon transition. The regression value of business R&D investment on the low-carbon transition in column (2) is 0.749, passing the 1% significance test, indicating that business R&D investment is significantly increased by the low-carbon transition. These results demonstrate that the low-carbon transition promotes firm digitalization effectively through reducing financing constraints and increasing R&D investment.

Table 5: Mechanism Test

	(1)	(2)
Variable	SA	RD
LC	-0.006***	0.749***
	(0.002)	(0.162)
size	0.004**	2.222***
	(0.002)	(0.108)
lev	0.050***	-2.103***
	(0.005)	(0.264)
roa	0.012	0.935*

	(0.009)	(0.540)
growth	0.008***	-0.399***
	(0.001)	(0.113)

4.5 Analysis of the Heterogeneity

4.5.1. Heterogeneity of Enterprise Nature

In the meantime, the digital transformation among different types of enterprises has a quite different distribution, especially in response to the Low Carbon City Pilot. During the heterogeneity analysis, the enterprises were divided into two groups according to ownership structure: state-owned and non-state-owned enterprises. As can be seen from Table 6, enterprise digitalization is positively correlated with low-carbon transformation; the regression coefficient is 0.095 in column (1) and statistically significant at the 1% significance level. In the same way, low-carbon transformation also promotes enterprise digitalization; the regression coefficient is 0.069 in column (2), which is significant at the 5% level. These findings suggest that LCT positively impacts enterprise digitalization, regardless of ownership type. More importantly, the coefficients from regression can be compared: the coefficient in column (1) is larger than that in column (2). This implies that their empirical P-value in the Fisher combination test was 0.066, significant at a 10% level. That implies that the low-carbon transformation provides the state-owned enterprises with a greater impact than the non-state-owned ones on digitalization.

4.5.2. Heterogeneity of Different Industries

Heavily polluting industries and industries that are not heavily polluting are affected differently by the policies of the Low Carbon City pilot project. Therefore, for the heterogeneity analysis, the sample is divided into heavy polluting and non-heavy polluting industries based on the industry to which the enterprise belongs (Wang & Li, 2023). As shown in the results of heterogeneity analysis in Table 6 below, the regression factor of low-carbon transformation on enterprise digitization in column (3) is .011, which does not pass the significance test; the regression factor of low-carbon transformation on enterprise digitization in column (4) is .087, which passes the significance test at the 1% level, and the empirical p-value is .000, which means that there is a difference in the factor between the groups at the 1% level. This suggests that low-carbon transformation has a greater impact on the digitisation of companies in non-polluting industries than in highly polluting industries.

Table 6: Heterogeneity Analysis (1)

	(1)	(2)	(3)	(4)
	state-owned	non-state-owned	Heavy pollution	non-heavy pollution
Variable	DCG	DCG	DCG	DCG
LC	0.095***	0.069**	0.011	0.087***
	(0.033)	(0.032)	(0.037)	(0.029)
size	0.159***	0.231***	0.215***	0.199***
	(0.024)	(0.020)	(0.025)	(0.019)
lev	0.108	-0.121*	-0.299***	0.049
	(0.102)	(0.074)	(0.103)	(0.072)
roa	0.050	-0.325**	-0.364*	-0.002
	(0.222)	(0.139)	(0.219)	(0.139)
growth	-0.010	0.034*	0.063*	0.013
	(0.025)	(0.020)	(0.032)	(0.019)
cashflow	-0.032	-0.036	-0.199	0.075
	(0.155)	(0.120)	(0.154)	(0.119)
board	0.144*	0.176***	0.132	0.191***
	(0.081)	(0.063)	(0.083)	(0.060)
top1	-0.308**	-0.438***	-0.400**	-0.533***
	(0.145)	(0.130)	(0.161)	(0.118)
firmage	-0.875***	0.114	-0.123	0.105
	(0.153)	(0.108)	(0.142)	(0.114)
Constant	-0.380	-4.255***	-3.741***	-3.582***
	(0.677)	(0.513)	(0.616)	(0.521)
Individual fixed	Yes	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes	Yes
Observations	6,680	15,923	6,298	16,305
R-squared	0.755	0.776	0.654	0.777
p-value	0.066*		0.000***	

