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A digital path to carbon neutrality: Heterogeneous green innovations and their spatial impact for Chinese cities

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ABSTRACT

With the accelerating growth of the digital economy, digital technology—as a type of general-purpose technology—creates a more inclusive and open environment for innovation, thereby facilitating the shift toward a low-carbon economy by promoting green innovation. However, we know little about whether there are differences in the roles of various types of green innovation. Therefore, this study evaluates the impact of DE on low-carbon development (LCD) through heterogeneous green innovation. The results show that DE has a significant nonlinear effect on LCD, with an initial suppressing effect that turns positive and strengthens as DE develops. Green innovation is a crucial mechanism through which DE promotes LCD. Moreover, compared to other types of green innovation, invention green innovation, source-control green innovation, and enterprise green innovation play a more significant role in this process. From a spatial perspective, the spillover effect of DE on LCD of neighbouring cities exhibits a shift from a "neighbour-beggar" to a "neighbour-companion" dynamic, demonstrating a U-shaped change. This spillover effect diminishes as geographic distance increases and is significant only within a range of 100–400 km. The green innovation spillover is a key mechanism driving this U-shaped transformation. Our findings offer valuable theoretical and practical insights for other developing countries undergoing a low-carbon transition.

1. Introduction

In the context of global efforts to combat climate change, the pursuit of low-carbon development (LCD) has become increasingly urgent, primarily aimed at resolving the dilemma between environmental protection and economic development (Bai et al., 2023a; Du et al., 2019). In practice, LCD is understood as a transition that decouples economic growth from carbon emissions, an approach that does not rely on slowing growth but rather positions itself as an effective response to climate change and a strategic enhancer of long-term economic growth. Traditionally, economists have regarded innovation as a fundamental driver of economic growth (Link and Siegel, 2007). However, under the pressing need for LCD, the focus must shift from innovation in general to specifically green-oriented technological innovation (Popp et al., 2022). This shift is necessary because, compared to general technological innovation, green innovation is more effective in enabling the transition to LCD (Cainelli et al., 2015; Rennings, 2000).

However, green innovation is characterised by a "double externality", that is, a technological externality at the innovation stage that benefits non-green competitors and an environmental externality at the diffusion stage that benefits society as a whole (Ning and Wang, 2018). This double-externality feature implies that innovators often struggle to appropriate sufficient returns from their efforts (Barbieri et al., 2020) and must also bear higher R&D costs, making them reluctant to engage in risky green innovation. In addition, path dependency is an important challenge for green innovation and may hinder the generation and diffusion of more transformative green innovations (Cecere et al., 2014). Nevertheless, a recent study conducted in the automotive industry found that inventors in a digitalised context are able to break free from traditional innovation path dependencies (Bohnsack et al., 2021), implying that the emergence of digitisation might mitigate the costs, risks, and the presence of the double externality feature. Indeed, this

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view is highly consistent with Freeman's vision of environmental sustainability, whereby LCD can be achieved through the realignment of innovation systems and major institutional changes, rather than by halting growth (Cole et al., 1973; Perez, 2014). Moreover, Freeman argued that the ICT paradigm could evolve in a green direction, thereby providing innovative underpinnings to promote LCD (Freeman, 1996).

The digital economy (DE) is a broader concept that extends beyond ICT, although ICT adoption is widely seen as marking the emergence of a new ICT-based techno-economic paradigm. Adapting to digitalisation requires sectors to innovate technologically while adapting in their development models and strategies (Pedota et al., 2023). Overall, the intensifying digital revolution marks a fundamental shift in the traditional ways of producing, consuming and operating (Stornelli et al., 2021), providing an ideal environment for green innovation and LCD. This view suggests that DE can influence LCD by improving green innovation and facilitating structural upgrading toward less carbon-intensive activities (Li and Wang, 2022). Yet such effects may not be immediate, because early-stage digital expansion can entail higher energy demand from infrastructure and transitional frictions, potentially weakening low-carbon outcomes in the short run (Moyer and Hughes, 2012; Sorrell et al., 2009). As digital adoption deepens and complementary capabilities accumulate, efficiency gains and cleaner upgrading may become more salient, implying a strengthened LCD effect (Wang and Ding, 2023). Against this backdrop, green innovation provides a natural mechanism through which DE can translate into sustained low-carbon progress. However, we know little about whether there are differences in the roles played by heterogeneous green innovations. When focusing on the role of green innovation, it is essential to analyse the regional context. Innovation spillovers are often more pronounced at the regional level, with geographically closer regions having more opportunities for innovation exchanges. Therefore, it becomes particularly important to explore the role of green innovation spillovers between regions for achieving regional synergistic development in the low-carbon transition.

Therefore, this study aims to provide empirical evidence on whether DE promotes LCD in China. Specifically, we ask: (1) Does DE development significantly promote LCD? (2) If so, is there a threshold level of DE development beyond which its effect on LCD becomes significant? (3) Is the effect of DE on LCD realised through the promotion of green innovation? (4) Does this mechanism differ across types of green innovation? In addition, given the regional context, we examine whether DE affects the LCD of neighbouring cities through green-innovation spillovers, and whether such spillovers exhibit a beggar-thy-neighbour effect or a neighbour-companion effect. Currently, global carbon emissions (CE) are still increasing, and extreme weather and climate events are occurring frequently. By examining the role of green innovation in the impact of DE on LCD, this study can make great contributions to global climate control, and provide many references for other developing countries, especially those in the process of industrialisation, and help them less detour and gain more experience in dealing with greenhouse gases.

To solve the problems noted above, this study constructs a panel dataset of 280 Chinese cities from 2009 to 2023 and measures LCD using a super-efficiency SBM model with undesirable outputs. The nonlinear effect, the green-innovation mechanism and spatial spillovers are examined using a threshold model, a simultaneous-equation framework with heterogeneous green patents, and a spatial Durbin model. The main findings can be summarised from two perspectives. Locally, DE promotes LCD only after it exceeds a threshold, and heterogeneous green innovations play distinct mediating roles. Spatially, DE exhibits a U-shaped spillover effect on neighbouring cities' LCD within a 100–400 km distance band, which appears to be associated with green-innovation spillovers. Overall, these results contribute to the literature on innovation and environmental economics in several ways.

First, our focus on LCD in a digital context provides policy-relevant insights for developing countries on leveraging digitalisation to support a growth-compatible low-carbon transition. LCD is measured using a super-efficiency SBM model with undesirable outputs, which embeds multiple inputs, GDP, and carbon emissions in a unified production framework. More importantly, existing studies often assume linear effects of digitalisation on LCD (Li et al., 2024; Liu et al., 2024), despite the likelihood of stage-dependent impacts during digital transition. By explicitly examining nonlinear effects, this study shows that the low-carbon benefits of digitalisation may emerge only after digital development surpasses a critical level, offering more realistic guidance for developing economies facing the "growth–carbon" tension.

Second, this study moves beyond treating green innovation as a single aggregate and clarifies which types are most effective in translating digitalisation into LCD. Although green technologies can promote LCD through source prevention, process upgrading, and end-of-pipe treatment, these routes differ markedly in their long-run efficiency and emission-reduction potential (Kim and Lee, 2015; Tchórzewska et al., 2022). We therefore classify green patents by innovation degree (invention vs. utility model), innovation chain (source-control and end-of-pipe), and innovation subject (enterprise and university–research). This distinction matters for LCD because invention and source-control innovations are more likely to deliver durable productivity gains and source-side emission reductions, whereas end-of-pipe solutions may entail additional energy use and weaker long-term effects (Chen et al., 2012; Gu et al., 2018; Heikkilä and Lorenz, 2018). Moreover, enterprise-driven innovation is closer to adoption in major emitting sectors and thus more likely to generate measurable low-carbon outcomes than upstream university–research outputs (Conti and Gaule, 2011; Trajtenberg et al., 1997).

Third, we extend the analysis from local impacts to spatial interdependence, revealing a distance-bounded spillover pattern and highlighting the role of green-technology spillovers under uneven digital development. Regional externalities are central to both innovation diffusion and environmental outcomes, yet many studies still focus on within-city effects and provide limited evidence on how digitalisation reshapes interregional low-carbon co-development. Building on the view that latecomers may exhibit catch-up and imitation dynamics relative to frontier regions (Lee, 2024), this study examines spatial spillovers and shows that the impact of DE on neighbouring cities' LCD can shift from inhibition to facilitation (a U-shaped pattern) within a specific distance range. By linking this evolution to green-innovation spillovers, the study contributes to understanding when digitalisation induces "neighbour-beggar" versus "neighbour-companion" dynamics, and it provides a spatially grounded basis for coordinated digital and innovation policies.

The paper is structured as follows: Section 2 reviews the existing literature; Section 3 presents the theoretical basis and hypothesis development; Section 4 presents the method and data; Section 5 discusses and analyses the results; and the final section provides the conclusions.

2. Literature review

2.1. The impact of DE on LCD

The importance of digitisation in driving innovation, development and economic transformation has been widely noted (Upadhayay et al., 2024; Wang et al., 2021). Freeman further argued that different technological revolutions (such as the steam engine, electric power, and information technology) have produced different ways of economic development and social change (Freeman, 1996). The widespread use of digital technology offers multiple opportunities to promote a more sustainable and equitable growth path, making it necessary to consider the role of DE when examining the drivers of LCD. Many studies show that digital technology can reduce CE (Li et al., 2024). The discussion on the specific mechanism is also more extensive. Specifically, industrial transformation and upgrading (Bai et al., 2023b), technological progress (Li and Wang, 2022), resource allocation efficiency enhancement (Cao et al., 2024), and reduction of energy consumption intensity (Liu et al., 2024) are widely regarded as important ways for DE to realise LCD.

However, while digital technology has a positive potential to contribute to LCD, this positive path may lead to a counter-intuitive increase in energy demand through lower energy prices, which in turn will trigger an increase in CE (Moyer and Hughes, 2012). Myovella et al. (2020) found that DE does not contribute to high-quality development in all regions and that it can lead to premature industrialisation in Sub-Saharan Africa. This means that in less developed regions, backward technologies are preferred (Dong et al., 2020). Some studies suggest that digital technology consumes significant energy and resources, while also generating electronic waste, which can hinder the economy's transition to low-carbon (Belkhir and Elmeligi, 2018).

In addition, considering the ability of DE to break spatial and temporal constraints, examining the LCD effects of digitisation at the spatial level also received attention from scholars, but the conclusions were inconsistent. Yi et al. (2022) found that DE reduces CE in neighbouring cities; Wang and Zhong (2023) also supported this finding. On the contrary, Bai et al. (2023b) argued that DE leads to the transfer of polluting industries, exacerbating neighbouring cities' CE. Zhang et al. (2022) found that there is no significant spatial spillover effect of DE on CE in neighbouring cities, while Li and Wang (2022) found an inverted U-shaped relationship in the spatial dimension.

2.2. The impact of DE on GI

Climate-change-driven economic transformation increases the demand for innovation-based solutions. In the context of rapid digital adoption, the deep integration of DE with the real economy can promote green innovation by facilitating enterprise digitisation and strengthening social responsibility (Sun et al., 2024). Digital technology can also enable business reinvention—changes in production modes and improvements in goods and services—thereby reshaping traditional innovation practices and fostering green innovation (Chen et al., 2024; Nambisan et al., 2017). Empirically, Gao et al. (2023) find that the deep integration of DE and manufacturing promotes green innovation by improving factor allocation efficiency, and Xu et al. (2024) examine the green-innovation effects of enterprise digital transformation. However, an important question remains underexplored: does DE promote all types of green innovation in the same way? Existing evidence is limited and not fully consistent. Liu et al. (2022) find that green innovation driven by DE is substantive, whereas Dou and Gao (2022) suggest that DE does not necessarily facilitate green innovation and instead exhibits an inverted U-shaped relationship.

From a spatial perspective, green innovation shares characteristics with general technological innovation, including potential technology spillover effects. Additionally, Bai et al. (2024) identified a spatial spillover effect where local digitalisation fosters green innovation in neighbouring regions. However, some studies suggest that the spillover effects of DE are complex. For instance, Luo et al. (2023), after examining local impacts, also found that DE may inhibit such innovation through factors like restricted talent and industry transfer. This may be related to the significant disparities in digital development across regions. Similar to the traditional theory of technological catch-up (Lee, 2024), regional disparities in DE, which generate uneven levels of green innovation, may also lead to inter-regional catch-up behaviour in green innovation development.

2.3. Research gap

In summary, existing studies have made significant progress, but several gaps remain.

Firstly, although some studies discussed the impact of DE on CE from the perspective of technology innovation and overall GI, there are fewer studies from the perspective of heterogeneous GI. The limited studies briefly explored the role of R&D inputs (Ma et al., 2022), technological innovation (Li and Wang, 2022), and overall green innovation (Liu et al., 2024). Research has shown that the impact of different types of green innovations on business performance varies significantly. For instance, green process innovations positively affect performance, while green product innovations do not (Vasileiou et al., 2022). This prompts further exploration into whether similar differences exist in the role of heterogeneous green innovations in digitally driving LCD. The gap needs to be supplemented urgently. A simultaneous equation model is constructed to put DE, heterogeneous GI, and CEP into a unified framework, which fills these gaps.

Secondly, although previous studies already classified green innovation into source-control and end-of-pipe according to the innovation chain, and into utility model and invention according to the innovation degree, the breakthrough of core technologies still requires the joint efforts of multiple innovation subjects. At present, less attention is paid to innovative subjects. Based on the existing innovation classification, this paper classifies green innovation into university–research institutions and enterprises based on the IPC classification number, to further explore through which type of green innovation the DE can better contribute to the LCD.

Thirdly, the spatial impacts of DE on CE have only been briefly discussed in terms of the direction of the impacts (Zhang et al., 2022), and there is still no consistent conclusion. Therefore, this paper examines the spatial nonlinear effects. As the innovation potential of modern economies is largely linked to knowledge diffusion and technological spillovers (Audretsch and Feldman, 1996), it is worth considering whether green innovations stimulated by DE also generate spillover effects, potentially influencing neighbouring regions' LCD. Studies on the spatial impact are also limited. Therefore, this paper examines the spatial impact mechanism of DE on LCD through green innovation spillover, providing useful theoretical support for the synergistic governance of CE reduction in cities.

