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THE DIGITAL ECONOMY AND CITY INNOVATION CONVERGENCE – AN EMPIRICAL RESEARCH BASED ON THE INNOVATION VALUE CHAIN THEORY

Yijiu DING[1], Jianqiang GUO[1], Yu JI[2]✉, Kaiyi GUO[3], Shenglin MA[4]

[1] *School of International Business, Shandong Vocational University of Foreign Affairs, Weihai, China*
[2] *School of Economics, Changchun University, Changchun, China*
[3] *School of Business, Shandong University, Weihai, China*
[4] *School of Economics and Management, North University of China, Taiyuan, China*

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Abstract. Within China's strategy for innovation-driven development, digital economy (DE) plays a crucial role, significantly influences city innovation convergence. This study, grounded in the theoretical perspective of the innovation value chain theory (IVCT), divides innovation activities into two major phases: technological research phase and results transformation phase, and uses data from 283 Chinese cities spanning 2011 to 2021, it systematically explores, for the first time, the convergence characteristics of city innovation activities in each phase and delves deeply into the role of DE in this process. The findings reveal that city innovation in China's cities demonstrates notable convergence characteristics during both technological research and achievements transformation phases. These convergence traits persist in both phases, even when accounting for spatial effects, particularly regarding the engagement of DE. Furthermore, in technological research phase, fiscal pressures faced by local governments diminish the effectiveness of DE in fostering city innovation convergence; but, during achievements transformation phase, such fiscal pressures do not impede DE's capacity to enhance city innovation convergence. Lastly, the difference of city Innovation and entrepreneurial vitality during both technological research and achievements transformation phases restrict DE's potential to support city innovation convergence, with a more pronounced diminishing effect observed in technological research phase. This study provides important decision-making support for policymakers and helps further uncover and unleash the potential of DE in promoting city innovation convergence.

Keywords: digital economy, city innovation convergence, innovation value chain theory, fiscal pressure, city innovation and entrepreneurial vitality.

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✉Corresponding author. E-mail: ***dingyj9996@163.com***

1. Introduction

With the emergence of neoclassical growth theory, technological advancements have been recognized as a crucial factor that propels economic growth (Solow, 1956). As a prominent example of technological advancements, innovation inherently serves as the primary driving force behind both economic and social progress (Zhao et al., 2022). Innovation refers to the process of creating new products or services that did not previously exist, based on new ideas and utilizing new knowledge, and gaining market acceptance (Schumpeter, 1912). Centered around the core definition of innovation, the innovation value chain theory (IVCT) naturally emerges. As an important analytical framework for studying innovation-driven economic and social development, the basic content of IVCT posits that innovation is not merely a singular technology breakthrough or the generation of new ideas, but a continuous process involving multiple phases such as technological research, product development and commercialization (Hansen & Birkinshaw, 2007). From the fundamental viewpoint of IVCT, innovation is categorized into two principal phases: technological research and achievements transformation phases. These phases are interdependent and together form a comprehensive sequence of innovative activities. In technological research phase, innovation entities concentrate on discovering new knowledge and technologies to develop new production tools (Zhao et al., 2022; Li et al., 2021); however, during the achievements transformation phase, the goal of innovation efforts is to introduce new technological products to the market, thereby translating them into economic value and maximizing financial gains (Roper et al., 2008). Presently, the problem of economic inequality across different regions in China remains pronounced, with the disparities accentuated by variations in regional innovation capabilities (Lyu et al., 2023). This inequality not only highlights the differences in technological research abilities across regions but also significantly demonstrates the varying capacities of each region to utilize new technology advancements and generate economic value. Hence, analyzing the differences in regional innovation capacities at technological research and achievements transformation phases, from IVCT perspective, is vital for a comprehensive understanding of regional economic disparities and for addressing the innovation gap between regions, thereby facilitating the high-quality growth of an innovation-driven economy.

At the same time, the swift progress of advanced digital technologies – including artificial intelligence, cloud computing, and blockchain – has driven the expansion of digital economy (DE) at an extraordinary pace, highlighting notable transformative patterns (Xiao et al., 2023). The "White Paper on Global Digital Economy (2023)" (CAICT, 2024) (reveals that by 2023, the contribution of DE in the five leading countries – specifically USA, China, Germany, Japan, and South Korea – had reached $33 trillion, which represents over 60% of their gross domestic product, accompanied by an annual growth rate of 8% in DE's scale. This significant growth in the digital domain has notably impacted the innovative capacities of the conventional economy by effectively enabling its transformation, enhancement, and entrepreneurial drive (Paunov & Rollo, 2016; Niebel, 2018; Herman & Oliver, 2023). It serves as a crucial means to promote efficient resource utilization and accelerate the achievement of sustainable development (Wang et al., 2024b). As per data released by the "World Intellectual Property Report 2024" (WIPO, 2024), digital technologies have emerged as the leading force behind one-third of global innovations. In particular, the growth of patents related to digital advancements, especially in artificial intelligence and big data, is occurring at double the speed of patents in other industries. This highlights the emergence of DE as an essential catalyst for altering economic dynamics, enhancing efficiency, and improving quality (Sturgeon, 2021). Additionally, the spillover effects of knowledge and information generated by DE have greatly facilitated the cross-regional transfer of production factors, providing a practical avenue to mitigate regional disparities in innovation.

The phenomenon of convergence in economic development has been a vital area of examination within the field of macroeconomics for a considerable time (Baumol, 1986). According to Neoclassical Growth Theory, due to the effects of diminishing returns on production factors, regional economies often exhibit a pattern of convergence: areas with higher initial development standards generally experience slower growth, while those starting from lower levels can leverage advantages associated with being late entrants to their markets, enabling them to achieve rapid growth. This process ultimately results in a convergence of economic growth rates among these areas (Lall & Yilmaz, 2001). In contrast, Endogenous Growth Theory emphasizes the significance of innovation and introduces the concept of innovation convergence. This theory posits that innovation serves as a fundamental driver of economic growth, fostering a convergence in growth rates between regions that are late to develop – where rapid advancements in innovation capabilities occur – and those that are more established, where enhancements in innovation capabilities transpire more gradually (Barrios et al., 2019). This context reveals a clear trend of innovation convergence across different regions. In light of the growing DE, an important question arises: can DE, by mitigating disparities in regional innovation capabilities, empower regions with lower innovation capacities to capitalize on their latecomer status to achieve elevated levels of innovation growth, thereby promoting convergence in regional innovation? Ultimately, analyzing the characteristics of convergence in regional innovation through the lens of the IVCT within the context of DE not only holds significant theoretical relevance but also offers substantial practical benefits.