4.5.3. Regional Heterogeneity

The levels of digital economy development and external conditions for digital transformation vary across different regions (Guo & Jiang, 2023). Therefore, this paper conducts a heterogeneity analysis by dividing the sample into eastern, central, and western regions based on the enterprise's location. In Table 7, enterprise digitalization is not significantly affected by low-carbon transformation in column (1), with a regression coefficient of 0.037. In column (2), low-carbon transformation significantly affects enterprise digitalization, showing a regression coefficient of 0.174, which passes the 1% significance test. In column (3), enterprise digitalization is impacted by low-carbon transformation with a regression coefficient of -0.119, passing the 5% significance test. These regression results demonstrate that enterprises in the central region experience a more significant driving effect from low-carbon transformation on digitalization than those in the eastern and western regions.

Table 7: Heterogeneity Analysis (2)

	(1)	(2)	(3)
	East	Central	West
Variable	DCG	DCG	DCG
LC	0.037	0.174***	-0.119**
	(0.030)	(0.052)	(0.056)
size	0.234***	0.200***	0.142***
	(0.019)	(0.033)	(0.037)
lev	0.041	-0.116	0.208
	(0.072)	(0.143)	(0.139)
roa	-0.056	-0.646**	-0.185
	(0.146)	(0.265)	(0.284)
growth	0.015	0.070*	0.013
	(0.021)	(0.038)	(0.035)
cashflow	-0.008	0.181	-0.427*
	(0.119)	(0.205)	(0.248)
board	0.126**	0.306***	0.329***
	(0.064)	(0.093)	(0.127)
top1	-0.504***	-0.249	-0.145
	(0.123)	(0.181)	(0.218)
firmage	0.064	0.286	-1.272***
	(0.109)	(0.188)	(0.269)
Constant	-4.157***	-4.849***	0.757
	(0.502)	(0.831)	(1.001)
Individual fixed	Yes	Yes	Yes
Time fixed	Yes	Yes	Yes
Observations	15,886	3,882	2,835
R-squared	0.773	0.754	0.707

5.0 Conclusions and Implication

5.1 Summary and Academic Interpretation of Findings

This study employs a multi-period difference-in-differences design to identify the causal effect of low-carbon city pilot policies on the digital transformation of Chinese manufacturing enterprises. The results robustly support the central hypothesis that policy-induced low-carbon transition serves as a significant driver for enterprise digitalization. This primary finding contributes to the ongoing debate on the Porter Hypothesis by presenting evidence that environmental regulation can spur innovation beyond immediate, end-of-pipe green technologies, extending to foundational digital capabilities that reshape operational processes (He, 2016; Xu et al., 2023). The identified positive effect aligns with the perspective that regulatory pressure can catalyze strategic renewal and long-term competency building.

The mechanism analysis reveals that alleviating financing constraints and

increasing R&D investment are two critical transmission channels. This insight bridges macro-level policy and micro-firm behavior through the lens of resource allocation. It suggests that the policy's impact is not merely coercive but also enabling, as it helps mitigate a key barrier (financing) and stimulates a core activity (innovation) essential for digital adoption (Chernenko et al., 2022; Yu et al., 2023). This finding refines our understanding of how environmental governance instruments operate, highlighting their role in reshaping the resource environment and incentive structures within firms.

Furthermore, the observed heterogeneity—stronger effects in state-owned enterprises, less polluting industries, and the central region—underscores the contingent nature of this relationship. It indicates that the policy's efficacy in promoting digitalization is moderated by firm-specific resources, historical burdens, and regional institutional landscapes. This complexity echoes the nuanced findings in the literature regarding differentiated corporate responses to regulatory shocks (Wang & Li, 2023; Yang et al., 2023).