3. Hypotheses development

3.1. Conceptual rationale for a nonlinear DE–LCD relationship

The DE reflects a transformation in the organisation of economic activities during the digitalisation process, forming a new development model driven by digital transformation. Digital technologies are widely considered general-purpose and complementary technologies that can promote efficiency improvements and organisational change across the economy (Bresnahan and Trajtenberg, 1995; Helpman, 1998). Accordingly, the overall impact of the digital economy on low-carbon development can operate through economy-wide efficiency improvements and structural transformation. When digital technologies such as big data, artificial intelligence, and cloud computing are integrated into production and management processes, they can support cleaner production upgrading (Jiang et al., 2019). At the same time, the widespread adoption of these technologies across industries can accelerate industrial upgrading and reduce reliance on high-carbon development paths (Bai et al., 2023b).

Meanwhile, the DE–LCD relationship may be nonlinear. Expanding digital infrastructure, operating data centres, and the proliferation of smart devices can increase electricity demand and e-waste pressures, generating scale-expansion effects that may raise emissions in the short run (Moyer and Hughes, 2012). During early diffusion, induced demand and scale expansion may partially offset efficiency gains, consistent with the rebound-effect logic (Sorrell et al., 2009). As DE deepens, technological efficiency improvements and network-enabled coordination can reduce energy use and emissions per unit of service/output, implying a strengthening net impact over time (Wang and Ding, 2023). Accordingly, we propose Hypothesis 1.

Hypothesis 1. The effect of DE on LCD is nonlinear, turning from negative at low levels to positive at higher levels.

3.2. The green-innovation mechanism: theoretical framework and hypotheses

3.2.1. The green-innovation channel

This section develops a stylised endogenous-innovation model to formalise how DE enhances LCD through GI. Innovation is conceptualised as an expansion of the technology set, following the canonical product-variety framework (Grossman and Helpman, 1991; Romer, 1990). The model also incorporates the core insight from the literature on directed technical change in environmental economics: the composition of technologies determines emissions intensity (Acemoglu et al., 2012). Specifically, the level of digital enablement, denoted by ϕ, enters the green R&D process by either raising R&D productivity or alleviating R&D frictions, thereby yielding a closed-form analytical channel linking DE, GI, and LCD.

(1) Production and the set of green technologies

Consider a continuum of industries $i \in [0,1]$. Aggregate output is a CES composite of industry outputs, as in Eq. (1):

$$Y = \left(\int_0^1 y_i^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}}, \sigma > 1 \tag{1}$$

Industry output is given by:

$$y_i = A_i T_i^{\alpha} S_i^{\beta} M_i^{1-\alpha-\beta}, \quad 0 < \alpha, \beta < 1, \alpha + \beta < 1 \tag{2}$$

where $A_i$denotes productivity, $T_i$and $S_i$represent task inputs, and $M_i$is the composite intermediate input.

To capture green technological progress that is directly relevant for the LCD, we introduce a subset of intermediates that embody green technologies and use the number of green varieties $N_{g,i}$to proxy the level of GI. Accordingly, the composite of green intermediates is defined as follows:

$$M_i = \left(\int_0^{N_{g,i}} x_i(v)^{\frac{\eta-1}{\eta}} dv \right)^{\frac{\eta}{\eta-1}}, \eta > 1 \tag{3}$$

in Eq. (3), M_i denotes the composite of green intermediates (green-technology inputs), rather than implying that all intermediates in production are green. This "technology-set expansion" representation is standard in variety-expansion models (Grossman and Helpman, 1991; Romer, 1990).

(2) Monopolistic competition and innovation incentives

Following Romer (1990), we assume monopolistic competition in intermediate varieties. This standard assumption ensures that each newly introduced green variety earns a positive profit flow, which can cover the fixed costs of R&D and entry and closes the profit–R&D–entry mechanism in a tractable way.

Then, the demand for variety v is:

$$x_i(v) = \left(\frac{p_i(v)}{P_{M,i}} \right)^{-\eta} M_i \tag{4}$$

With marginal cost normalised to 1, optimal markup pricing is:

$$p_i(v) = \frac{\eta}{\eta - 1} \tag{5}$$

Based on eq. (5), per-variety operating profit is:

$$\pi_i(v) = (p_i(v) - 1)x_i(v).p_i(v) = \frac{\eta}{\eta - 1} \tag{6}$$

In eq. (6), these profit flows provide incentives for R&D-driven entry of new green varieties. For simplicity, let $\pi_i$denote the representative per-variety profit.

(3) Green R&D with DE entering the innovation process

Innovators invest in green R&D $R_{g,i}$to introduce new green varieties:

$$\dot{N}_{g,i} = \lambda(\phi) R_{g,i}, \lambda'(\phi) > 0 \tag{7}$$

In eq. (7), $\lambda(\phi)$is green R&D productivity increasing in ϕ. R&D costs are assumed to be convex, with unit frictions decreasing in ϕ:

$$\mathscr{C}(R_{g,i}) = \frac{\kappa_g(\phi)}{1+\nu} R_{g,i}^{1+\nu}, \nu > 0, \kappa_g'(\phi) < 0 \tag{8}$$

In eq. (8), $\kappa_g(\phi)$captures R&D frictions (search, coordination, and trial-and-error), and $\kappa_g'(\phi) < 0$reflects that a higher DE level reduces unit R&D costs. The value of a new green variety is the present value of expected monopoly profits:

$$V_{g,i} = \frac{\pi_i}{\rho + \delta}, \rho > 0, \delta \geq 0 \tag{9}$$

Innovators choose $R_{g,i}$ to maximise expected net returns:

$$\max_{R_{g,i} \geq 0} \lambda(\phi) R_{g,i} V_{g,i} - \frac{\kappa_g(\phi)}{1+\nu} R_{g,i}^{1+\nu} \tag{10}$$

The first-order condition is:

$$\lambda(\phi) V_{g,i} = \kappa_g(\phi) R_{g,i}^{\nu} \tag{11}$$

Thus,

$$R_{g,i}^* = \left(\frac{\lambda(\phi) V_{g,i}}{\kappa_g(\phi)} \right)^{1/\nu} \tag{12}$$

Substituting eq. (12) into eq. (7) gives:

$$\dot{N}_{g,i}^* = \lambda(\phi) \left(\frac{\lambda(\phi) V_{g,i}}{\kappa_g(\phi)} \right)^{1/\nu} \tag{13}$$

Since $\lambda'(\phi) > 0$and $\kappa_g'(\phi) < 0$, it follows that:

$$\frac{\partial \dot{N}_{g,i}^*}{\partial \phi} > 0 \Rightarrow \frac{\partial N_{g,i}}{\partial \phi} > 0 \tag{14}$$

Eq. (3.14) shows that DE promotes the expansion of the green technology set $N_{g,i}$. Since our LCD measure jointly accounts for GDP and CE within a single efficiency framework, we next describe how $N_{g,i}$affects production efficiency and emissions intensity, and thereby LCD.

First, let the green variety expansion raise the effectiveness of the intermediate bundle:

$$M_i = \Omega(N_{g,i}) \widetilde{M}_i, \Omega'(N_{g,i}) > 0. \tag{15}$$

where, $M_i$is the composite of green intermediates used in production, $\widetilde{M}_i$captures the quantity component, and $\Omega(N_{g,i})$represents the efficiency/quality gain induced by green variety expansion.

Substituting (15) into Eq. (2):

$$y_i = A_i T_i^{\alpha} S_i^{\beta} \left(\Omega(N_{g,i}) \widetilde{M}_i \right)^{1-\alpha-\beta} \tag{16}$$

From Eq. (13), it follows that:'

$$\frac{\partial y_i}{\partial N_{g,i}} > 0. \tag{17}$$

Second, emissions are proportional to output via an emissions-intensity term that decreases in $N_{g,i}$:

$$C_i = \theta(N_{g,i}) y_i, \theta'(N_{g,i}) < 0. \tag{18}$$

Combining Eqs. (16) and (18) yields the following expression:

$$\frac{C_i}{y_i} = \theta(N_{g,i}), \frac{\partial(C_i/y_i)}{\partial N_{g,i}} < 0. \tag{19}$$

This aligns with the directed-technical-change logic that technology composition shapes emissions intensity (Acemoglu et al., 2012).

Building on Eqs. (14)–(20), a higher DE level ϕincreases the expansion of the green technology set (proxied by $N_{g,i}$) by raising the productivity of green R&D and lowering R&D frictions. Green variety expansion then (i) improves production efficiency ($y_i\uparrow$) and (ii) reduces emissions intensity ($C_i/y_i\downarrow$). Under our LCD measure defined in a desirable–undesirable output framework, these two effects jointly imply a higher level of LCD performance as DE deepens. We therefore propose:

Hypothesis 2.1. Green innovation is a key channel through which the DE improves LCD.

3.2.2. *Heterogeneity in the GI channel*

In the mechanism model above, green innovation improves LCD through two channels: enhancing productive efficiency, captured by a technology-efficiency term $A(\cdot)$, and reducing CE intensity, captured by an emissions-intensity term $\theta(\cdot)$. DE, denoted by ϕ, reflects local digitalisation and affects green knowledge accumulation by raising R&D productivity and reducing R&D frictions (Chen et al., 2024; Liu et al., 2023a).

To further analyse heterogeneity, we index GI by type τ (invention vs utility model; source-control vs end-of-pipe; enterprise-led vs university-research-led) and embed type variation into the same notation. Let G_{it}^{τ}denote the type-τ green knowledge stock in city $i$at time t, and $R_{it}^{\tau}$the corresponding R&D input. The knowledge accumulation process is:

$$\dot{G}_{it}^{\tau} = \lambda_{\tau}(\phi_{it})R_{it}^{\tau} \tag{20}$$

where $\lambda_{\tau}(\phi_{it}) > 0$ is the type-specific R&D productivity, with $\partial\lambda_{\tau}(\phi)/\partial\phi > 0$. R&D costs are represented by a convex cost function:

$$\mathscr{C}_{\tau}(R_{it}^{\tau}) = \frac{\kappa_{\tau}(\phi_{it})}{1+\nu_{\tau}}(R_{it}^{\tau})^{1+\nu_{\tau}} \tag{21}$$

where $\nu_{\tau} > 0$captures cost convexity and $\kappa_{\tau}(\phi_{it}) > 0$summarizes informational, coordination, and trial-and-error frictions, with $\partial\kappa_{\tau}(\phi)/\partial\phi < 0$ under digitalisation.

Under this setup, type -τ innovation supply can be summarised by a compact marginal condition. Let MB_{it}^{τ}denote the marginal contribution of type -τ green knowledge to LCD, jointly determined by the efficiency and intensity channels implied by $A'(G_{it}^{\tau})$and $\theta'(G_{it}^{\tau})$. The optimal R&D choice can be written as:

$$MB_{it}^{\tau}\cdot\lambda_{\tau}(\phi_{it}) = \kappa_{\tau}(\phi_{it})(R_{it}^{\tau})^{\nu_{\tau}} \tag{22}$$

This condition indicates that DE strengthens type-τ green innovation by increasing $\lambda_{\tau}(\phi)$and decreasing $\kappa_{\tau}(\phi)$, while the mediated impact on LCD further depends on type-specific conversion efficiency MB_{it}^{τ}. Hence, heterogeneity in the GI channel follows systematically from cross-type differences in MB_{it}^{τ}, $\partial\lambda_{\tau}/\partial\phi$, and $\partial\kappa_{\tau}/\partial\phi$.

For interpretability, we adopt a cost–benefit incentive lens: type differences reflect (i) how digitalisation reshapes the R&D productivity/friction structure and (ii) how effectively innovations translate into efficiency gains and emissions-intensity reductions. This is consistent with the "double externality" of GI (Ning and Wang, 2018; Rennings, 2000) and with arguments that DE mitigates information and coordination frictions in complex innovation processes (Bohnsack et al., 2021; Viardot, 2017).

(1) Innovation degree: invention and utility model.

Invention-based GI typically involves longer cycles and higher uncertainty, making it more responsive to digital improvements in information feedback and coordination—i.e., larger increases in $\lambda_{\tau}(\phi)$and/or larger reductions in $\kappa_{\tau}(\phi)$(Bohnsack et al., 2021; Liu et al., 2022). It is also more likely to generate persistent efficiency improvements, implying a larger MB_{it}^{τ}. By contrast, utility-model GI is often more incremental and shorter-cycle, with potentially weaker and less persistent impacts on both channels underlying LCD (Qi et al., 2022). Thus, the DE-induced LCD gains are expected to be stronger through invention-based GI than through utility-model GI.

(2) Innovation chain: source-control and end-of-pipe.

Source-control GI operates directly on production processes and emission-generation stages, and thus is more likely to improve resource-use efficiency while reducing emissions intensity, implying a larger MB_{it}^{τ}(Chen et al., 2012). Moreover, source-control innovation relies on process data, monitoring, and feedback control, so digitalisation can more strongly reduce coordination frictions and raise effective R&D productivity (Khin and Ho, 2018; Wang et al., 2022). In contrast, end-of-pipe GI is more "add-on" in nature and may entail additional energy use, which can constrain its marginal contribution to emissions-intensity reductions (Gu et al., 2018).

(3) Innovation subjects: enterprise-led and university-research-led

Enterprise-led GI is closer to production and adoption, making innovation outcomes more readily embedded into operational routines and reflected in observable efficiency and abatement performance, i.e., a higher MB_{it}^{τ}(He et al., 2021; Jin et al., 2021). Digitalisation further enhances firms' opportunity recognition and coordination capabilities, thereby raising $\lambda_{\tau}(\phi)$and lowering $\kappa_{\tau}(\phi)$(Bohnsack et al., 2021). University-research-led GI is more oriented toward basic knowledge creation, with longer translation chains and lags to implementation, which can weaken contemporaneous effects on the two LCD channels (Conti and Gaule, 2011; Trajtenberg et al., 1997).

Based on the heterogeneity analysis above, we propose:

Hypothesis 2.2. The indirect effect of DE on LCD through invention-based GI is stronger than that through utility-model GI.