As city environments undergo rapid development, they increasingly serve as central entities of competition at both national and regional levels (Mullen & Marsden, 2015). Acting as hubs for concentrated innovative resources (Athey et al., 2008), cities not only attract significant talent, technology, and capital but also draw a diverse array of businesses and research institutions to establish their operations, thereby fostering a cohesive City Innovation Ecosystems (CIES) (Gomes et al., 2018). Meanwhile, the digital economy plays a significant role in urban development by enhancing city governance and boosting urban competitiveness (Cong et al., 2024). This study collects sample data from 283 cities across China, covering the period from 2011 to 2021, and constructs a comprehensive panel dataset. Utilizing the theory of CIES, it meticulously examines the core relationship between DE and city innovation convergence, while conducting empirical assessments. The main innovative contributions of this study are as follows: First, from the perspective of the IVCT, this paper divides innovation activities into two phases – technological research phase and achievements transformation phase – and systematically explores, for the first time, the convergence characteristics of city innovation activities in each phase, and analyzes the role of DE in this process. Considering that new economic geography suggests spatial correlations among cities and the strong spatial spillover effects of DE, this study employs the Spatial Durbin Model to investigate the impact of DE on the spatial convergence of innovation activities in each phase. Second, a spatial moderation effect model is developed to study the roles of two critical aspects of CIES – local government fiscal pressure and city innovation vitality – in the process by which DE influences city innovation convergence. To the best of our knowledge, this paper is the first to incorporate the spatial moderation effect model into studies related to innovation convergence. Third, from a public policy perspective, the paper proposes recommendations for improving investment in digital infrastructure to fully leverage the impact of DE on innovation convergence.

This paper is structured as follows: Section 2 analyzes the current literature on CIES within the framework of DE, providing a comprehensive assessment of existing knowledge and identifying areas that necessitate further exploration. Section 3 presents the research hypotheses, clearly delineating the specific questions and predictions that this study aims to examine and substantiate. Section 4 outlines the variables, methods, and data sources employed in the research, detailing the techniques and strategies used to empirically evaluate the hypotheses. Section 5 discusses and analyzes the empirical results, interpreting these findings and their significance for enhancing our understanding of CIES in the context of DE. Section 6 concludes with a summary of the study's results, highlighting the critical insights derived from the research and offering relevant policy recommendations informed by the outcomes.

2. Literature review

2.1. Digital economy (DE)

The concept of digital economy (DE) was first articulated by Tapscott in 1996, where it was described as an innovative economic structure primarily driven by digital technologies and operating through networks of human intellect. In the context of China, the "White Paper on China's Digital Economy" (CAICT, 2024) provides a comprehensive definition that encompasses three distinct yet interrelated layers of interpretation. Firstly, it identifies the core sectors of Information and Communication Technology (ICT) as the foundational industry of DE, highlighting its significant reliance on ICT assets. Secondly, within a more specific framework, DE is characterized by economic activities focused on the production of digital products and services, facilitated by the utilization of digital tools. Lastly, from a broader perspective, DE is defined by economic practices that prioritize digital innovation as the primary driving force, with data elements functioning as essential resources, internet platforms acting as critical conduits, and the emergence of new business formats and models as notable outcomes. This expansive definition also includes digital infrastructure, such as high-speed internet access, computing capabilities, and security services, along with various forms of e-commerce transactions, including B2B, B2C and C2C. The comprehensive nature of this definition closely links DE with the tangible economy, and its impact on innovation is particularly immediate and profound. Consequently, in alignment with the research approach employed by Zhang et al. (2023), this paper adopts this extensive definition of DE to enable a thorough and integrated analysis.

Currently, a strong connection exists between DE and capacity for innovation (Ding et al., 2021a). Innovations driven by DE have increasingly become a crucial factor in economic expansion, transcending the mere increase in the quantity of innovative outputs to significantly enhance the quality of these outcomes. This enhancement can be observed in two primary aspects. Firstly, companies, as key innovators, demonstrate the substantial impact of DE through their use of digital technologies. The adoption of these technologies fosters collaboration among firms, facilitates knowledge sharing (Pouri & Hilty, 2021) strengthens cooperative relationships, and enhances value creation among innovative entities (Pagani & Pardo, 2017). It also broadens the availability of innovation resources and cultivates a more conducive environment for overall innovation. Secondly, data has emerged as an essential element, influencing companies' production processes and leading to new resource combinations (Pan et al., 2022). This development expands the potential for innovation within organizations (Xiao et al., 2024), thereby fueling the continuous enhancement of their innovative capabilities. Furthermore, as DE integrates with and advances traditional industries, it has significant implications for innovation linkages, prompting improvements in industrial frameworks and supporting growth and innovation across the entire sector. Simultaneously, the reduces regional and sectoral barriers, facilitating the cross-border flow of innovation resources (Chen et al., 2023a). Consequently, this fosters pronounced spatial spillover effects and strengthens regional innovation capacities, further underscoring the transformative impact of DE on promoting innovation and economic growth.

2.2. City Innovation Ecosystems (CIES)

The investigation of ecosystems originated within the field of biology, with Moore (1993) being the pioneer who adeptly integrated the concept of ecosystems into economic analysis. This interdisciplinary approach transcended the limitations of traditional economic investigations, which primarily focused on isolated components such as businesses or industries. Instead, it cultivated a holistic perspective that views the economy as an interconnected organic system composed of numerous interrelated parts (Teece, 2007). Building on this foundation, the concept of innovation ecosystems emerged, representing a flexible and open framework that encompasses participants in innovation, who are in a state of continual evolution, a variety of innovative activities, a range of innovative offerings, and an environment conducive to innovation that significantly influences the innovation processes (Granstrand & Holgersson, 2020). Furthermore, the City Innovation Ecosystems (CIES), a specific application of innovation ecosystem principles at the city level, is characterized as a complex interactive network of diverse innovative actors and their associated innovation environments, highlighting the intricate relationship between city dynamics and the processes of innovation (Spigel, 2017).

The dynamics of evolutionary processes within CIES arise from the complex interactions among various innovation entities and the synergistic cycles that develop between these entities and their innovation context (Schwartz & Bar-El, 2015; Adner, 2006; Doloreux, 2002). Specifically, the innovation entities present in CIES can be categorized into three main types: technology-driven entities, which include enterprises; knowledge-based entities, represented by universities and research institutions; and service-oriented entities, exemplified by intermediary agencies and financial institutions (Liu et al., 2015; Gu et al., 2021). Within these CIES, knowledge-based entities are responsible for providing technology-driven organizations with innovative insights and concepts that are essential for fostering innovation. In turn, technology-driven entities transform this new knowledge and ideas into practical technologies and tools. Concurrently, service-oriented entities play a crucial role in supplying the necessary support resources for the entire innovation process (Liu et al., 2022). Furthermore, the setting for innovation, which is an essential element of the CIES, relates to the particular geographic environment where entities engaged in innovation function. This environment encompasses not only intangible factors such as cultural influences and regulatory frameworks but also tangible elements like infrastructure (Gomes et al., 2018). A high-quality and effective innovation environment has the potential to attract and integrate a diverse array of top-tier innovation components, thereby establishing a robust foundation and substantial support for those engaged in innovative activities. The innovation environment's evolution within CIES is influenced by governmental direction (Robaczewska et al., 2019) and affected by aspects like local geography, historical background, and cultural heritage (Liu et al., 2022).