5.2 Theoretical and Practical Implications

5.2.1. Theoretical Implications

This study offers several theoretical contributions. First, it extends institutional theory by empirically demonstrating how a specific coercive isomorphism—low-carbon city policy—drives the adoption of isomorphic practices in the digital realm. Second, it enriches the resource-based view by showing how external policy shocks can reconfigure internal resource conditions (easing financial constraints, boosting R&D), thereby facilitating strategic change towards digitalization. Third, it provides a nuanced test of the Porter Hypothesis in a developing economy context, suggesting that the “innovation offset” can manifest as digital transformation, which may indirectly support environmental goals through efficiency gains.

5.2.2. Practical Implications

For policymakers, the results argue for an integrated approach to climate and industrial policy. Designing low-carbon policies with explicit channels for financial and innovation support can unlock their co-benefits for digital advancement. For business managers, the findings highlight the strategic imperative to leverage policy-driven opportunities, such as green financing, to fund digital upgrades that enhance both sustainability and competitiveness.

5.3 Limitations and Avenues for Future Research

This study is subject to several limitations that offer directions for future inquiry. First, while the text-based measure of digitalization is widely used, it

captures strategic emphasis rather than the depth or effectiveness of implementation. Future research could employ alternative metrics, such as investment in digital assets or patents. Second, although the DID design addresses many endogeneity concerns, the possibility of omitted time-varying variables cannot be entirely ruled out. Third, the focus on listed manufacturing firms limits the generalizability of findings to small and medium-sized enterprises or the service sector. Future studies could explore these domains. Fourth, the mechanisms tested, though significant, may not be exhaustive; other channels, such as human capital adaptation or supply chain coercion, warrant investigation. Finally, the long-term dynamics and performance consequences of this policy-induced digital transition remain an open and vital question for subsequent research.

References

- Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99-120. <https://doi.org/10.1177/014920639101700108>
- Chen, F., & Sun, W. (2023). How does carbon emissions efficiency affect OFDI? Evidence from Chinese listed companies. *Sustainability*, 15(17), 13145. <https://doi.org/10.3390/su151713145>
- Chen, W., Yin, X., & Zhang, H. (2016). Towards low carbon development in China: a comparison of national and global models. *Climatic Change*, 136, 95-108. <https://doi.org/10.1007/s10584-013-0937-7>
- Chernenko, I., Kelchevskaya, N., & Pelymskaya, I. (2022). Regional determinants of low carbon transition in Russian companies: The impact of human capital and digitalization on corporate carbon management practices. *R-Economy*, 8(1), 77-89. <https://doi.org/10.15826/recon.2022.8.1.007>
- Colombo, M., & Garrone, P. (1996). Technological cooperative agreements and firm's R & D intensity. A note on causality relations. *Research Policy*, 25(6), 923-932. [https://doi.org/10.1016/0048-7333\(96\)00883-9](https://doi.org/10.1016/0048-7333(96)00883-9)
- DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, 48(2), 147-160. <https://doi.org/10.2307/2095101>
- Dong, Q. (2013). Discussion on strategic transformation situation and motivation for enterprises in a low-carbon economy. *Science and Technology Management Research*. <https://consensus.app/papers/discussion-strategic-transformatio-n-situation-qiuyu/7f97b2682edc580d871dfe4c6c1f0fee/>
- Ebinger, F., & Omondi, B. (2020). Leveraging digital approaches for transparency in sustainable supply chains: A conceptual paper. *Sustainability*, 12(15), 6129. <https://doi.org/10.3390/su12156129>
- Folqué, M., Escrig-Olmedo, E., & Corzo Santamaría, T. (2021). Sustainable development and financial system: Integrating ESG risks through sustainable investment strategies in a climate change context. *Sustainable Development*, 29(5). <https://doi.org/10.1002/sd.2181>
- Gómez-Plana, A., & Latorre, M. (2019). Digitalization, multinationals and employment: An empirical analysis of their causal relationships. *Jahrbücher für Nationalökonomie und Statistik*, 239(3), 399-439. <https://doi.org/10.1515/jbnst-2017-0153>
- Gujjala, L.K.S, Kim, J., & Won, W. (2022). Technical lignin to hydrogels: An