Hypothesis 2.3. The indirect effect of DE on LCD through invention-based GI is stronger than that through utility-model GI.

Hypothesis 2.4. The indirect effect of DE on LCD through source-control GI is stronger than that through end-of-pipe GI.

3.3. *Spatial impacts of DE on LCD and the role of green innovation spillovers*

The efficient information transfer characteristic of DE can overcome constraints of physical time and space, enhancing inter-regional connectivity (Luo et al., 2023). In addition, CE can easily diffuse across neighbouring regions (Bai et al., 2023b). These features imply that DE development may generate spatial spillover effects on LCD. However, under uneven regional DE development, such spillovers may exhibit two contrasting forces: an early-stage echo effect and a later-stage diffusion effect. Drawing on the technological catch-up view that latecomers require time to accumulate capabilities before catching up with frontier regions (Lee, 2013), the spillover effect of DE on neighbouring LCD is expected to evolve with the level of DE. Specifically, in the early stage of DE growth, substantial infrastructure investment and the concentration of digital resources can attract high-quality factors from neighbouring regions to more developed regions (Luo et al., 2023). Meanwhile, neighbouring regions may lack sufficient capacity to imitate and absorb advanced digital technologies. As a result, while advanced regions strengthen their own digitalisation and green initiatives, they may crowd out neighbouring regions' development and hinder their LCD, generating a neighbour-beggar effect. As DE enters a phase of rapid development, data accumulation and faster technological iteration enhance the permeability and external economic effects of DE, strengthening diffusion to neighbouring regions. This diffusion effect helps leverage the role of DE in promoting LCD and fosters inter-regional linkages in low-carbon transition and governance (Li and Wang, 2022), thereby shifting toward a neighbour-companion effect. Accordingly, we propose Hypothesis 3.1:

Hypothesis 3.1. The spillover effect of DE on neighbouring cities' LCD shifts from negative to positive as DE increases, implying a transition from a neighbour-beggar to a neighbour-companion pattern.

Furthermore, spatial spillovers from green innovations tend to be stronger than those from polluting technologies (Dechezleprêtre et al., 2014). However, due to the high costs and risks associated with the double externality inherent in green innovation, the rate of green patenting was generally low in the early years of green innovation development, with a reversal observed in recent years (EPO and IEA, 2021). Green innovation spillovers are facilitated through information exchange, talent flows, and industrial linkages. In the initial stage of DE development, talent and capital inflows from neighbouring regions can promote local green innovation while inhibiting green innovation in those neighbouring regions. In addition, backwards polluting industries may face disruptions and be pushed out of the local market before completing transformation (Bai et al., 2023b), leading to the relocation of polluting technologies. Consequently, the early stage of DE may promote local green innovation but inhibit green innovation in neighbouring regions. As DE increases, it reduces traditional regional barriers, facilitates cross-regional division of labour, and accelerates information diffusion within the economic system, thereby promoting the spread of local green technology to neighbouring regions (Liu et al., 2023a) and supporting neighbouring LCD. At the same time, as integration between digital technology and traditional industries improves (Li et al., 2024), firms are more likely to pursue local upgrading rather than shifting pollution to other regions, weakening the spillover of polluting technologies. Overall, the impact of DE on green innovation spillovers is expected to be non-monotonic and consistent with a U-shaped evolution. Since green innovation is a crucial mechanism for achieving LCD, green innovation spillovers can constitute a key transmission channel through which DE influences LCD in neighbouring regions. Accordingly, we propose Hypothesis 3.2:

Hypothesis 3.2. Green innovation spillovers constitute a key transmission mechanism underlying the U-shaped relationship between DE and neighbouring cities' LCD.

4. Method and data

In this section, we present the econometric methodology and the data used in the analysis, and describe the spatio-temporal evolution of DE, heterogeneous green innovation, and LCD across Chinese cities from 2009 to 2023.

4.1. Model specification

4.1.1. Benchmark regression

To verify the impact of DE on China's LCD, we follow Zhang et al. (2022), and a benchmark regression model is developed:

$$LCD_{it} = \alpha_0 + \alpha_1 DE_{it} + \gamma X + \lambda_i + \lambda_t + \mu_{it} \tag{23}$$

where i denotes the city; t denotes the year; LCD is the carbon emission performance. DE denotes the digital economy; $\alpha_0$is the intercept term; $\alpha_1$represents the coefficient of DE; $\gamma$is a vector of control variables; $\lambda_i$and $\lambda_t$are city and year fixed effects, respectively; and $\mu_{it}$is the residual term.

4.1.2. Threshold models

To test Hypothesis 1, based on the model of Hansen (2000), the segmented function of DE on LCD is constructed on the basis of Eq. (1), and then its threshold value and threshold effect are tested. Under the single threshold assumption, the model is as follows:

$$LCD_{it} = \alpha_0 + \alpha_1 DE \cdot I(DE \le \phi)_{it} + \alpha_2 DE \cdot I(DE \ge \phi)_{it} + \gamma X + \lambda_i + \lambda_t + \mu_{it} \tag{24}$$

where $I$is the indicator function. When the relationship between DE and the parameter (ϕ) is satisfied, $I(\cdot)$equals 1; otherwise, it equals 0. The estimating equation for multiple thresholds can be obtained by expanding Eq. (24).

4.1.3. Mechanism test (three-stage least squares)

Previous studies found a direct effect of GI on LCD (Xu et al., 2021) and an effect of LCD on GI (Bai et al., 2023a). If the interaction between them is ignored, it may lead to distorted results. To verify the impact of DE on LCD through heterogeneous green innovations (Hypotheses 2.1–2.4), the three-stage least squares (3SLS) estimation method is used, which is more effective than single-equation estimation under CE. Therefore, following the method of Yang et al. (2021), this study conducts the mechanism test in a similar way. Accordingly, this paper develops a simultaneous equation system consisting of two regression models, with LCD and green innovation as the explained variables, respectively:

$$\begin{cases} LCD_{it} = \beta_0 + \beta_1 DE_{it} + \beta_2 Ln\,GI_{it} + \gamma X + \lambda_i + \lambda_t + \mu_{it} \\ Ln\,GI_{it} = \chi_0 + \chi_1 DE_{it} + \chi_2 LCD_{it} + \gamma X + \lambda_i + \lambda_t + o_{it} \end{cases} \tag{25}$$

where GI represents green innovation, which is further divided into total GI; utility model GI and invention GI; end-of-pipe GI and source-control GI; and university-research institution GI and enterprise GI. City fixed effects (λ_i), year fixed effects (λ_t), and error terms (μ_{it} and o_{it}) are added to the model.

4.1.4. Spatial effects test (Spatial Durbin model)

Studies found that CE exhibit a certain symbiotic effect between regions (Xu et al., 2021). DE has the important feature of compressing spatial and temporal distances. Many studies also support the conclusion that DE has spatial spillovers (Luo et al., 2023). Can the positive externalities of DE inhibit the symbiotic effect of CE and promote a shift from neighbour-beggar to neighbour-companion? To test Hypothesis 3, following Bai et al. (2023b), a spatial Durbin model (SDM) is constructed, and Eq. (26) is used to test whether there is a U-shaped effect of DE on LCD (a shift from neighbour-beggar to neighbour-companion). Eq. (27) is used to further test whether green innovation is the mechanism through which DE leads to a U-shaped effect on LCD. The specific model setup is as follows:

$$\begin{aligned} LCD_{it} = {} & \alpha_0 + \rho WLCD_{it} + \xi_1 WDE_{it} + \xi_2 WDE^2 + \alpha_1 DE_{it} \\ & + \alpha_2 DE_{it}^2 + \gamma X + \mu_{it} \end{aligned} \tag{26}$$

$$\begin{aligned} \text{Ln total\_GI}_{it} = {} & \beta_0 + \nu WLn\text{total\_GI}_{it} + \omega_1 WDE_{it} + \omega_2 WDE^2 \\ & + \beta_1 DE_{it} + \beta_2 DE_{it}^2 + \gamma X + \sigma_{it} \end{aligned} \tag{27}$$

In Eqs. (26) and (27), $\rho$and $\nu$are spatial autoregressive coefficients; $\xi$and $\omega$are the elastic coefficients of the spatial lag terms. $\mu_{it}$and $\sigma_{it}$are spatial error terms; $W$is the geographical distance weight matrix, $W_d = 1/d_{ij}$, where d_{ij}represents the distance between regions $i$and j.

4.2. Data

4.2.1. Low-carbon development

Measurement of LCD. Following Liu et al. (2023b), we measure LCD using the super-efficiency SBM model with undesirable outputs (see Supplementary Text 1 for model specification). LCD is not a single efficiency or intensity metric; rather, it integrates economic output, resource and energy inputs, and carbon-emission constraints within a unified framework. The specific inputs and outputs used in the model are summarised in Table 1. Accordingly, LCD captures a city's ability to pursue economic growth while curbing carbon emissions under limited resource and energy conditions—emphasising that low-carbon transition should advance with economic development, not at its expense.

Fig. 1 depicts the spatiotemporal evolution of CE and LCD across China's regions. Fig. 1a indicates that regional CE remain ranked, from high to low, as eastern, northeastern, central, and western China. The eastern region shows the largest within-region disparity, with both very low and very high emission cities coexisting. The northeastern region exhibits a relatively narrower distribution of CE, consistent with its more homogeneous heavy-industry structure. The central and western regions also display substantial heterogeneity, and in the western region, emissions are concentrated in a limited number of cities. Over time, CE generally increase in the eastern, central, and western regions, while growth is comparatively more moderate in the northeast. In Fig. 1b, LCD increases overall across all regions, with the eastern region consistently leading, followed by the northeastern and central regions, and the western region remaining the lowest. Compared with CE, cross-city differences in LCD are smaller, suggesting that LCD is less uneven than absolute emissions. Regions with higher CE, especially the eastern and northeastern regions, also tend to exhibit higher LCD, likely reflecting advantages in technology, efficiency, and governance capacity. Notably, LCD has become less smooth in recent years. Given that LCD is an efficiency-based indicator jointly reflecting output and emissions, macro shocks such as the COVID-19 pandemic can temporarily weaken measured LCD performance even if underlying structural relationships remain stable.

4.2.2. Digital economy

Based on the National Bureau of Statistics' *Statistical Classification of the Digital Economy and Its Core Industries* (2021) and following Lyu et al. (2024), we construct a prefecture-level digital economy index along four dimensions: digital industrialisation, industrial digitalisation, digital governance, and data value realisation. After standardising all sub-indicators, we use principal component analysis (PCA) to derive a composite digital economy index. The indicators and definitions are reported in Table 2.

Fig. 2 illustrates the changes in China's DE from 2009 to 2023. DE exhibits a clear upward trajectory across all four regions over the study period. The eastern region remains the national leader and shows the largest cumulative increase, with DE rising by 0.479 from 2009 to 2016 and a further 0.665 from 2016 to 2023. The central region records steady improvement and a slightly faster rise after 2016. In contrast, DE growth in the northeastern and western regions is more modest. The northeast increases by 0.186 in 2009–2016 and 0.099 in 2016–2023, indicating a noticeable post-2016 slowdown, which may reflect the higher adjustment costs and structural constraints of digital transformation in traditional heavy-industry bases. The western region increases by 0.216 in 2009–2016 and 0.165 in 2016–2023, suggesting continued progress but at a relatively moderate pace. Overall, the regional gaps in DE remain substantial.

Table 1
Index evaluation system of LCD.

Type	Variable name	Meaning
Input	Capital	The stock of urban fixed asset investment at a constant price with 2003 as the base period
	Employees	The number of employees in urban areas
	Land	Urban construction land area
	Energy	Energy consumption, such as electricity, gas and heating, is converted to standard coal
Desirable output	GDP	The GDP at a constant price with 2003 as the base period
Undesirable output	Carbon emission	The sum of carbon emissions from electricity, heating, gas and liquefied petroleum gas, transportation, etc.

4.2.3. Mechanism variables: heterogeneous green innovations

Following Luo et al. (2023), green innovation is proxied by green patents. In the empirical analysis, we measure it as the natural logarithm of (the number of green patents +1). Green patents are obtained by searching the State Intellectual Property Office using IPC classification numbers of green patents from WIPO. To further explore the differences in the role of heterogeneous green innovations between DE and LCD, this study classifies green innovation according to innovation degree, innovation chain and innovation subject based on the approach of Xu et al. (2021). Table 3 shows the definitions of specific variables.

Fig. 3 depicts the evolution of heterogeneous GI from 2009 to 2022. At the subregional level, the eastern region shows sustained growth across all types of GI, with a mild slowdown and slight pullback after the 2020–2021 peak. The northeastern region exhibits a clear N-shaped pattern, with more pronounced fluctuations than other regions. The central and western regions display rapid growth after the mid-2010s, followed by noticeable volatility in the later years, including a temporary decline around 2020 and a subsequent rebound. Across all regions, enterprise GI consistently exceeds that of university–research institutions, with the gap remaining particularly evident in the northeastern and eastern regions. Invention GI is higher than utility model GI, and this advantage generally widens over time. Source-control GI remains above end-of-pipe GI in all regions, but the gap narrows in the northeastern, central, and western regions in the later period, whereas it stays relatively larger and more stable in the eastern region. Overall, the regional ranking and temporal changes in green innovation broadly align with the patterns observed for DE and LCD.

4.2.4. Control variables

This study follows Li et al. (2022a) and Li et al. (2024) and uses the following control variables. Economic growth (*eg*) and its square term (*eg*^{2}): the real GDP per capita and its square term. Population density (den): the number of people per unit of administrative area. Industrialisation (*indus*): the proportion of secondary industry in GDP. Government intervention (*gov*): the proportion of government expenditure in GDP.

Given the availability of data, 280 Chinese cities are used from 2009 to 2023. Indicators involving price factors have been handled in constant prices using the 2003 base period. Table 4 shows the descriptive statistics of the variables.