2.3. Fiscal pressure

Fiscal pressure refers to the tense state or predicament faced by the government when its fiscal revenue is insufficient to meet the demand for fiscal expenditure, or when the growth rate of fiscal expenditure surpasses that of fiscal revenue, during the process of fulfilling its functions and providing public services (Ma & Qin, 2023; Xue et al., 2023). In the developing of city innovation environment, the government plays a crucial guiding and foundational role (Fan et al., 2021). Firstly, it implements various strategies, including direct financial incentives as well as specific tax reductions and exemptions, to bolster the innovative activities of entities engaged in innovation (Zhang & Song, 2022), thereby facilitating the growth of CIES. Secondly, the government actively supports the enhancement of innovation-related infrastructure, thereby creating a conducive physical setting for innovation endeavors (Chen et al., 2023b). Simultaneously, it fosters a positive soft environment for innovation by refining innovation policies, streamlining regulatory frameworks, and expediting administrative approvals (Peng & Tao, 2022). Consequently, the government enhances both the hard and soft dimensions of the city innovation environment, which leads to an improved CIES. Nonetheless, it is important to recognize that the series of initiatives implemented by the government to foster CIES heavily rely on substantial financial backing (Li & Yang, 2018). In reality, as the fiscal expenditures of local governments increase in numerous regions, the financial challenges they encounter are also becoming increasingly varied and complex (Zheng & Lu, 2021). The rise in fiscal pressure significantly impacts not only the patterns of revenue and expenditure behaviors undertaken by the government but also modifies the approach to economic intervention and encourages adjustments in the regional industrial framework (Kim & Warner, 2021). In terms of fiscal revenue, when faced with fiscal pressure, it is common for the government to intensify its tax collection and administration activities to secure a more robust tax income, thereby broadening the fiscal revenue base (Song & Zhang, 2021). This strategy undoubtedly heightens the tax obligations imposed on businesses, consequently increasing their operational expenses and negatively influencing their investments in innovation research (Ding et al., 2021b; Lerner, 2009). Regarding fiscal expenditures, the theory of austerity urbanism suggests that under fiscal strain, the government tends to drastically reduce public service funding (Peck, 2012), leading to a skewed fiscal expenditure that favors production over innovation (Zheng & Lu, 2021). This preference compresses the government's investment capacity in long-term, strategic sectors such as scientific and technology advancements, resulting in inadequate innovation infrastructure and services. Consequently, this hinders innovation entities' access to necessary resources and support (Yi et al., 2021). In summary, fiscal pressure triggers a transformation of various governmental actions, influences the city innovation landscape, and significantly affects the establishment of CIES.

2.4. City innovation and entrepreneurial vitality

City innovation and entrepreneurial vitality, as the core spirit of the CIES, is often used to describe the prosperity of a city's innovation and entrepreneurial activities during a specific period (Barreneche García, 2014). It encompasses various aspects such as the entrepreneurial environment, the innovation atmosphere, and the fluidity of innovation resources within the city. Furthermore, the activities related to city innovation demonstrate complex relationships with their local contexts, as each city possesses a distinctive innovation ecosystem and exhibits unique functional characteristics (Sun & Hou, 2019). The formation and expansion of CIES are significantly influenced by the surrounding innovation environment. Variations in innovation-related aspects, socio-economic structures, and industrial patterns across different cities result in notable diversity within their CIES. This diversity is reflected in the differing levels of vibrancy observed in city innovation and entrepreneurship (Escalona-Orcao et al., 2021; Sweeney, 1991). The city innovation and entrepreneurship vitality is the dynamic embodiment of new productive forces in the digital age (Elia et al., 2020). Notably, cities that exhibit strong innovation and entrepreneurial activity often foster a vibrant innovation culture, which attracts both talent and businesses, thereby promoting the ongoing rejuvenation of innovation entities and infusing lasting vigor into CIES. Furthermore, a thriving CIES for innovation and entrepreneurship significantly enhances resource sharing and information flow among various stakeholders, facilitating optimal resource distribution and improving the comprehensive efficacy of the innovation framework. Undoubtedly, the vibrancy of innovation and entrepreneurship in city areas plays a vital role in the development and sustainability of CIES. This energy not only serves as a vital indicator of CIES' health but also acts as a key catalyst for the continuous innovation and advancements of city.

2.5. Summary

In summary, existing studies have extensively explored the role of DE in driving innovation development and the CIES, offering significant reference value for this research. However, several gaps remain: first, while current literature focuses on the positive impact of DE on innovation, it has yet to sufficiently address its role in mitigating regional disparities in innovation capabilities and fostering city innovation convergence. Second, current research on the relationship between DE and innovation primarily focuses on innovation as technological research activities, without delving deeply into the entire innovation process. This has resulted in an incomplete understanding of innovation. Therefore, from the perspective of the IVCT, thoroughly examining the convergence characteristics of innovation activities at each phase holds significant research value. Third, few studies have analyzed how CIES, particularly in terms of fiscal pressure and Innovation and Entrepreneurial Vitality, influence the process by which DE promotes city innovation convergence. While some research has begun to touch upon these issues, delving deeper into how DE affects the convergence characteristics of innovation in the phases of technological research and achievement transformation – while considering the roles of local fiscal pressure and innovation and entrepreneurial vitality – remains a valuable avenue for exploration. This provides an opportunity for further advancement in this field of study.

3. Research hypotheses

3.1. The role of DE in city innovation convergence

In the realm of development driven by innovation, the significance of DE has increasingly come to the forefront. Its impaction is evident through knowledge spillover effects and substantial externalities (Colombelli et al., 2024), enabling DE to transcend geographical barriers among cities, thereby greatly improving regional integration and facilitating connections between previously isolated CIES. In turn, this leads to the establishment of a more extensive regional innovation network (Liu et al., 2022). Such interconnections enhance the exchange of knowledge across CIES among cities, thereby expediting collaborative innovation efforts. During technological research phase, the regional innovation network serves as a foundation for DE, allowing innovation entities within each CIES to access diverse external information and technology assets. This access fosters the smooth movement of research resources between different CIES (Colombelli et al., 2024). Throughout this process, innovation actors in less developed CIES can integrate into the broader regional innovation activity chain, leveraging their unique capabilities to reduce the technology divide with more advanced CIES through learning and imitation (Shankar et al., 1998), subsequently encouraging a convergence trend in city innovation during the technological research phase. As innovation initiatives move into achievements transformation phase, DE become increasingly essential for improving the effectiveness of information dissemination. They facilitate the rapid exchange and promotion of innovative results among different entities within various CIES. By leveraging the regional innovation network, these CIES enable stakeholders to efficiently share their advancements, ensuring that groundbreaking ideas and solutions reach a wider audience promptly. This interconnectedness not only accelerates the distribution of knowledge but also fosters collaboration and synergy among diverse players in the innovation landscape. This significantly advances the cross-CIES application and realization of these innovations (Su et al., 2023). Simultaneously, DE has the potential to augment the efficiency of the entire industrial chain, leverage regional innovation networks to facilitate the integration of economies of scale and scope (Peng et al., 2023), improve product matching across CIES, and reduce circulation time. This fosters the cross-CIES transformation of innovative achievement, narrows the disparities in achievement transformation capabilities among CIES, and further initiates a convergence trend in innovation capabilities at the city level during achievements transformation phase. Given this analysis, the current paper formulates the following research Hypothesis:

H1: *DE can improve city innovation convergence during both technological research and achievements transformation phases.*

3.2. The moderating role of fiscal pressure

During technological research phase, DE – characterized by its significant knowledge and information spillover effects – greatly enhances the movement of innovation components within CIES, thus serving as a vital element propelling city innovation convergence forward. To fully harness the catalytic influence of DE in this context, a strong digital infrastructure is crucial as a foundational support (D'Amico et al., 2021). Acting as the bedrock of DE, this infrastructure delivers essential physical and technical backing for a range of digital economic endeavors (Wang et al., 2024a). Considering the extensive timeframes and the considerable investments needed for developing digital infrastructure, alongside its public good attributes of being non-excludable and non-competitive (Li, 2020), substantial government financial backing is frequently required for its advancement. However, in situations where governments encounter fiscal strains, their expenditure priorities tend to lean towards a "heavy on assets, light on innovation" approach (Zheng & Lu, 2021), focusing on investments in lower-risk projects that yield quick returns (Grisorio & Prota, 2015). Given that digital infrastructure initiatives are inherently long-term and carry considerable risk, they are particularly vulnerable to fiscal constraints, which can result in insufficient digital infrastructure. In turn, this impacts the efficiency of DE and diminishes its capacity to foster city innovation convergence during the technological research phase. As innovation activities advance into achievements transformation phase, the focus shifts to applying existing research achievement in production and everyday life, thus turning them into economic advantages. This phase increasingly depends on market dynamics (Chiesa & Frattini, 2011) and is comparatively less influenced by fiscal pressures. A strong market environment and a well-organized industrial framework are essential for promoting the transformation and application of scientific and technology advancements. This process not only yields economic advantages but also strengthens and integrates the abilities to transform city innovation achievement. Consequently, even in times of fiscal constraints, governments are less likely to experience significant adverse effects on the transformation of innovative accomplishments. Based on this analysis, the subsequent Hypotheses are presented in this paper:

H2: *During technological research phase, fiscal pressures experienced may reduce the capacity of DE to promote city innovation convergence. Conversely, during achievements transformation phase, fiscal pressures do not affect the ability of DE to facilitate city innovation convergence.*

3.3. The moderating role of city innovation and entrepreneurship vitality

City innovation and entrepreneurship vitality act as focused examples of the innovative environmental characteristics found within CIES. This dynamic significantly influences the development of CIES and is vital to the role of DE in driving city innovation convergence. During technological research phase, a key factor enabling DE to enhance city innovation convergence is its capacity to facilitate the cross-CIES exchange of information and knowledge among cities. However, while knowledge and information are critical components of technological research, traditional resources such as skilled labor and financial capital remain essential determinants of success in this domain (Sun et al., 2020; Lin & Ma, 2022). In resource allocation, the vitality of city innovation and entrepreneurship exerts a crucial effection, particularly evident in the effects of capital scaling and entrepreneurial clustering (Liu & Liu, 2024). Specifically, cities characterized by high levels of innovative vitality are typically more adept at attracting and consolidating significant investments, skilled personnel, and technology resources (Lee et al., 2004), integrating these assets with the knowledge and information provided by DE. This integration enables them to advance new technological research successfully and achieve innovative outcomes. Such phenomena during the technological research phase can exacerbate the innovation gap among cities, creating challenges for city innovation convergence. As innovation activities transition into the application realization phase, the influence of DE primarily revolves around facilitating information flow, while the market's acceptance of innovation outcomes becomes increasingly crucial for their successful implementation (Romano, 1990). In this context, city areas characterized by a high level of entrepreneurial energy showcase distinct advantages. Such cities are not only vibrant economically (Sun & You, 2023) but also show a greater propensity to experiment with new technologies, resulting in a comparatively quicker rate of technology adoption. Conversely, cities with lower levels of innovation vitality frequently face slower dissemination of innovative products due to a lack of consumer awareness regarding new technologies or a more traditional market attitude. This issue during the stage of transforming achievement could exacerbate the innovation gap between different cities, underscoring the critical role of city innovation and entrepreneurial dynamism in fostering market acceptance of innovative solutions. Given this analysis, the current paper formulates the following research Hypothesis:

H3: *Throughout both technological research and achievements transformation phases, city innovation and entrepreneurship vitality may diminish capacity of DE to enhance city innovation convergence.*

4. Research design

4.1. Variable measurement

4.1.1. Dependent variable

As a holistic metric, city innovation efficiency considers both the input and output stages of innovation, thereby providing a more accurate assessment of a city's innovative capabilities. Drawing on the methodologies utilized by Bai and Chen (2022), this study employs city innovation efficiency to evaluate the innovation potential of various cities. Among the diverse approaches to assessing innovation efficiency, Stochastic Frontier Analysis (SFA) establishes a specific production function during its computations, which provides a solid economic foundation and more accurately reflects real-world innovation dynamics. Furthermore, SFA differentiates technology inefficiencies from the error component, enabling the estimation of innovation efficiency in a parametric format that minimizes the influence of errors. Given the substantial volume of data in this research, and considering that the experimental data comprises panel data, we implement the method proposed by Kumbhakar and Lovell (2003) to develop a panel random frontier model for evaluating city innovation efficiency.