- Eclectic review on suitability, synthesis, applications, challenges and future prospects. *Journal of Cleaner Production*, 363, 132585. <https://doi.org/10.1016/j.jclepro.2022.132585>
- Guo, Y., & Jiang, F. (2023). How does the digital economy drive high-quality regional development? New evidence from China. *Evaluation Review*, 48(5), 638-669. <https://doi.org/10.1177/0193841X231213128>
- He, J. (2016). Global low-carbon transition and China's response strategies. *Advances in Climate Change Research*, 7(4), 204-212. <https://doi.org/10.1016/j.accre.2016.06.007>
- Hou, J., Bai, W., & Sha, D. (2023). Does the digital economy successfully facilitate carbon emission reduction in China? Green technology innovation perspective. *Science, Technology and Society*, 28(4), 409-426. <https://doi.org/10.1177/09717218231161235>
- Hou, J., Bai, W., & Sha, D. (2023). How does digital transformation promote low-carbon technology innovation? The case of Chinese manufacturing companies. *Polish Journal of Environmental Studies*, 32(4), 3145-3159. <https://doi.org/10.15244/pjoes/161983>
- Jiang, T. (2022). Mediating and moderating effects in empirical studies of causal inference. *China Industrial Economics*, (5), 100-120.
- King, G., & Nielsen, R. A. (2019). Why propensity scores should not be used for matching. *Political Analysis*, 27(4), 435-454. <https://doi.org/10.1017/pan.2019.11>
- Li, F., Xu, X., Li, Z., Du, P., & Ye, J. (2021). Can low-carbon technological innovation truly improve enterprise performance? The case of Chinese manufacturing companies. *Journal of Cleaner Production*, 293, 125949. <https://doi.org/10.1016/j.jclepro.2021.125949>
- Li, H., Wang, J., Yang, X., & Wu, T. (2018). A holistic overview of the progress of China's low-carbon city pilots. *Sustainable Cities and Society*, 42, 289-300. <https://doi.org/10.1016/j.scs.2018.07.019>
- Liu, B., Li, Y., Tian, X., Sun, L., & Xiu, P. (2023). Can digital economy development contribute to the low-carbon transition? Evidence from the city level in China. *International Journal of Environmental Research and Public Health*, 20(3), 2733. <https://doi.org/10.3390/ijerph20032733>
- Liu, L. (2023). Green supply chain innovation management strategy based on the combination of low carbon economy and e-commerce with big data technology. *Applied Mathematics and Nonlinear Sciences*, 9(1), 177. <https://doi.org/10.2478/amns.2023.1.00177>
- Liu, L., Zhang, Y., Gong, X., Li, M., Li, X., Ren, D., & Jiang, P. (2022). Impact of digital economy development on carbon emission

- efficiency: A spatial econometric analysis based on Chinese provinces and cities. *International Journal of Environmental Research and Public Health*, 19(22), 14838. <https://doi.org/10.3390/ijerph192214838>
- Lyu, Y., Zhang, L., & Wang, D. (2023). The impact of digital transformation on low-carbon development of manufacturing. *Frontiers in Environmental Science*, 11, 1134882. <https://doi.org/10.3389/fenvs.2023.1134882>
- Ma, S., & Sun, Y. (2024). Low-carbon transformation and enterprise digitalisation: Evidence from low-carbon city pilots. *Research in Industrial Economics*, (4), 43-57.
- Ma, J., Hu, Q., Shen, W., & Wei, X. (2021). Does the low-carbon city pilot policy promote green technology innovation? Based on green patent data of chinese a-share listed companies. *International Journal of Environmental Research and Public Health*, 18(7), 3695. <https://doi.org/10.3390/ijerph18073695>
- Ma, Y., & Tao, P. (2023). A perspective on management myopia: The impact of digital transformation on carbon emission intensity. *Sustainability*, 15(12), 9417. <https://doi.org/10.3390/su15129417>
- Parida, V., Sjödin, D., & Reim, W. (2019). Reviewing literature on digitalization, business model innovation, and sustainable industry: Past achievements and future promises. *Sustainability*, 11(2), 391. <https://doi.org/10.3390/su11020391>
- Peduzzi, P., Concato, J., Kemper, E., Holford, T. R., & Feinstein, A.R. (1996). A simulation study of the number of events per variable in logistic regression analysis. *Journal of Clinical Epidemiology*, 49(12), 1373-1379. [https://doi.org/10.1016/s0895-4356\(96\)00236-3](https://doi.org/10.1016/s0895-4356(96)00236-3)
- Piao, X., & Cui, X. (2020). Assessing China's digital economy and environmental sustainability: A regional low-carbon perspective. *EGU General Assembly* 2020, EGU2020-12740. <https://doi.org/10.5194/egusphere-egu2020-12740>
- Porter, M. E., & van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of Economic Perspectives*, 9(4), 97-118. <https://doi.org/10.1257/jep.9.4.97>
- Rogetzer, P., Nowak, T., Jammernegg, W., Wakolbinger, T. (2019). Impact of Digitalization on Sustainable Supply Chains. In Luks, F. (Ed.), *Chancen und Grenzen der Nachhaltigkeitstransformation* (pp. 131-144). Springer Gabler. https://doi.org/10.1007/978-3-658-22438-7_8
- Tyfield, D., Ely, A., & Geall, S. (2015). Low carbon innovation in China: From overlooked opportunities and challenges to transitions in power relations