5. Results and analysis

5.1. Benchmark regression results

In Columns (1)–(6) of Table 5, the coefficient on DE is positive and statistically significant, indicating that DE plays a significant role in promoting LCD. This result is consistent with Ma et al. (2022), suggesting that DE can support high-quality development with environmental benefits. A plausible channel is that DE accelerates the digitisation of conventional production factors and allows data to function as a new factor of production, reshaping growth in a more low-carbon direction (Pan et al., 2022; Zhang et al., 2022). Because LCD is measured as an efficiency-based indicator that jointly reflects economic output and CE, the estimated effect is best interpreted as improved low-carbon transition performance alongside development. This interpretation aligns with China's current transition agenda, which emphasises cutting emissions through efficiency gains and technological upgrading rather than through growth slowdowns.

In Column (6), the coefficients of economic growth (ey) and its squared term (ey2) are −0.015 and 0.008, respectively, but the former is significant, and the latter is not. This may be because most regions in China have not yet fully transformed their development mode toward greening (Bai et al., 2023a). This finding further confirms that DE, as a new mode of economic development, is a significant driver of LCD. The coefficient of population density (den) is significantly positive, which

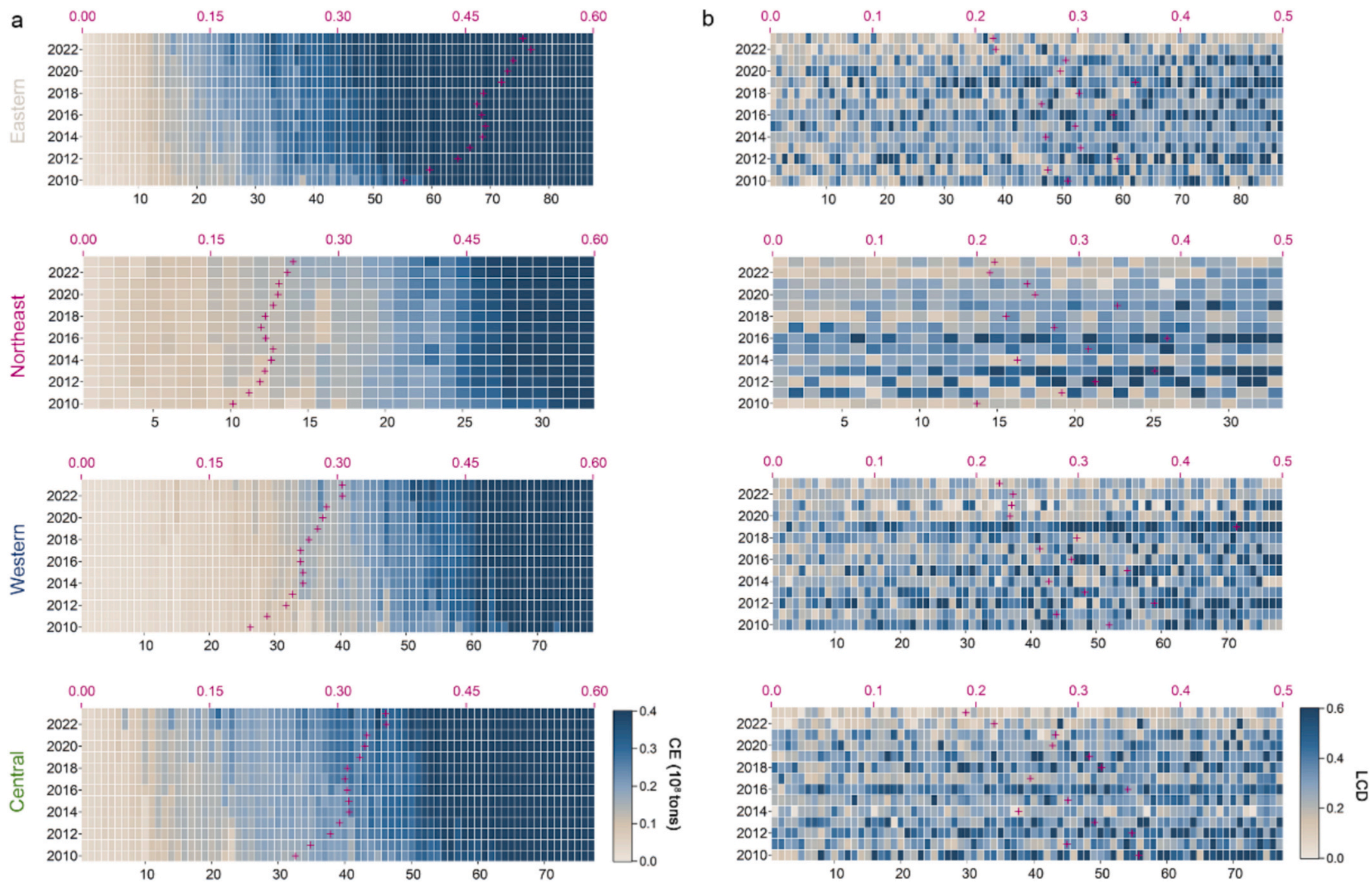

Fig. 1. The changing trends of CE and LCD in different Chinese regions.

Table 2
Index evaluation system of DE.

Primary index	Secondary index	Indicator Definition
Digital Industrialisation	Telecommunications Industry	Per capita total telecom services
	Electronic Information Manufacturing	Number of listed firms in computer, communication, and other electronic equipment manufacturing
	Broadcasting & Television	Number of listed firms in broadcasting, TV, film, and audiovisual production
	Software Industry	Number of listed firms in software and IT services
Industrial Digitization	Intelligent Production	Number of listed firms engaged in intelligent manufacturing
	Digital Presence	Enterprise domain registration count
Digital Governance	Policy Attention to Digital Governance	Frequency of digital economy-related keywords in local government work reports
	Digital Users	Internet broadband subscribers per 100 people
Data Monetization	Data Transaction Regulation	Number of data trading centres

suggests that higher population density exerts an intensification effect, leading to more efficient use of public infrastructure and a reduction in transportation and energy costs. The coefficient of Industrialisation (indus) is significantly negative, and industrialisation, represented by the secondary industry, inhibits the LCD, which verifies the findings of Li et al. (2022b). Because China's current industry is still dominated by heavy industry, the industry's reliance on non-clean energy sources such as fossil fuels remains strong, which negatively impacts the LCD. The coefficient of government intervention (gov) is significantly negative. Because government actions that prioritise economic growth at the expense of the environment still persist, the government may intervene in CE reduction for the sake of development, thus hindering LCD.

5.2. Nonlinear effects analysis

Considering Metcalfe's law, which implies increasing marginal returns as digital networks expand (Li and Wang, 2022), this study further investigates whether the impact of DE on LCD exhibits nonlinear characteristics. Column (1) of Table 6 and Fig. 4 report the results of the single-threshold test. The likelihood ratio statistics clearly reject the null hypothesis of linearity, indicating the presence of a statistically significant single threshold in the DE–LCD relationship. The estimated threshold value is -0.225,[1] with a narrow confidence interval, confirming the robustness of the threshold identification.

As shown in Column (2) of Table 6, when DE < -0.225, its effect on LCD is significantly negative. This suggests that at relatively early stages of DE development, digitalisation may be accompanied by higher energy use and carbon pressures, partly due to infrastructure construction, rising electricity demand, and related environmental costs such as e-

[1] This negative threshold does not indicate a "negative" digital economy in an absolute sense. Because the DE index is constructed using principal component analysis, it is standardized around zero; thus, values below zero simply indicate that a city's DE development is below the sample average, whereas values above zero indicate a relatively higher level of DE.

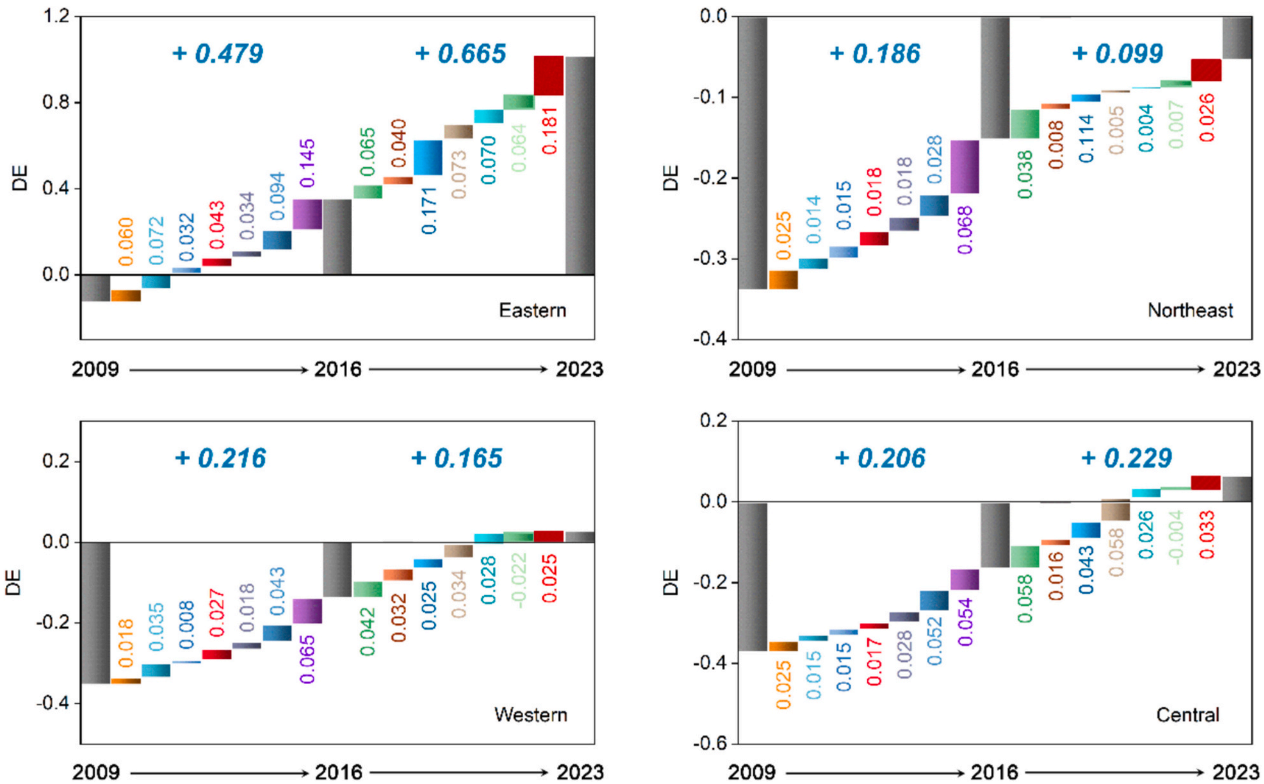

Fig. 2. The changing trends of DE in different Chinese regions.

Table 3
Measurement of heterogeneous green innovation.

	Types	Variable	Meaning
Heterogeneous GI	Total GI	Ln (total GI)	Logarithm of the total number of green patents
	Innovation degree	Ln (invention GI)	Logarithm of the number of invention-based green patents
		Ln (utility model GI)	Logarithm of the number of utility model green patents
	Innovation chain	Ln s(ource-control GI)	Logarithm of the number of green patents on energy conservation and alternative energy
		Ln (end-of-pipe GI)	Logarithm of the number of green patents on waste management
	Innovative subject	Ln (university-research institution GI)	Logarithm of the total number of green patents filed by universities and research institutions.
		Ln (enterprise GI)	Logarithm of the total number of green patents filed by enterprise.

waste (Belkhir and Elmeligi, 2018). In contrast, once DE exceeds the threshold, the coefficient becomes significantly positive, indicating that as digitalisation deepens, its efficiency-enhancing effects begin to dominate, allowing energy-efficiency gains and cleaner upgrading to offset or even surpass the initial carbon costs (Moyer and Hughes, 2012). Moreover, with the continued penetration of DE into broader economic activities (Yan et al., 2023), digital tools are more likely to facilitate systematic efficiency improvement and low-carbon transformation, thereby strengthening LCD.

Overall, the single-threshold result reveals a clear stage-dependent effect of DE on LCD, characterised by a transition from inhibition to promotion as digital development deepens. This finding provides strong empirical support for Hypothesis 1 and highlights that the low-carbon benefits of digitalisation are not immediate but emerge only after a certain level of digital maturity is reached.

In addition, Fig. 5 visualises the spatiotemporal pattern associated with the threshold effect. The maps for 2009, 2014, 2019, and 2023 illustrate how cities gradually move across the single threshold. In 2009, most cities remained below the threshold, and the spatial pattern was characterised by limited and scattered high-LCD observations. In this stage, improvements in LCD appear less systematically aligned with digital development. By 2014, the number of cities crossing the threshold increases, and these cities are more visibly concentrated in major urban agglomerations, especially the Yangtze River Delta, the Pearl River Delta, and the Chengdu–Chongqing region. Notably, the cities above the threshold tend to exhibit higher LCD levels than those remaining below it, suggesting that once digitalisation reaches the threshold, the efficiency-improvement and structural-upgrading effects emphasised in the literature begin to manifest more clearly. By 2019 and further in 2023, the expansion of threshold-crossing cities becomes more pronounced and takes on a cluster-based form. Notably, although LCD in 2023 is slightly lower than in 2019 in aggregate, the spatial pattern remains consistent with the threshold-based differentiation. The spatial correspondence between above-threshold DE and relatively higher LCD becomes clearer within these city clusters, indicating that as DE deepens, the benefits are less confined to a few leading cities and more likely to diffuse within integrated regional systems.

5.3. Endogeneity and identification strategy

Given that LCD can spur advances in green innovation, which in turn may serve as a model for DE (Chen, 2023). This implies that DE may be incentivised by LCD. To address endogeneity, we follow Bai et al. (2023b) to select the following instrumental variables (IV). The IV is the spherical distance from the sample city to the node cities of the "eight vertical and eight horizontal" fibre optic backbone network (Detailed distribution is shown in Supplementary Fig. 1.) (*fiber_distance*).