Adhering to the research methodology delineated by Wen et al. (2023), the general structure of the test model is established as follows:

$$y_{it} = f(x_{it}, b)\exp(v_{it} - u_{it}). \quad (1)$$

In this expression, y_{it} indicates the output for city i during period t; the function $f\left(x_{it}, \beta\right)$ characterizes the production process, where x_{it} refers to the input factors utilized by city i at time t, and β represents the corresponding coefficient. The term $exp\left(v_{it}\right)$ acts as a stochastic disturbance component, while $exp\left(-u_{it}\right)$ illustrates the efficiency of input-output related to innovative research and development for a city. By applying the logarithmic transformation, we derive:

$$\ln y_{it} = \ln(x_{it}, \beta) + v_{it} - u_{it}. \tag{2}$$

Building upon the foundational structure of IVCT, this paper categorizes innovation activities into two distinct stages, with the outcomes of innovation efforts serving as the delineation point. In technological research phase, there are two types of configurations for the input-output functions: the C-D production function and the transcendental logarithmic production function. As the objective of this study is to evaluate technological research efficiency within the broader context of city innovation efficiency, rather than examining the effects of specific factors, we utilize the research methodology proposed by Bai and Chen (2022) and select the C-D production function as the primary configuration for the input-output model in this study. The model is defined as follows:

$$\ln patent_{it} = \alpha_0 + \alpha_1 \ln k_{it} + \alpha_2 \ln l_{it} + v_{it} - u_{it}. \tag{3}$$

In the model: *patent* indicates a product of innovation, k signifies innovation capital input and l represents the input of innovation personnel; α_1 and α_2 respectively denote the output elasticity of capital and labor. In terms of innovation input, following the principle of indicator selection set by Fan et al. (2021), the number of people employed in scientific research, technology services and geological exploration in each city is selected to measure the level of innovation talent input. For research capital input, this paper uses the level of technology expenditure as a measurement. In relation to innovation output, considering the intuitiveness of patents in reflecting achievement in technology innovation, they can be used to measure the output of innovation. The research method established by Bai and Jiang (2015) is adopted to use the number of patents granted in each region as the output variable for the measurement of innovation efficiency. Meanwhile, this paper further assumes that the noise from the impact of uncontrollable factors follows a normal distribution and is independent of the characteristic variables, which will be truncated at zero. Consequently, the city innovation efficiency in the technological research phase, or namely technological research efficiency (TIE) can be defined as:

$$TIE_{it} = \exp(-u_{it}). \tag{4}$$

In achievements transformation phase, the final output from technological research, when integrated with various market transformation resources, plays a crucial role in fostering regional economic development. Following the research methodology outlined by Zhang et al. (2023), we consider the volume of patent applications as a key indicator of innovative input during this phase, while city per capita GDP serves as the ultimate measure of innovation output. To establish the function, we utilize the C-D production function, with the detailed model presented in Equation (5).

$$\ln PGDP_{it} = b_0 + b_1 \ln patent_{it} + v_{it} - u_{it}. \tag{5}$$

In the model: $\ln PGDP_{it}$ represents the total production value of a certain region i at time period t after eliminating dimension differences and taking logarithms, indicating the ultimate output level of innovation, and b_1 refers to the output elasticity of patent achievement. Meanwhile, this paper further assumes that the noise from the impact of uncontrollable factors follows a normal distribution, is independent of the characteristic variables, and the characteristic variables will be truncated at zero. Therefore, the innovation efficiency of city innovation efficiency in achievements transformation phase, or namely achievement transformation efficiency (ATE), can be defined as:

$$ATE_{it} = \exp(-u_{it}). \tag{6}$$

4.1.2. Independent variable

Following the methods in literature such as (Pan et al., 2022), representative indicators reflecting DE infrastructure, digital industries or industrial digitalization are used to comprehensively assess DE development level of a region. Specifically, this paper primarily uses the following five categories of indicators: the proportion of Internet broadband access users per hundred individuals, the ratio of employees in the computer service and software industry to urban unit employees, average telecommunication service volume per person, the proportion of mobile phone users per hundred individuals, and the "Peking University Digital Inclusive Finance Index" proposed by Guo et al. (2020). The entropy approach is utilized to thoroughly assess the development level of cities at the prefectural level concerning DE.

4.1.3. Regulating variable

Fiscal pressure mainly manifests as an ongoing imbalance between local governments' revenues and expenditures, leading to a budget deficit. This study builds upon the existing literature, utilizing the index construction method proposed by Ma and Qin (2023), and evaluates fiscal pressure from both revenue and expenditure perspectives. On one hand, local government fiscal expenditure primarily consists of expenses related to debt and public-private partnership (PPP) fiscal disbursements. Due to the delayed availability of data on PPP expenditures and significant gaps in sample data, this paper opts to evaluate fiscal repayment obligations through the balance of local government debt. Conversely, recognizing that the principal sources of local government fiscal revenue stem from the general public budget and governmental fund budget, which also serve as key sources for repaying government debt and PPP liabilities, this study measures local government fiscal revenue by aggregating the general public budget revenue with governmental fund income. Following the analysis of both revenue and expenditure, the fiscal pressure index is devised as follows:

$$Fpwoer_{it} = \frac{Debt_{it}}{Rev_{it} + Fund_{it}}, \tag{7}$$

where $Fpwoer_{it}$ represents fiscal pressure; $Debt_{it}$ represents the balance of local government debt, including both general debt and special debt; Rev_{it} represents the income from the general public budget, and $Fund_{it}$ represents the income from government funds.

The city innovation and entrepreneurship vitality serves as a key indicator of the extent of entrepreneurial activities in a particular area and is frequently utilized to evaluate entrepreneurship on a larger scale. This study utilizes the methodologies delineated by Bai et al. (2022), in which the quantity of new startups established in each city during the observation period is collected using the "Qichacha" database https://www. qcc.com/, with the city's population serving as the standard reference. Consequently, the calculation of new startups per hundred individuals is conducted and utilized as an indicator of the city's entrepreneurial vitality.

4.1.4. Control variable

To mitigate the effect of omitting variables on estimates, this study employed control variables following the approaches established by Zhang et al. (2023), Huang et al. (2019) and other relevant studies for the following factors: (1) Education level (*edu*): The degree of education is closely linked to the standard or condition of the labor market and the human capital necessary for fostering innovation. Increased educational attainment leads to a greater number of R&D personnel and higher-quality human resources. In this paper, the level of education in a region is assessed using the proportion of government education spending to GDP. (2) Basic communication level (*ppost*): Communication infrastructure plays a crucial role in the progress of DE. The quality of basic communication services serves as a direct indicator of the sophistication and reach of a city's information and communication technology framework. This study measures this aspect through per capita income derived from postal and telecommunications services. (3) Financial environment (*fina*): The financial sector plays a pivotal role in promoting innovation, influencing both the accessibility and costs associated with funding innovative endeavors. A favorable financial climate supports innovative institutions by supplying necessary financial resources, thereby facilitating the successful execution of innovative projects. This study measures the financial landscape by assessing the ratio of bank loan amounts in comparison to GDP. (4) Industrial structure (*inds*): Various industries exhibit different degrees of technology intensity, innovation propensity, and research and development needs. The enhancement and reconfiguration of industrial structures significantly influence the innovation efficiency of a city. This research utilizes the proportion of value added in the secondary sector compared to that in the tertiary sector as a metric for evaluation. (5) Standard of living (*green*): Cities with elevated living standards tend to attract migrants, thereby broadening the landscape for innovative endeavors. The standard of living is assessed in this paper by measuring per capita green space.