- and practices. *Sustainable Development*, 23(4), 206-216. <https://doi.org/10.1002/sd.1588>
- Wang, S., & Li, J. (2023). 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. *Sustainability*, 15(21), 15600. <https://doi.org/10.3390/su152115600>
- Wang, Y., Song, Q., He, J., & Qi, Y. (2015). Developing low-carbon cities through pilots. *Climate Policy*, 15(1), S81-S103. <https://doi.org/10.1080/14693062.2015.1050347>
- Wang, Z., Guo, J., & Luo, G. (2022). The impact of Chinese carbon emissions trading system on efficiency of enterprise capital allocation: Effect identification and mechanism test. *Sustainability*, 14(20), 13151. <https://doi.org/10.3390/su142013151>
- Wu, F., Hu, H., Lin, H., & Ren, X. (2021). Enterprise digital transformation and capital market performance: Empirical evidence from stock liquidity. *Management World*, 37(7), 130-144.
- Xu, S., Pan, W., & Wen, D. (2023). Do carbon emission trading schemes promote the green transition of enterprises? Evidence from China. *Sustainability*, 15(8), 6333. <https://doi.org/10.3390/su15086333>
- Yang, G., Wang, F., Deng, F., & Xiang, X. (2023). Impact of digital transformation on enterprise carbon intensity: The moderating role of digital information resources. *International Journal of Environmental Research and Public Health*, 20(3), 2178. <https://doi.org/10.3390/ijerph20032178>
- Yu, W., Lan, N., Tan, X., Zhang, S., & Chen, J. (2023). Does the digital economy drive low-carbon urban development? The role of transition to sustainability. *Frontiers in Ecology and Evolution*, 11, 1248515. <https://doi.org/10.3389/fevo.2023.1248515>
- Yu, Z., Liu, S., & Zhu, Z. (2022). Has the digital economy reduced carbon emissions?: Analysis based on panel data of 278 cities in China. *International Journal of Environmental Research and Public Health*, 19(18), 11814. <https://doi.org/10.3390/ijerph191811814>
- Zhang, H., Ding, X., & Liu, Y. (2023). The impact of low-carbon pilot cities on the development of digital economy: Empirical evidence from 284 cities in China. *Sustainability*, 15(13), 10392. <https://doi.org/10.3390/su151310392>
- Zhang, W., Zhou, H., Chen, J., & Fan, Z. (2022). An empirical analysis of the impact of digital economy on manufacturing green and low-carbon

transformation under the dual-carbon background in China. *International Journal of Environmental Research and Public Health*, 19(20), 13192. <https://doi.org/10.3390/ijerph192013192>

Zhu, Z., Liu, B., Yu, Z. & Cao, J. (2022). Effects of the digital economy on carbon emissions: Evidence from China. *International Journal of Environmental Research and Public Health*, 19(15), 9450. <https://doi.org/10.3390/ijerph19159450>