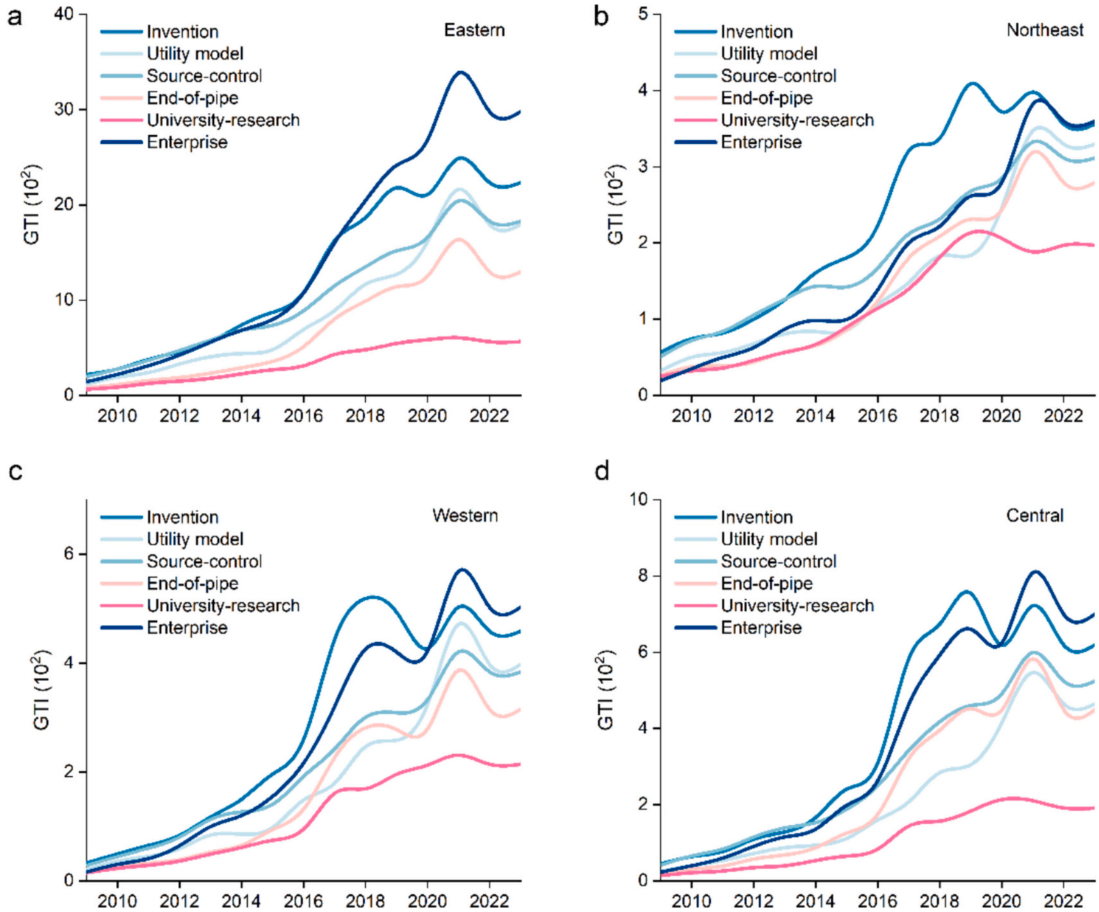

Fig. 3. The changing trends of heterogeneous green innovation in different Chinese regions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
The descriptive statistics and data source of variables.

Variable	Obs	Mean	Std. Dev.	Min	Max	Source
LCD	4200	0.289	0.107	0.065	1.250	China City Statistical Yearbook and the China Urban and Rural Statistical Yearbook
DE	4200	0.00087	1.069	−0.469	16.575	China City Statistical Yearbook
ey	4200	2.281	1.455	0.017	24,228	China City Statistical Yearbook
ey^2	4200	7.322	14.393	0.00052	587.005	
den	4200	0.044	0.035	0.0005	587.005	
indus	4200	0.459	0.110	0.107	0.909	
gov	4200	0.192	0.098	0.044	1.485	
Ln (total_GI)[1]	4200	1.390	1.187	0	6.287	State Intellectual Property Office of China
Ln (invention GI)	4200	1.013	1.067	0	6.008	
Ln (utility model GI)	4200	0.959	0.944	0	4.961	
Ln (source-control GI)	4200	0.963	0.997	0	5.330	
Ln (end-of-pipe GI)	4200	0.848	0.915	0	5.031	
Ln (enterprise GI)	4200	1.055	1.094	0	5.918	
Ln (university-research institution GI)	4200	0.445	0.795	0	4.621	

[1] Take the logarithm of (number of green patents +1).

Because cities closer to backbone nodes have lower fixed costs for broadband deployment and better technological conditions, this improves local digital infrastructure, thereby supporting a higher level of digital economic development. Furthermore, the layout of backbone nodes is primarily determined by national trunk line construction projects and network planning logic, exhibiting characteristics of preplanned deployment. After controlling for city and year fixed effects and baseline control variables, distance to backbone nodes primarily affects low-carbon development through its impact on the DE channel, rather than by directly altering local emissions or production structures. Therefore, this instrumental variable is expected to be relevant and to satisfy the exogeneity condition.

To address potential endogeneity of *DE*, we employ a 2SLS approach:

$$DE_{it} = \pi_0 + \pi_1 IV_{it} + \pi_2^{'} X_{it} + \mu_i + \gamma_t + u_{it} \tag{29}$$

$$LCD_{it} = \alpha + \beta \widehat{DE}_{it} + \theta^{'} X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{30}$$

Where, LCD_{it}denotes low-carbon development performance for city $i$in

Table 5
Benchmark regression results.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	LCD	LCD	LCD	LCD	LCD	LCD
DE	0.005**	0.0048**	0.005**	0.006***	0.007***	0.008***
	(0.002)	(0.0024)	(0.002)	(0.002)	(0.0025)	(0.003)
ey		−0.006	−0.015***	−0.015***	−0.017***	−0.015***
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ey^2			0.0005***	0.0005***	0.0007***	0.0006***
			(0.001)	(0.0001)	(0.0001)	(0.0001)
den				0.235*	0.283*	0.278*
				(0.121)	(0.153)	(0.154)
indus					−0.010**	−0.012**
					(0.005)	(0.006)
gov						−0.009*
						(0.005)
Constant term	0.214***	0.227***	0.244***	0.255***	0.273***	0.264***
	(0.004)	(0.010)	(0.009)	(0.013)	(0.015)	(0.016)
Year-fixed effect	YES	YES	YES	YES	YES	YES
City-fixed effect	YES	YES	YES	YES	YES	YES
Observations	4200	4200	4200	4200	4200	4200
R^2	0.171	0.172	0.173	0.173	0.173	0.175

Table 6
Nonlinear effects results.

(1)		Variable	(2)
Threshold estimator and effect test			CEP
Single threshold	−0.225***	DE·*I* (*Th* <-0.225)	−0.054***
P value	0.000		(0.014)
Lower value	−0.249	DE·*I* (*Th* ≥ −0.225)	0.015**
Upper value	−0.224		(0.006)
Control variables	YES		
Fixed effect	YES		
Observations	4200		
R^2	0.266		

year t; $DE_{it}$is the digital-economy index; $IV_{it}$is the instrument; $X_{it}$is a vector of controls; and $\mu_i$and $\gamma_t$are city and year fixed effects, respectively. The fitted value $\widehat{DE}_{it}$captures the exogenous variation in *DE*induced by the instrument, and $\beta$is the parameter of interest.

In addition, to further support the exclusion restriction, we follow Fu et al. (2020) and provide two complementary supportive checks:

(1) Alternative-channel tests

$$PGDP_{it} = \eta_0 + \eta_1 IV_{it} + \eta_2' X_{it} + \mu_i + \gamma_t + \nu_{it} \tag{31}$$

$$INDUSTRY_{it} = \xi_0 + \xi_1 IV_{it} + \xi_2' X_{it} + \mu_i + \gamma_t + \omega_{it} \tag{32}$$

(2) Mechanism-consistency (augmented reduced-form) test

$$LCD_{it} = \rho_0 + \rho_1 DE_{it} + \rho_2 IV_{it} + \rho_3' X_{it} + \mu_i + \gamma_t + \epsilon_{it} \tag{33}$$

Eqs. (31)–(32) test whether the instrument systematically predicts key non-digital channels. Specifically, *PGDP* is defined as real GDP per capita, capturing local economic development, while *INDUSTRY* is measured by the tertiary-to-secondary value-added ratio, reflecting industrial upgrading. Eq. (33) examines whether the instrument retains residual explanatory power for *LCD* after conditioning on *DE*. Since *DE*may be endogenous, (33) is interpreted as supportive evidence and considered jointly with (30).

Table 7 indicates that *fiber_distance* serves as a valid IV that effectively alleviates endogeneity concerns regarding DE. The coefficient of *fiber_distance* on DE is significantly negative, suggesting that cities located closer to backbone nodes face lower fixed costs of broadband deployment and better network conditions, and thus are more likely to develop a higher DE level. In Column (2), the IV-identified effect of DE

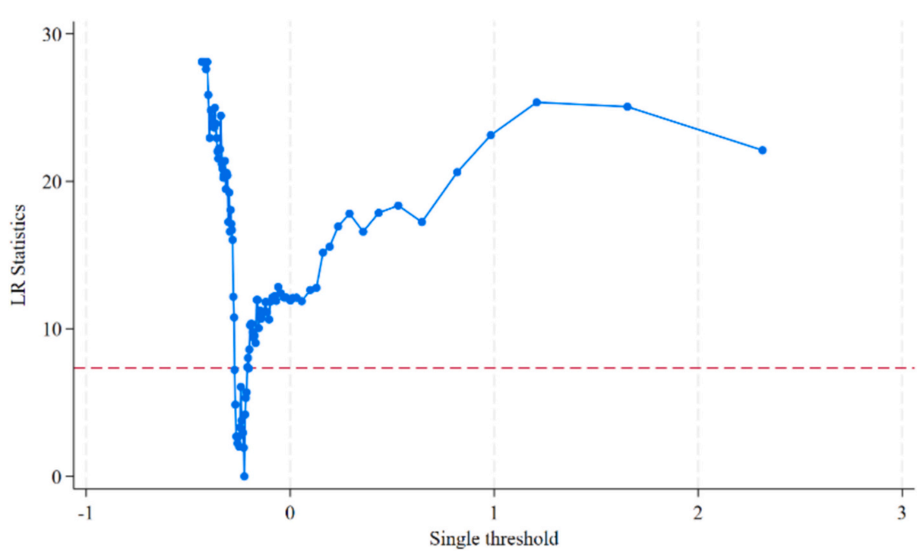

Fig. 4. Results of single threshold estimation for DE.

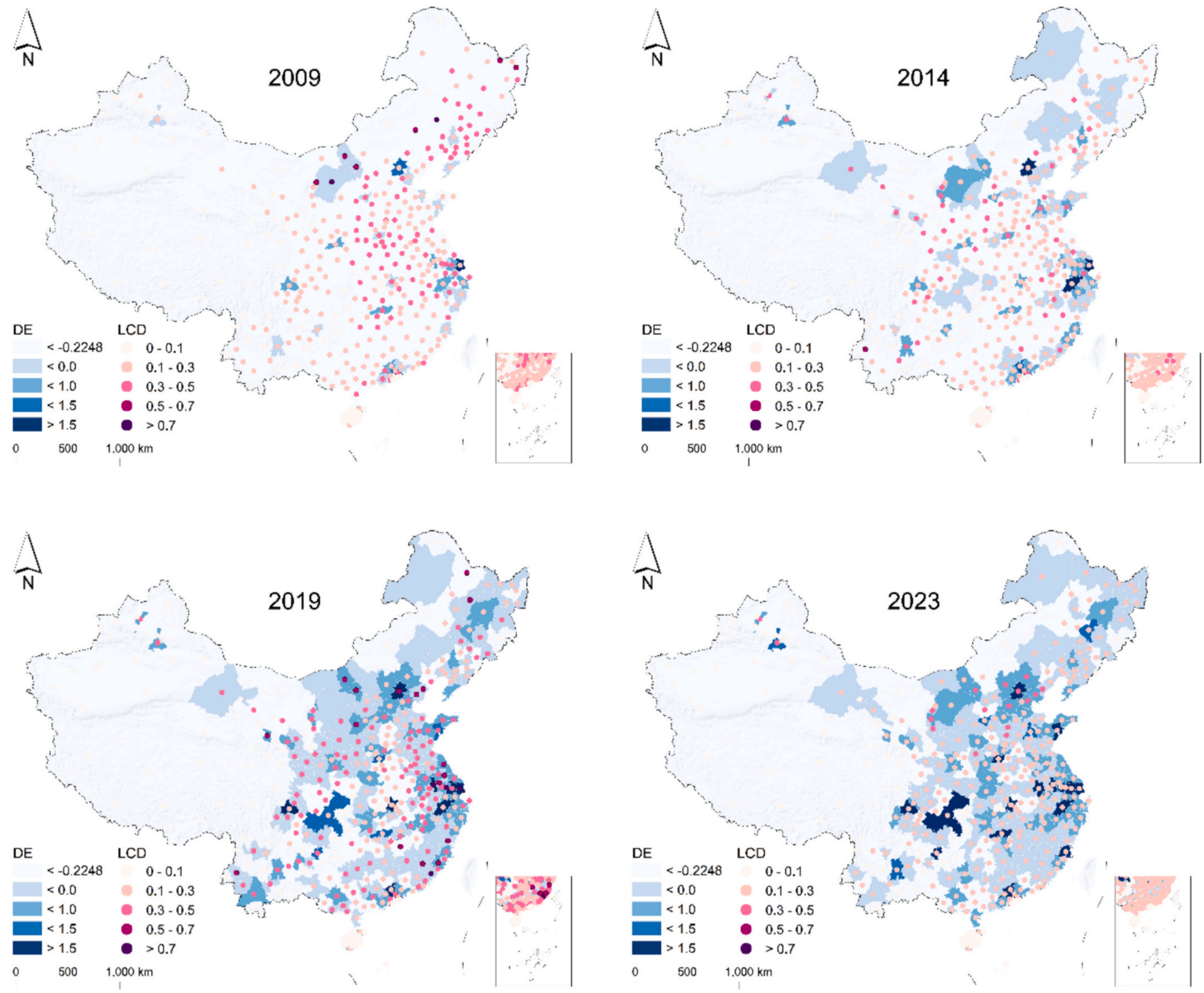

Fig. 5. Spatial and temporal visualisation of the threshold effect.

Table 7
The test results of IV.