4.2. Estimation method

The measurement methods for innovation convergence mainly include σ-convergence and β-convergence. σ-convergence refers to the gradual narrowing of innovation dispersion in different regions over time. β-convergence refers to an inverse relationship between the innovation growth rate in different regions and the initial level, i.e., the more backward the region, the faster the innovation capability growth, ultimately achieving a convergent development across different regions (Cook, 2012). Firstly, to test the convergence of innovation in Chinese cities, this study draws upon the research methodologies established by Cheng et al. (2020), based on the perspective of IVCT, constructing absolute β-convergence models and conditional β-convergence models from both of technological research and achievements transformation phases. Secondly, to investigate how DE influences innovation convergence in cities across China, this research refers to the treatment methodology of Yang et al. (2021), constructs an interaction term between DE and innovation convergence. The coefficient of this interaction term reveals the influence of DE on the innovation convergence process. The model construction is as follows:

$$DTIE_{it} = \alpha_0 + \beta \ln(TIE_{it-1}) + \beta_1 DE_{it} + \beta_2 \ln(TIE_{it-1}) \times DE_{it} + \alpha_1 \Sigma control_{it} + \mu_i + \sigma_{tp} + \varepsilon_{it}; \quad (8)$$

$$DATE_{it} = \alpha_0 + \beta \ln(ATE_{it-1}) + \beta_1 DE_{it} + \beta_2 \ln(ATE_{it-1}) \times DE_{it} + \alpha_1 \Sigma control_{it} + \mu_i + \sigma_{tp} + \varepsilon_{it}, \quad (9)$$

where $DTIE_{it} = (1/T) ln(TIE_{it} / TIE_{it-T})$ represents the technological research growth rate of city i in year t, $DATE_{it} = (1/T) ln(ATE_{it} / ATE_{it-T})$ represents the result transformation growth rate of city i in year t. Here, T represents the time period of the sample set, and this study sets the time period $T = 1$. In the model, β is the convergence coefficient. If $\beta < 0$, it indicates a convergence trend in innovation, namely the innovation growth speed in less developed areas is faster than in more developed areas, and vice versa. β_2 represents the coefficient of the interaction term between the development variable DE and city innovation convergence. If the direction of β_2 is consistent with the direction of the convergence coefficient β, it indicates that DE significantly intensifies city innovation convergence. $control_{it}$ represents control variables, μ_i represents the fixed effects of individual city entities, σ_{tp} signifies fixed effects interacting between time and provinces, and ε_{it} stands for random disturbances. To provide the convergent coefficient with more intuitive economic implications, this paper conducts a de-centralization process on the interaction terms in actual analysis.

Furthermore, to investigate the influence of DE on city innovation convergence, taking into account spatial factors, this research draws upon the methodologies employed by Feng et al. (2023) and develops an SDM model that incorporates interaction terms. The specific model construction is as follows:

The impact of DE on city innovation convergence during the technological research phase is shown in Equation (10).

$$\begin{aligned} DTIE_{it} &= \alpha_0 + \beta \ln(TIE_{it-1}) + \beta_1 DE_{it} + \beta_2 \ln(TIE_{it-1}) \times DE_{it} + \alpha_1 \Sigma control_{it} + \\ &\rho \Sigma \omega_{ij} DTIE_{jt} + \theta \Sigma \omega_{ij} \ln(TIE_{jt-1}) + \varphi_1 \Sigma \omega_{ij} DE_{jt} + \varphi_2 \Sigma \omega_{ij} \ln(TIE_{jt-1}) \times DE_{jt} + \\ &\varphi_3 \Sigma \omega_{ij} control_{jt} + \mu_i + \sigma_t + \varepsilon_{it}. \end{aligned} \quad (10)$$

The impact of DE on city innovation convergence during the achievements transformation phase is shown in Equation (11).

$$\begin{aligned} DATE_{it} &= \alpha_0 + \beta \ln(ATE_{it-1}) + \beta_1 DE_{it} + \beta_2 \ln(ATE_{it-1}) \times DE_{it} + \alpha_1 \Sigma control_{it} + \\ &\rho \Sigma \omega_{ij} DATE_{jt} + \theta \Sigma \omega_{ij} \ln(ATE_{jt-1}) + \varphi_1 \Sigma \omega_{ij} DE_{jt} + \varphi_2 \Sigma \omega_{ij} \ln(ATE_{jt-1}) \times DE_{jt} + \\ &\varphi_3 \Sigma \omega_{ij} control_{jt} + \mu_i + \sigma_t + \varepsilon_{it}, \end{aligned} \quad (11)$$

where ω_{ij} signifies the spatial weight matrix, θ represents the spatial spillover effect coefficient of proximate city innovation levels, ρ is the coefficient of the spatial lag term of the dependent variables, and φ is the coefficient of the spatial lag term. If both the convergence coefficient β and interaction term coefficient β_2 are significantly negative, this implies that DE promotes the strengthening of the negative correlation between the growth rates of city innovation and their initial levels of innovation. That is to say, DE helps promote city innovation convergence, decrease disparities in innovation across regions, and foster the formation of a balanced regional innovation pattern.

Although SDM with interaction terms demonstrates superior performance in revealing the effect of DE on city innovation convergence, it is undeniable that SDM itself has certain limitations. The estimation results of SDM are highly dependent on the construction of the spatial weight matrix, which is often based more on the subjective judgment of researchers, lacking solid economic theory support. This situation leads to the possibility that SDM constructed based on different spatial weight matrix settings may yield significantly divergent estimation results. To minimize the chance of deriving accidental conclusions due to improper use of the spatial weight matrix, this study employs various types of spatial weight matrices for comparative analysis during the analytical process. Considering that although the spatial spillover effect of DE facilitates the flow of intangible resources such as information across geographic and temporal boundaries, the corresponding physical and human resources cannot easily achieve extensive cross-regional flow. Their movement is more confined to small-scale intercity interactions among nearby cities, leading to a more pronounced spatial correlation between each city and its neighboring cities in geographic space. Because of the stronger geographical spatial correlation between each city and its surrounding cities, this study employs the geographic distance matrix alongside the adjacency matrix to serve as the spatial weight matrix. In the case of the geographic distance matrix, a greater spatial distance between different cities results in lower weights and weaker correlations between them. The specific geographic distance matrix value used implies that each city has a strong correlation with nearby cities but a weaker correlation with those located in more distant regions. This study analyzes the spatial spillover effect using both a spatial adjacency matrix and a geographical distance matrix.

$$\omega_{ij}^{1} = \begin{cases} 1, \, i \text{ and j share common border} \\ 0, \, i \text{ and j share common border} \end{cases}'$$

$$\omega_{ij}^{2} = \begin{cases} \dfrac{1}{d^2}, \, i \neq j \\ 0, \quad i = j \end{cases}, \tag{12}$$

where d represents the geographical distance between the government seats of city i and city j. If the convergence coefficient β is significantly negative, it indicates a convergence in regional innovation. If both the convergence coefficient β and the interaction term coefficient β_2 are significantly negative, this demonstrates DE helps reinforce the inverse correlation between regional innovation growth rates and initial innovation levels. This suggests DE is beneficial for promoting city innovation convergence, for reducing the disparity in innovation between cities, and for encouraging the formation of a balanced regional innovation pattern.