Variable	IV test		Alternative-channel tests		Mechanism consistency
	DE	LCD	INDUSTRY	PGDP	LCD
fiber_distance	−0.140*** (0.030)	0.079** (0.033)	0.352 (0.394)	0.079 (0.058)	0.010 (0.007)
DE					0.007*** (0.002)
Kleibergen-Paap rk LM		21.641 [0.000]			
Kleibergen-Paap rk Wald F		20.638 [16.38]			
Control variables	YES	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES	YES
City fixed	YES	YES	YES	YES	YES
Observations	4200	4200	4200	4200	4200
R^2	0.426	0.317	0.377	0.169	0.173

on LCD remains significantly positive, indicating that the central conclusion that DE promotes LCD is robust after accounting for potential reverse causality and omitted-variable bias. To further support the exclusion restriction, this section conducts two complementary checks. First, the alternative-channel tests show that *fiber_distance* does not systematically predict key non-digital channels, implying that the instrument is unlikely to affect LCD directly through pathways such as economic development or industrial upgrading. Second, in the mechanism-consistency test, after controlling for DE, the direct effect of *fiber_distance* on LCD is insignificant, further supporting that it operates primarily through the DE channel. Overall, the IV results are consistent with the baseline regressions, reinforcing the credibility of the causal interpretation.

5.4. Robustness test

(1) Replacement of the measurement of the LCD. The non-radial directional distance function (NDDF) model enables the projection of invalid DMUs onto the frontier along any set direction by defining a vector of directions and distinguishes between good and bad outputs. This solves the problem of inconsistent proportional increases and decreases in the two types of output and slack bias (Chung et al., 1997). In addition, the NDDF model does not consider redundant variables, although it considers

directional variables. Therefore, the SBM-DDF model is further employed to compensate for the shortcomings of the traditional DDF in terms of radiality and directionality, and also to avoid the inaccuracy of the computed efficiency results when there is an over- or under-input or an under-output. In Table 8, Columns (1) and (2) show that there is still a significant effect of DE on LCD after the replacement of LCD, which verifies the robustness of the results.

(2) Replacement of the dependent variable with emission-based indicators. To further test the robustness of our findings from an emissions-oriented perspective, we replace the dependent variable with two alternative measures: per capita CO_2 emissions and CE intensity, defined as CO_2 emissions per unit of GDP. The results (see Table 8, Column (3)–(4)) show that the estimated effect of DE remains negative and statistically significant for both alternatives, consistent with the baseline findings. This suggests that the observed role of DE in advancing low-carbon transition is not solely driven by gains in economic efficiency; it also holds when focusing directly on emission reduction.

(3) Control for macro factors. To mitigate the influence of macro-level shocks and province-specific time-varying factors, we augment the baseline specification by including province fixed effects and province-by-year fixed effects. Column (5) indicates that the driving effect of DE on LCD is robust.

(4) Timing robustness: lagged digital economy. Given that the effects of DE may unfold with adjustment and diffusion lags, we test timing robustness by replacing the contemporaneous DE measure with its lagged values, while keeping the baseline specification unchanged. In Column (6) of Table 8, the results show that DE at $t - 1$ remains significantly positive ($\beta = 0.033$, $p = 0.012$), whereas DE at $t - 2$ and $t - 3$ is no longer statistically significant. This suggests that the positive impact of DE on LCD mainly materialises in the year following its adoption, rather than accumulating over multiple years. It also helps rule out concerns that the baseline findings are driven by the same-year shocks or simultaneity bias.

5.5. Heterogeneity analysis

Given substantial cross-city differences in China, the effect of DE on LCD may vary with structural constraints and governance capacity. We therefore conduct subgroup analyses along three dimensions. (1) Resource dependence is defined using the official list of resource-based cities in the National Plan for Sustainable Development of Resource-based Cities (2013−2020), which captures path dependence and factor allocation tied to resource-oriented industries. (2) Industrial structure upgrading (ISU) is proxied by the ratio of the tertiary-sector share to the secondary-sector share; cities are split into high and low upgrading groups based on the sample median of this indicator. This dimension reflects whether a city's sectoral composition provides a stronger foundation for digital-enabled green upgrading. (3) Administrative hierarchy distinguishes municipalities, provincial capitals, and sub-provincial cities from other prefecture-level cities, reflecting systematic differences in policy authority, fiscal capacity, and cross-sector coordination.

The subgroup regressions reveal clear heterogeneity in Table 9. The DE coefficient is insignificant for resource-dependent cities but significantly positive for non-resource-dependent cities. DE significantly improves LCD in above-median industrial-upgrading cities, whereas the effect is insignificant in below-median cities. A similar pattern holds by administrative hierarchy: the DE–LCD association is significant in higher-administrative-level cities, but not in ordinary prefecture-level cities. Overall, these patterns suggest that structural dependence and governance capacity condition the extent to which digital development can be converted into low-carbon transition performance.

5.6. Analysis of the heterogeneous green innovations mechanism

In Table 10, Panel A reports the results using total GI as the mechanism. The coefficient of DE on Ln (total GI) is 0.034 and is significant at the 1% level. In the LCD equation, the coefficient of Ln (total GI) on LCD is 0.033, also significant at the 1% level, indicating that DE can promote LCD through its effect on total GI. The implied indirect effect is 0.0011. This supports Hypothesis 2.1. Because DE helps break down information barriers, it increases the transparency of information and knowledge, which can reduce firms' green-innovation costs and thereby contribute to LCD. Moreover, digital platforms facilitate rapid diffusion and exchange of technologies, further stimulating green innovation (Mubarak et al., 2021).

Panel B presents the results using green innovation with different innovation degrees as the mechanism. Columns (1) and (2) show that the coefficient of DE on Ln (invention GI) is 0.021, significant at the 1% level. In the LCD equation, the coefficient of Ln (invention GI) on LCD is 0.029, significant at the 5% level. The implied indirect effect is 0.0006. Columns (3) and (4) report the utility model results. The coefficient of DE on Ln (utility model GI) is 0.007, significant at the 5% level, while the coefficient of Ln (utility model GI) on LCD is −0.013 and statistically insignificant. The implied indirect effect is −0.00009. Overall, the mechanism through the invention GI is more stable and economically meaningful than that through the utility model GI. This suggests that DE promotes LCD primarily by strengthening higher-quality green innovation, rather than by expanding incremental utility model patents. Hypothesis 2.2 is therefore supported. This conclusion is consistent with Liu et al. (2022). A plausible interpretation is that firms often rely on the utility model GI, which typically involves lower costs and lower

Table 8
Robustness test results.

Variable	Replacement of explained variable				Control of macro-factors	lagged digital economy
	LCD_NDDF	LCD_SBMDDF	CE per capita	CE intensity	LCD	LCD
DE	0.044**	0.021**	−0.226**	−0.169**	0.016**	
	(0.022)	(0.010)	(0.112)	(0.079)	(0.008)	
DE_{t-1}						0.033***
						(0.013)
DE_{t-2}						−0.018
						(0.019)
DE_{t-e}						−0.023
						(0.016)
Control variables	YES	YES	YES	YES	YES	YES
Province fixed	No	No	No	No	YES	No
Province - year	No	No	No	No	YES	No
Year fixed	YES	YES	YES	YES	YES	YES
City fixed	YES	YES	YES	YES	YES	YES
Observations	4200	4200	4200	4200	4200	3360
R^2	0.117	0.120	0.203	0.188	0.486	0.160

Table 9
Heterogeneity analysis.

Variable	Resource-dependent cities	Non-resource-dependent cities	The higher ISU	The lower ISU	Higher-administrative-level cities	ordinary prefecture-level cities
	LCD	LCD	LCD	LCD	LCD	LCD
DE	−0.016	0.007***	0.009***	−0.023	0.008**	−0.007
	(0.029)	(0.002)	(0.002)	(0.015)	(0.003)	(0.007)
Control variables	YES	YES	YES	YES	YES	YES
Year fixed	YES	YES	YES	YES	YES	YES
City fixed	YES	YES	YES	YES	YES	YES
Observations	1350	2850	1582	2618	525	3675
R^2	0.170	0.189	0.208	0.143	0.205	0.175

innovative content and is sometimes adopted mainly to meet policy requirements (Qi et al., 2022). Higher-quality invention GI, in turn, is more likely to translate into greater improvements in LCD.

Panel C reports the mechanism results by innovation chains. Columns (1) and (2) show that the coefficient of DE on Ln (source-control GI) is 0.049, significant at the 1% level. In the LCD equation, the coefficient of Ln (source-control GI) on LCD is 0.015, significant at the 5% level. The indirect effect is 0.0007. Columns (3) and (4) report the end-of-pipe results. The coefficient of DE on Ln (end-of-pipe GI) is 0.017, significant at the 10% level. However, the coefficient of Ln (end-of-pipe GI) on LCD is 0.008 and statistically insignificant. Overall, the mechanism through source-control GI is more robust and economically meaningful, indicating that DE is more likely to foster LCD by encouraging upstream, prevention-oriented innovation rather than relying on downstream abatement technologies. Hypothesis 2.3 is therefore supported. This contrasts with Xu et al. (2021), who focused on GI and CE, whereas our results indicate that DE is more strongly associated with source-control GI than end-of-pipe GI, implying a shift in innovation incentives toward cleaner production and source prevention (Wang et al., 2022).

Panel D reports the mechanism results by innovation subjects. Columns (1)–(2) show that DE has a significantly positive effect on Ln (enterprise GI). In the LCD equation, Ln (enterprise GI) is also significantly positive, implying an indirect effect of 0.00005. Columns (3)–(4) show that DE is positively associated with Ln (university–research GI) (0.002, 10% level), but the coefficient of Ln (university–research GI) on LCD is positive yet statistically insignificant. The corresponding indirect effect is 0.0002, but its mechanism support is weaker because the second-stage effect is not significant. Overall, these results suggest that the green-innovation channel through enterprises is more clearly linked to LCD than the university–research channel, supporting Hypothesis 2.4.

This is consistent with Ai et al. (2024), who argue that digitisation can foster firm-level innovation and thereby improve environmental performance; our results further highlight the role of enterprise green innovation in the relationship between DE and LCD. Because enterprises, as an important main subject of pollution emission, are subject to more external regulatory pressure than non-profit organisations, and thus enterprises will respond to government regulation and their own sustainable development through green innovation (Jin et al., 2021). Moreover, enterprise GI is more at the application level, while university-research institution GI is mostly at the theoretical level, with a lower conversion rate of scientific and technological achievements, which makes it difficult to be effectively applied to LCD.

5.7. Nonlinear spatial effect

5.7.1. Spatial correlation and evolutionary patterns

Before exploring the spatial effects of DE, green innovation and LCD, their spatial correlations are explored. In Fig. 6, under the geographic matrix, Moran's index is greater than 0 and all values are significant, which indicates that, overall, the distributions of DE, green innovation and LCD show positive spatial correlation characteristics, respectively.

To further examine the spatial association among the DE, GI, and LCD, Fig. 7 presents bivariate maps illustrating their paired spatial distributions and temporal evolution in 2009, 2016, and 2023.

In Fig. 7a, the 2009 pattern is dominated by cities located in low–low or mixed low–medium combinations, while high–high observations are limited and dispersed. This indicates that, at an early stage of digital development, the local co-movement between DE and LCD had not yet become systematic, and the spatial linkage between leading digital cities and their neighbours was still weak. In Fig. 7b, the 2009 distribution closely resembles Fig. 7a: cities with relatively higher DE tend to co-locate with relatively higher GI, whereas most cities remain in the low end of both dimensions. This spatial parallelism suggests that GI is likely to be an important bridge connecting digital development to LCD. Consistently, Fig. 7c shows that cities with stronger LCD are more frequently observed in places with relatively higher GI, and the footprint of "high GI–high LCD" broadly aligns with that of "high DE–high GI," providing descriptive support for the GI mechanism.

By 2016, the spatial structure had become more cluster-oriented. In Fig. 7a, the number of cities exhibiting higher DE together with higher LCD increases substantially, and these cities are increasingly concentrated within major urban agglomerations. Meanwhile, neighbouring areas more often shift toward intermediate combinations, which is consistent with the emergence of spatial spillovers. Digital development is no longer confined to isolated leading cities, and its low-carbon relevance becomes more visible at the regional scale. A similar strengthening is observed in Fig. 7b and Fig. 7c: the expansion of high-DE and high-GI cities and the corresponding rise in high-GI and high-LCD cities occur in a broadly matched way, implying that the spatial co-evolution among DE, GI, and LCD becomes tighter over time.

In 2023, the clustering of DE is further reinforced, and Fig. 7b shows an even clearer expansion of high-DE and high-GI combinations. Fig. 7c also exhibits a wider spread of relatively higher GI coexisting with relatively higher LCD, indicating that green innovation remains a key spatial channel through which DE may translate into LCD. At the same time, Fig. 7a suggests that the overall LCD level in 2023 is slightly weaker than in 2016 in some areas, even though the spatial concentration of higher DE continues to strengthen. This implies that while the long-run spatial linkage among DE, GI, and LCD becomes more pronounced, the absolute level of LCD may still be sensitive to post-2019 macro shocks, which can temporarily dampen LCD without overturning the structural relationship identified in the econometric results.

Overall, Fig. 7 provides an intuitive spatial complement to the mechanism and spillover analysis: as DE deepens and becomes more clustered, GI co-moves more closely with DE and aligns more visibly with LCD, motivating the subsequent use of spatial econometric models to formally test spillovers and the GI channel.

5.7.2. Model applicability test

In Table 11, the hypothesis that SDM can degenerate into a spatial lag model and a spatial error model is found to be not valid by the LR and Wald tests (*P* values are less than 0.01.) The Hausman test shows that the fixed effects model is applicable. Therefore, the fixed effects SDM model

Table 10
Test results of mechanisms.

Panel A: DE, total GI and LCD

(1)		(2)	
Ln (total GI)		LCD	
DE	0.034***	DE	−0.109
	(0.001)		(0.061)
LCD	0.762**	Ln (total) GI	0.033***
	(0.372)		(0.011)
Control variables	YES	Control variables	YES
Year fixed	YES	Year fixed	YES
City fixed	YES	City fixed	YES
Observations	4200	Observations	4200
R^2	0.875	R^2	0.155
Value of indirect effects (DE → Ln (total GI) → LCD)	0.0011		

Panel B: DE, GI of different innovation degree and LCD

(1)		(2)		(3)		(4)	
Ln (invention GI)		LCD		Ln (utility model GI)		LCD	
DE	0.021***	DE	−0.075**	DE	0.007**	DE	0.007
	(0.008)		(0.021)		(0.004)		(0.008)
LCD	2.466**	Ln (invention GI)	0.029**	LCD	−0.399***	Ln (utility model GI)	−0.013
	(0.595)		(0.014)		(0.071)		(0.008)
Control variables	YES	Control variables	YES	Control variables	YES	Control variables	YES
Year fixed	YES	Year fixed	YES	Year fixed	YES	Year fixed	YES
City fixed	YES	City fixed	YES	City fixed	YES	City fixed	YES
Observations	4200	Observations	4200	Observations	4200	Observations	4200
R^2	0.285	R^2	0.184	R^2	0.679	R^2	0.189
Indirect effects (DE → Ln (utility model GI) → LCD)		0.0006		Indirect effects (DE → Ln (utility model GI) → LCD)		−0.0009	

Panel C: DE, GI of different innovation chains and LCD

(1)		(2)		(3)		(4)	
Ln (source-control GI)		LCD		Ln (end-of-pipe GI)		LCD	
DE	0.049***	DE	−0.001	DE	0.017*	DE	0.009
	(0.003)		(0.010)		(0.010)		(0.009)
LCD	−0.170	Ln (source-control GI)	0.015**	LCD	1.391**	Ln (end-of-pipe GI)	0.008
	(0.168)		(0.007)		(0.615)		(0.009)
Control variables	YES	Control variables	YES	Control variables	YES	Control variables	YES
Year fixed	YES	Year fixed	YES	Year fixed	YES	Year fixed	YES
City fixed	YES	City fixed	YES	City fixed	YES	City fixed	YES
Observations	4200	Observations	4200	Observations	4200	Observations	4200
R^2	0.734	R^2	0.212	R^2	0.647	R^2	0.213
Indirect effects (DE → Source-control GI → LCD)		0.0007		Indirect effects (DE → End-of-pipe GI → LCD)		0.0001	

Panel D: DE, GI of different innovative subjects and LCD

(1)		(2)		(3)		(4)	
Ln (Enterprise GI)		LCD		Ln (university-research GI)		LCD	
DE	0.015***	DE	−0.011	DE	0.002*	DE	−0.003
	(0.0005)		(0.013)		(0.0009)		(0.010)
LCD	−0.519	Ln (Enterprise GI)	0.013**	LCD	1.237**	Ln (university-research GI)	0.026
	(0.297)		(0.005)		(0.576)		(0.017)
Control variables	YES	Control variables	YES	Control variables	YES	Control variables	YES
Year fixed	YES	Year fixed	YES	Year fixed	YES	Year fixed	YES
City fixed	YES	City fixed	YES	City fixed	YES	City fixed	YES
Observations	4200	Observations	4200	Observations	4200	Observations	4200
R^2	0.891	R^2	0.205	R^2	0.676	R^2	0.273
Indirect effects (DE → University-research institution GI → LCD)		0.0002		Indirect effects (DE → Enterprise GI → LCD)		0.00005	

Note: Control variables, year, and city fixed effects are included in Panels A-D but omitted here for space reasons. All green innovation indicators are calculated as the logarithm of (number of green patents per 100 + 1).

is employed.

5.7.3. *Analysis of nonlinear spatial effects: from neighbour-beggar to neighbour-companion*

Columns (1) and (2) in Table 12 report SDM results based on the geographic distance weight matrix to test the nonlinear spatial effect of DE on LCD. Column (1) shows that DE is positively associated with local LCD, but negatively associated with neighbouring cities' LCD. Building on the nonlinear effect of DE on local LCD, we further test whether DE also has a nonlinear spillover on neighbouring cities' LCD by adding the

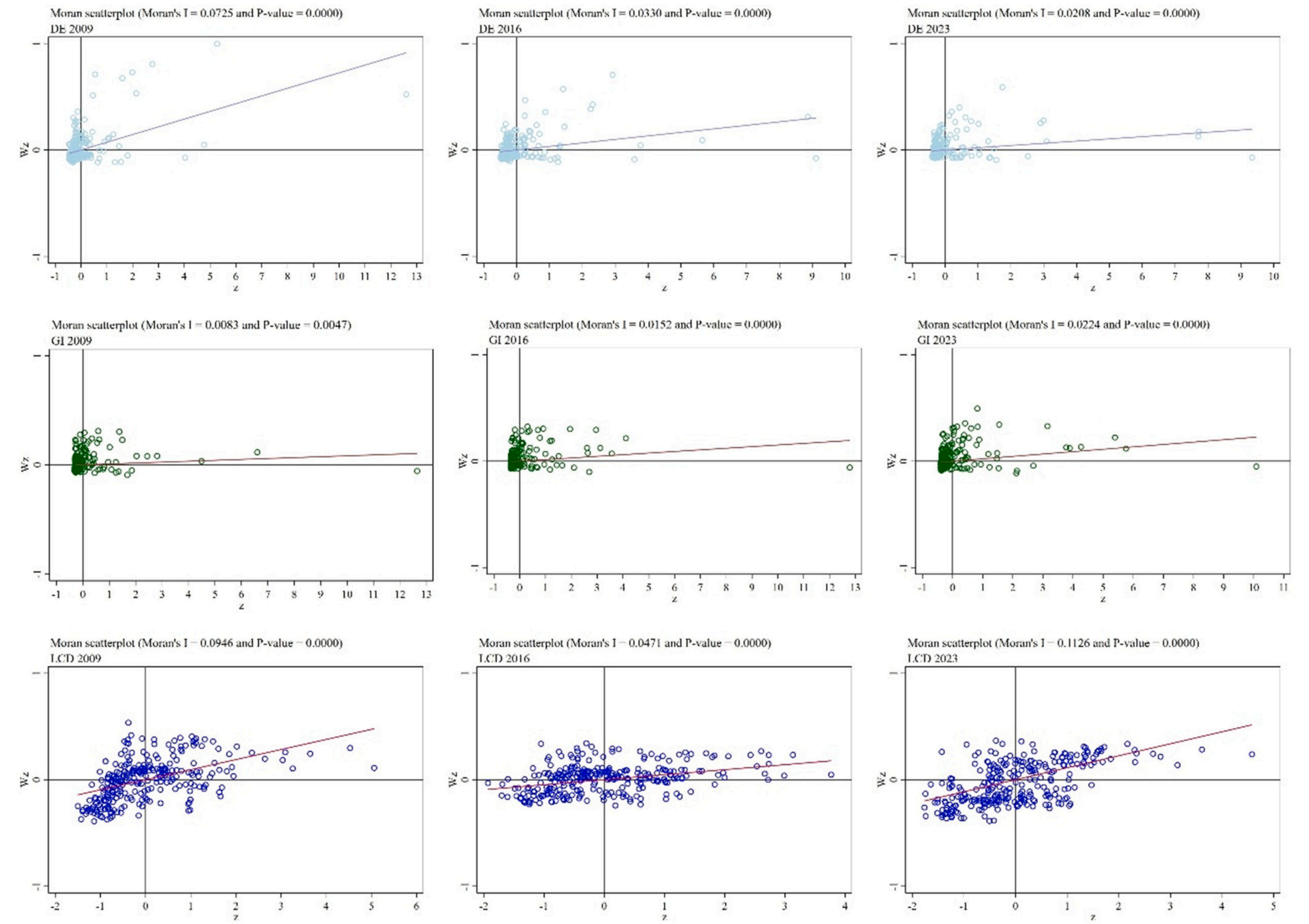

Fig. 6. Moran Index results for DE, GI and LCD.

squared term of spatially lagged DE. Column (2) shows a clear U-shaped relationship: at low DE levels, neighbouring cities' LCD is obviously suppressed (−0.365), but as DE deepens, the spillover turns positive and strengthens (0.023). This pattern is consistent with Li and Wang (2022). In the early stage, digital development is investment-intensive, and spillovers are limited, so leading cities may crowd out nearby areas through resource reallocation (Luo et al., 2023). In addition, inter-city competition in digital development can induce "catch-up" spending and higher energy use in surrounding cities, dampening their low-carbon performance (Zhang et al., 2022). Once DE reaches a more mature stage, diffusion and integration effects become stronger, facilitating the adoption of digital technologies and their integration with traditional industries in neighbouring cities, thereby improving LCD (Bai et al., 2023b). Overall, the spatial effect of DE evolves from an early "beggar-thy-neighbour" pattern to a later "neighbour-companion" pattern, echoing the regional technological catch-up mechanism emphasised by Lee (2013).

5.7.4. Re-testing from neighbour-beggar to neighbour-companion in different city economic zones

The results from the total domain spatial matrix indicate the presence of spatial nonlinearity in the impact of DE on LCD of neighbouring cities, transitioning from "neighbour-beggar" to "neighbour-companion". In fact, the existence of spatial nonlinear effects of DE on LCD may depend on specific distance conditions. For instance, the syphoning effect or spillover effect of DE may diminish gradually as the distance between two cities increases. The nonlinear impact of DE on LCD in neighbouring cities may have a more significant influence on cities that are closer together. Furthermore, the spatial clustering characteristics observed in DE and LCD, as demonstrated in section 5.6.1, can also lead to variations in results across different distance ranges. Therefore, we follow the approach of Bai et al. (2023b) and set a spatial weight matrix with thresholds of 100 km, 200 km, 300 km, 400 km, 500 km, and 600 km to examine the spatial nonlinear effects at varying distances from the city economic zones.

The results in Fig. 8 reveal that the spatial nonlinear impact varies significantly with geographical distance. Overall, the impact of DE and DE^2 on LCD of neighbouring cities follows a pattern of increasing and then decreasing, or even disappearing, with increasing distance. It reaches its peak within a distance range of 300 km. In 100–300 km, the impact of DE on the LCD of neighbouring cities exhibits a significant U-shaped relationship. However, this U-shaped relationship weakens when the distance exceeds 300 km, such as at 400 km, and disappears after 400 km. These findings suggest that the transition from the neighbour-beggar pattern to the neighbour-companion pattern occurs only within a specific geographical range. If the distance is too great, the environmentally friendly characteristics of DE and its spillover effect on LCD are relatively limited. This also indicates that there is a certain distance limitation for the positive radiation effect of DE, and a proximity principle applies to the facilitation effect of DE on LCD.

5.7.5. Mechanism tests for nonlinear spatial effects: green innovation spillover

Prior evidence suggests that GI and its spillovers are crucial for

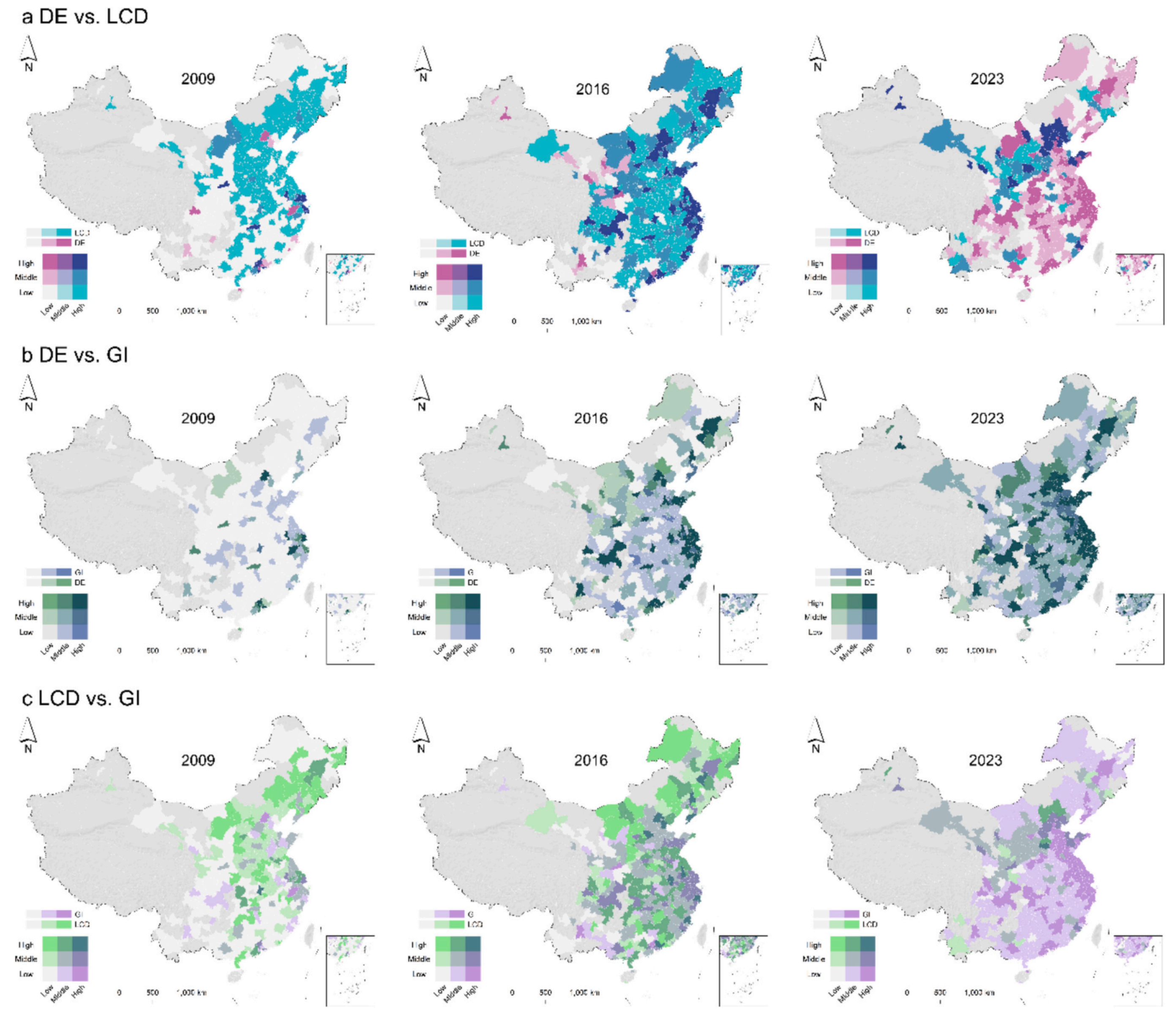

Fig. 7. Spatial correlation and evolutionary patterns.