Furthermore, this paper incorporates two moderating variables, fiscal pressure and city innovation and entrepreneurial vitality, during the analysis process. Their mechanism roles in the process of DE promoting city innovation convergence are examined. Following the approach of Dawson and Richter (2006), a multi-interaction term method is adopted, and fiscal pressure and city innovation and entrepreneurial vitality are respectively included in the model. Simultaneously, considering that the issue of city innovation convergence possesses strong spatial effects, The research utilizes the approach established by Feng et al. (2023) and develops a SDM model that incorporates various moderating effects of multiple variables.

The development of the SDM, incorporating the moderating effect of fiscal pressure, is as follows:

Equation (13) reflect the moderating role of fiscal pressure in the process of city innovation convergence influenced by DE during the technological research phase.

$$\begin{aligned} DTIE_{it} &= \alpha_0 + \beta \ln(TIE_{it-1}) + \beta_1 DE_{it} + \beta_2 Fpwor_{it} + \beta_3 \ln(TIE_{it-1}) \times DE_{it} + \\ &\beta_4 \ln(TIE_{it-1}) \times Fpower_{it} + \beta_5 DE_{it} \times Fpower_{it} + \beta_6 \ln(TIE_{it-1}) \times DE_{it} \times Fpower_{it} + \\ &\alpha_1 \Sigma control_{it} + \rho \Sigma \omega_{ij} DTIE_{jt} + \theta \Sigma \omega_{ij} \ln(TIE_{jt-1}) + \varphi_1 \Sigma \omega_{ij} DE_{jt} + \varphi_2 \Sigma \omega_{ij} Fpwoer_{jt} + \\ &\varphi_3 \Sigma \omega_{ij} \ln(TIE_{jt-1}) \times DE_{jt} + \varphi_4 \Sigma \omega_{ij} \ln(TIE_{jt-1}) \times Fpwoer_{jt} + \varphi_5 \Sigma \omega_{ij} DE_{jt} \times Fpwoer_{jt} + \\ &\varphi_6 \Sigma \omega i_j \ln(TIE_{jt-1}) \times DE_{jt} \times Fpwoer_{jt} + \varphi_7 \Sigma \omega_{ij} control_{jt} + \mu_i + \sigma_t + \varepsilon_{it}. \end{aligned} \tag{13}$$

Equation (14) reflect the moderating role of fiscal pressure in the process of city innovation convergence influenced by DE during the achievements transformation phase.

$$\begin{aligned} DATE_{it} &= \alpha_0 + \beta \ln(ATE_{it-1}) + \beta_1 DE_{it} + \beta_2 Fpwor_{it} + \beta_3 \ln(ATE_{it-1}) \times DE_{it} + \\ &\beta_4 \ln(ATE_{it-1}) \times Fpower_{it} + \beta_5 DE_{it} \times Fpower_{it} + \beta_6 \ln(ATE_{it-1}) \times DE_{it} \times Fpower_{it} + \\ &\alpha_1 \Sigma control_{it} + \rho \Sigma \omega_{ij} DATE_{jt} + \theta \Sigma \omega_{ij} \ln(ATE_{jt-1}) + \varphi_1 \Sigma \omega_{ij} DE_{jt} + \varphi_2 \Sigma \omega_{ij} Fpwoer_{jt} + \\ &\varphi_3 \Sigma \omega_{ij} \ln(ATE_{jt-1}) \times DE_{jt} + \varphi_4 \Sigma \omega_{ij} \ln(ATE_{jt-1}) \times Fpwoer_{jt} + \varphi_5 \Sigma \omega_{ij} DE_{jt} \times Fpwoer_{jt} + \\ &\varphi_6 \Sigma \omega i_j \ln(ATE_{jt-1}) \times DE_{jt} \times Fpwoer_{jt} + \varphi_7 \Sigma \omega_{ij} control_{jt} + \mu_i + \sigma_t + \varepsilon_{it}. \end{aligned} \tag{14}$$

Equation (15) reflect the moderating role of city innovation and entrepreneurial vitality in the process of city innovation convergence influenced by DE during the technological research phase.

$$\begin{aligned} DTIE_{it} &= \alpha_0 + \beta \ln(TIE_{it-1}) + \beta_1 DE_{it} + \beta_2 Ivitality_{it} + \beta_3 \ln(TIE_{it-1}) \times DE_{it} + \\ &\beta_4 \ln(TIE_{it-1}) \times Ivitality_{it} + \beta_5 DE_{it} \times Ivitality_{it} + \beta_6 \ln(TIE_{it-1}) \times DE_{it} \times Ivitality_{it} + \\ &\alpha_1 \Sigma control_{it} + \rho \Sigma \omega_{ij} DTIE_{jt} + \theta \Sigma \omega_{ij} \ln(TIE_{jt-1}) + \varphi_1 \Sigma \omega_{ij} DE_{jt} + \varphi_2 \Sigma \omega_{ij} Ivitality_{jt} + \\ &\varphi_3 \Sigma \omega_{ij} \ln(TIE_{jt-1}) \times DE_{jt} + \varphi_4 \Sigma \omega_{ij} \ln(TIE_{jt-1}) \times Ivitality_{jt} + \varphi_5 \Sigma \omega_{ij} DE_{jt} \times Ivitality_{jt} + \\ &\varphi_6 \Sigma \omega i_j \ln(TIE_{jt-1}) \times DE_{jt} \times Ivitality_{jt} + \varphi_7 \Sigma \omega_{ij} control_{jt} + \mu_i + \sigma_t + \varepsilon_{it}. \end{aligned} \tag{15}$$

Equation (16) reflect the moderating role of city innovation and entrepreneurial vitality in the process of city innovation convergence influenced by DE during the achievements transformation phase.