Table 11
Applicability test of SDM.

Test type	Statistical value	P value
LR-spatial-lag	203.15	0.000
Wald-spatial-lag	123.46	0.009
LR-spatial-error	200.42	0.000
Wald-spatial-error	171.41	0.000
Hausman test	27.35	0.000

Table 12
Test of nonlinear spatial effects.

Variable	(1)	(2)
	LCD	LCD
DE	0.011**	−0.006
	(0.005)	(0.010)
DE^2		0.001**
		(0.0005)
WDE	−0.180**	−0.365***
	(0.084)	(0.131)
WDE^2		0.023**
		(0.009)
Control variables	Yes	Yes
Time fixed	Yes	Yes
City fixed	Yes	Yes
rho	0.909***	0.909***
	(0.023)	(0.023)
LogL	4154.91	4154.85
Observations	4200	4200
R^2	0.355	0.383

reconciling economic growth with CE reductions and for fostering low-carbon synergy across cities (Xu et al., 2021). Because the DE is also a key driver of green innovation, we further ask whether the observed shift in DE's spatial effect on LCD—from "neighbour-beggar" to "neighbour-companion"—operates through GI spillovers.

Table 13 provides evidence consistent with this channel. Column (1) shows that DE significantly increases local green innovation (0.024), while the contemporaneous spillover effect on neighbouring cities' green innovation is negative (−0.055). This suggests that, at relatively low levels of DE, green-technology diffusion across cities may remain weak

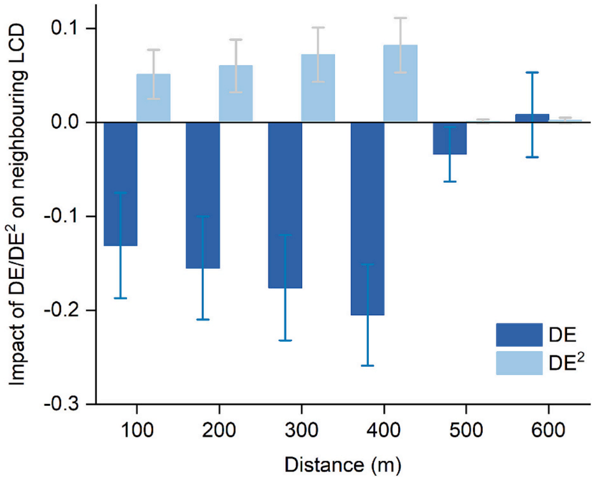

Fig. 8. The spatial nonlinear effects of DE on LCD at varying distances.

Table 13
Mechanism tests for nonlinear spatial effects.

Variable	(1)	(2)
	Total GI	Total GI
DE	0.024***	0.073
	(0.003)	(0.078)
DE^2		0.158**
		(0.062)
WDE	−0.055***	−0.143***
	(0.007)	(0.057)
WDE^2		0.012***
		(0.004)
Control variables	Yes	Yes
Time fixed	Yes	Yes
City fixed	Yes	Yes
rho	0.018***	0.165***
	(0.005)	(0.057)
LogL	4833.269	7702.657
Observations	4200	4200
R^2	0.547	0.863

and can even be offset by resource reallocation across space. When the nonlinear specification is introduced, Column (2) indicates a stage-dependent pattern. The promoting effect of DE on local green innovation strengthens as DE rises, and the spillover effect on neighbouring cities becomes U-shaped, shifting from inhibition to promotion. This spatial nonlinear pattern closely matches the U-shaped spillover found for LCD, which supports Hypothesis 3.2. The mechanism means that in the early stage, DE does not yet provide an efficient pathway for knowledge sharing and technology diffusion, so green-innovation spillovers are limited. At the same time, DE-driven restructuring can push pollution-intensive activities outward, which may bring non-green technologies into neighbouring areas and further weaken their green-innovation performance (Bai et al., 2023b; Dong et al., 2020). As DE deepens, digital platforms and cross-industry integration improve information flows and reduce the costs of technology exchange, allowing green technologies to diffuse more effectively across cities (Liu et al., 2022). Stronger green-innovation spillovers then contribute to improved LCD in neighbouring cities, which helps explain why the spatial effect of DE evolves toward a more cooperative outcome, as also documented by Li and Wang (2022).

6. Conclusions and discussion

In the context of mounting pressure for LCD in China, this study investigates the nonlinear impact of DE on LCD and the role of heterogeneous GI. Building on the environmental-sustainability perspective in innovation economics, the diffusion of digital technologies can redirect innovation toward greener trajectories and thereby support LCD. We also extend the analysis to the spatial dimension by examining how digitalisation, green-innovation spillovers, and LCD interact across regions. Using panel data for 280 Chinese cities over 2009–2023, we find that DE is associated with improved LCD overall, yet the relationship is distinctly nonlinear: at relatively low levels of DE, the effect on LCD is negative, whereas it turns positive as DE advances. Because the early-stage digital expansion is often accompanied by scale and adjustment pressures, the low-carbon gains are not immediately realised; once digitalisation deepens, efficiency improvements and cleaner upgrading become more salient, and the net effect turns favourable. Further tests show that GI plays a meaningful mediating role between DE and LCD, particularly through invention-based, source-control, and enterprise-led green innovation. The evidence is consistent with Freeman's view that major techno-economic shifts can be aligned with environmental sustainability: as a general-purpose technology, digitalisation increasingly supports LCD by weakening innovation path dependence and enabling higher-quality, more transformative green innovation.

Furthermore, the spillover effect of DE on neighbouring cities' LCD follows a U-shaped pattern. At earlier stages, the effect is negative, while it becomes positive as digitalisation advances. Green-innovation spillovers help explain this transition. In China's regional development setting, digital resources and innovation inputs often concentrate first in core cities within urban agglomerations, which can intensify factor reallocation toward the core and weaken latecomers' access to innovation networks. Under such conditions, spillovers are less likely to translate into observable low-carbon gains in the short run. As DE deepens, regional integration becomes more substantive. City-cluster planning and regional coordination policies improve intercity connectivity and strengthen cross-city collaboration in industrial upgrading and governance. Latecomer cities gradually build absorptive capacity and become better positioned to adopt external green knowledge. The diffusion and adoption of green innovations then become more feasible across city borders, and the spillover effect on neighbouring LCD turns supportive, contributing to a more coordinated low-carbon transition within regions.

This stage-dependent spillover pattern is also relevant for developing countries undergoing rapid structural change. In economies with large regional disparities, fast urbanisation, and ongoing industrial upgrading, early digital expansion may reinforce the concentration of digital capabilities in leading hubs, while surrounding areas benefit less from innovation spillovers. As digital infrastructure broadens and cross-regional linkages strengthen, spillovers can increasingly support wider low-carbon upgrading. The findings therefore provide a policy-relevant lens for countries pursuing digitalisation and climate goals in parallel, where narrowing the core–periphery divide and improving absorptive capacity are key to turning digital growth into region-wide low-carbon gains.

6.1. Theoretical implications

This study provides several significant theoretical implications. First, our findings highlight the key role of digitisation in promoting LCD. However, this effect is not immediately apparent at the outset of the DE's development. Instead, it is through the continuous penetration and diffusion of digital technology across various industries that its environmentally friendly characteristics are realised. Specifically, although studies have demonstrated the LCD effect of DE (Li et al., 2024), few have focused on whether this low-carbon effect is immediate or if it varies depending on the level of DE development. In addition, few studies have clearly demonstrated which Chinese regions have crossed the DE threshold that enables them to contribute to LCD. Our study bridges this gap by using a threshold regression model to identify which regions in China have already crossed the DE threshold and which have not. This approach provides valuable theoretical insights for adopting appropriate policies tailored to different regions.

Second, this study further advances research on using innovation for LCD in the context of digitisation by examining the role of green innovation in the impact of DE on LCD. It also highlights the differences in the roles played by various types of heterogeneous green innovations. Although existing studies have also examined the impact of technological innovation on LCD in the context of digitisation (Liu et al., 2024), they have only briefly analysed the role of total green innovation. In contrast, our study further focuses on the specific classification of green innovations, clarifying the roles played by different types of green innovations in the process of DE promoting LCD. Our exploration of different types of green innovations deepens the understanding of how to stimulate carbon-reducing green innovations to achieve LCD in the context of digitalisation. Specifically, our findings confirm the importance of firms as key agents of green innovation in driving LCD. Likewise, source-control green innovations and those with a high degree of invention play crucial roles in facilitating LCD.

More importantly, this study provides valuable insights into the much-debated spatial influence effect of DE on LCD. Our findings suggest that, while DE does promote local LCD, its impact on neighbouring regions follows a changing pattern of initially inhibiting and then promoting LCD. This shift reflects a transition from a "neighbour-beggar" effect to a "neighbour-companion" effect, indicating that the relationship is not a simple spatially linear one. We further analysed the specific transmission mechanisms, and the results show that green innovation not only plays a mediating role locally, but also that the spillover effects are a crucial transmission mechanism for the impact of DE on neighbouring LCD. It is the inhibitory and then facilitating relationship within the spillover effect of DE on green innovation that leads to the observed U-shaped relationship of DE's impact on neighbouring LCD. This finding is crucial because it not only highlights the existence of a spatial nonlinear impact of DE on LCD but also reveals that this nonlinear relationship is largely driven by green innovation spillovers. This phenomenon is closely related to the development cycle of digital technologies. Due to the innovation diffusion path dependency, an early-stage DE, lacking mature digital infrastructure and technologies, struggles to promote green investment, innovation, and generate spillover effects to neighbouring regions. However, as DE matures, advanced digital technology platforms facilitate faster dissemination of knowledge and technology. This promotes the diffusion of green innovations across regions, thereby helping to achieve synergies in LCD among regions.

Finally, our re-test analysis of the spatial dimension highlights the crucial role of geographic proximity in the DE's drive for inter-regional LCD. By re-testing the spatial nonlinear relationship between DE and LCD under different geographic matrices, we underscore the importance of geographic matrices in capturing the echo and diffusion effects that DE exerts on LCD in neighbouring regions. By emphasising the significant impact of DE on LCD within a 400 km range, our findings provide valuable insights and guidance for digital latecomers located at varying distances from digital economy pioneer regions. This can aid them in achieving green technology catch-up and fostering their own LCD.

6.2. Policy implications

First, given the pronounced stage-dependent effects of DE on LCD, local DE strategies should move beyond a scale-expansion mindset and adopt a differentiated approach oriented toward capability building and application outcomes. For cities with relatively weak digital foundations, a more realistic pathway is to prioritise closing gaps in data infrastructure, public digital platforms, and application standards systems, thereby forming a sustainable supply of digital capabilities. For digitally advanced cities, the emphasis should shift to deeper integration of digital technologies with industrial upgrading, energy management, and carbon governance, translating digital advantages into stable gains in energy efficiency and emissions-reduction performance, and avoiding a pattern of "high input, low conversion" in digital construction.

Second, considering both the transmission role of green innovation in the DE's contribution to LCD and the heterogeneity of that channel, the related policy support should shift from broad-based R&D incentives toward more targeted allocation linked to decarbonization performance, with a focus on easing constraints on firms' green R&D and innovation. Specifically, in terms of support priorities, local governments should steer more capital toward innovation domains that can directly reshape the emissions-generation process, and provide more stable medium- to long-term support for invention-oriented innovations with longer cycles and higher risks but more substantial long-run abatement benefits. In terms of policy targets, it is important to strengthen firms' leading role in green innovation and reduce the disconnect between theoretical innovation and industrialisation needs.

In addition, for resource-dependent cities and regions with relatively low levels of industrial-structure upgrading, governments should vigorously promote technological upgrading of traditional high-carbon capacities and foster substitute industries, while strengthening local technology absorption and supporting service capabilities, so as to improve the efficiency with which digital inputs are converted into low-carbon performance. By contrast, cities with higher administrative status and stronger factor agglomeration are better positioned to provide cross-regional demonstration effects and standards supply, developing replicable and scalable low-carbon technologies and governance solutions that help neighbouring cities collectively move past the phase turning point from "inhibition" to "promotion."

Finally, given the spatial nonlinearity in the DE's effects on LCD, regional-level coordinated governance is particularly important for crossing the turning point from "inhibition" to "promotion." In practice, coordination mechanisms across administrative boundaries can be strengthened at the scale of urban agglomerations and economic corridors. Through the interconnection of digital infrastructure, orderly sharing of data factors, and joint R&D on low-carbon technologies, the costs of regional environmental coordination can be reduced. The central government should also provide more targeted support to peripheral and late-developing regions to narrow the digital divide and the green-capability gap. Combined with institutional arrangements such as ecological compensation and linkage mechanisms in carbon markets, such efforts can curb inefficient competition and the shifting of externalities, guiding a pattern of green and digital coordinated development characterised by a clear division of labour and shared benefits.

6.3. Limitations and future studies

Compared to existing studies, there are still some limitations. Enterprise green innovation plays a more significant role in DE's impact on LCD compared to university-research institution green innovation. Considering that enterprises are a pivotal factor in CE control and an important innovation subject, future research will examine the effect of enterprise digital transformation on LCD and whether there are differences due to enterprise heterogeneity. In addition, pollutants and CE exhibit a high degree of similarity, both spatially and temporally (Li et al., 2022b). The control of both can be mutually reinforcing. Therefore, future research will focus on the impact of DE on the synergistic development for reducing pollution and carbon through green innovation.

CRediT authorship contribution statement

Tingting Bai: Writing – original draft, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Dong Xu:** Writing – original draft, Visualization, Validation, Investigation, Data curation. **Muhammad Ali Nasir:** Writing – review & editing, Validation, Supervision, Conceptualization.

Declaration of competing interest

No potential conflict of interest was reported by the authors.

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Appendix A. Supplementary data

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Data availability

Data will be made available on request.

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