$$\begin{aligned} DATE_{it} &= \alpha_0 + \beta \ln(ATE_{it-1}) + \beta_1 DE_{it} + \beta_2 Ivitality_{it} + \beta_3 \ln(ATE_{it-1}) \times DE_{it} + \\ &\beta_4 \ln(ATE_{it-1}) \times Ivitality_{it} + \beta_5 DE_{it} \times Ivitality_{it} + \beta_6 \ln(ATE_{it-1}) \times DE_{it} \times Ivitality_{it} + \\ &\alpha_1 \Sigma control_{it} + \rho \Sigma \omega_{ij} DATE_{jt} + \theta \Sigma \omega_{ij} \ln(ATE_{jt-1}) + \varphi_1 \Sigma \omega_{ij} DE_{jt} + \varphi_2 \Sigma \omega_{ij} Ivitality_{jt} + \\ &\varphi_3 \Sigma \omega_{ij} \ln(ATE_{jt-1}) \times DE_{jt} + \varphi_4 \Sigma \omega_{ij} \ln(ATE_{jt-1}) \times Ivitality_{jt} + \varphi_5 \Sigma \omega_{ij} DE_{jt} \times Ivitality_{jt} + \\ &\varphi_6 \Sigma \omega i_j \ln(ATE_{jt-1}) \times DE_{jt} \times Ivitality_{jt} + \varphi_7 \Sigma \omega_{ij} control_{jt} + \mu_i + \sigma_t + \varepsilon_{it}. \end{aligned} \tag{16}$$

$Fpower_{it}$ and $Fpower_{jt}$ serves as the measure of local government financial pressure in this city and other cities. Among them, $Ivitality_{it}$ and $Ivitality_{jt}$ is the measure of city innovation vitality in this city and other cities.

4.3. Data source

Taking into account the availability and consistency of data, as well as the thoroughness of the data samples, this study excludes cities that experience significant data deficiencies. Ultimately, it selects data from 283 cities at the city level for measurement, covering the timeframe spanning from 2011 to 2021. The primary data sources comprise the "China City Statistical Yearbook" (National Bureau of Statistics of China, n.d.-a), patent authorization statistics from the "China Patent Database" (https://data.cnki.net) managed by the SIPO of the People's Republic of China, information on city startups from the "Qichacha" Database (https://www.qcc.com/), and various municipal fund revenue figures obtained from government budget execution documents. In cases where certain cities lack data for specific years, an estimated annual growth rate has been utilized to fill these gaps.

5. Results and discussion

5.1. Descriptive statistics

A statistical analysis of descriptive data was conducted on the primary variables discussed in this paper, with the findings presented in Table 1. The overall number of participants involved in the study amounted to 3,113. Among these, the mean value of TIE is 0.686, with a standard deviation of 0.107. In contrast, the ATE is recorded at 0.430, accompanied by a standard deviation of 0.074. The mean of the key explanatory variable, DE is noted as 0.336, with a standard deviation of 0.118.

Table 1. Descriptive statistical analysis

Variable	N	Mean	Std	Min	Max
TIE	3,113	0.686	0.107	0.071	0.873
ATE	3,113	0.430	0.074	0.111	0.674
DE	3,113	0.336	0.118	0.064	1.000
edu	3,113	0.237	0.262	0.010	3.599
ppost	3,113	0.243	0.612	0.001	10.07
fina	3,113	4.763	8.850	0.111	101.6
inds	3,113	0.454	0.110	0.107	0.893
green	3,113	0.004	0.012	0.007	0.218

5.2. Benchmark regression analysis

The results shown in Columns (1) and (2) of Table 2 illustrate the influence of DE on both TIE and ATE. The interaction coefficient between DE and TIE is recorded at –0.734, while the coefficient for DE and ATE is –0.484. Both coefficients have successfully passed the 1% significance level test. These results indicate that, in terms of absolute convergence, DE plays a role in enhancing the efficiency of city innovation throughout both technological research and achievements transformation phases. The discussion focuses on the impact of DE on the conditional convergence related to innovation in technological research and achievements transformation phases, in Columns (3) and (4). Here, the interaction coefficient between DE and TIE is –0.735, and the coefficient linking DE to ATE is –0.495. These coefficients have also been validated through the 1% significance level test. The studies carried out by Zhao et al. (2023), Tang and Cui (2023), Xu et al. (2023), additionally reinforce this finding. The findings suggest that, under the concept of conditional convergence, DE likewise supports city innovation convergence during both technological research and achievements transformation phases, thus strengthening the credibility of Hypothesis 1. DE acts as a vital catalyst for the contemporary economy, promoting the equitable distribution of innovative resources across cities by enabling extensive information sharing and knowledge spillover. Furthermore, it enhances the application of innovative achievement across diverse regions, thereby contributing to the reduction of disparities in innovation capabilities among different areas and fostering city innovation convergence.

Table 2. Analysis of impact of DE on city innovation convergence

	Test for absolute convergence		Test for relative convergence	
	(1)	(2)	(3)	(4)
	DTIE	DATE	DTIE	DATE
DE	0.488*** (0.178)	0.203** (0.093)	0.489*** (0.178)	0.208** (0.094)
TIE	–0.327*** (0.061)		–0.328*** (0.061)	
TIE#DE	–0.734*** (0.241)		–0.735*** (0.241)	
ATE		–0.417*** (0.051)		–0.415*** (0.051)
ATE#DE		–0.484** (0.200)		–0.495** (0.202)
edu			0.019 (0.021)	0.007 (0.011)
ppost			0.000 (0.004)	0.002 (0.002)
fina			–0.001 (0.001)	–0.001 (0.000)
inds			–0.004 (0.032)	–0.010 (0.016)
green			0.203 (0.264)	0.015 (0.135)
Constant	0.243*** (0.046)	0.191*** (0.024)	0.245*** (0.046)	0.195*** (0.024)
City F.E.	Yes	Yes	Yes	Yes
Province-year F.E.	Yes	Yes	Yes	Yes
N	2770	2770	2770	2770
F	74.918	76.571	30.076	30.840
R2	0.529	0.532	0.530	0.532

Note: The indicators within the parentheses refer to the standard errors of robust clustering at the city level; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (same below).

5.3. Endogeneity test

5.3.1. IV-2SLS

To tackle the impact of endogeneity on regression results, this research first utilizes the instrumental variable method, performing a two-stage least squares analysis on the principal model to confirm the reliability of the outcomes. In accordance with the methodology proposed by Zhang et al. (2023), the interaction variable, which represents the average value of the digital finance development index at the national level (excluding the city itself), and the spherical distance from the city to Hangzhou serves as an instrumental variable. Furthermore, for model construction, we adopt the techniques suggested by Nunn and Qian (2014) to create interaction terms between the instrumental variable and the two stages of innovation efficiency, followed by an examination of their regression coefficients.

The results obtained from the two-stage instrumental variable analysis are summarized in Table 3. After controlling for endogeneity, the coefficients of the interaction terms related to DE, as well as TIE and ATE, continue to demonstrate a significantly negative relationship at the 1% significance level. This result suggests that DE efficiently promotes city innovation convergence throughout both technological research and achievements transformation phases, even when considering endogeneity effects.

Table 3. Endogeneity test: 2SLS

	Test for absolute convergence		Test for relative convergence	
	(1)	(2)	(3)	(4)
	DTIE	DATE	DTIE	DATE
DE	0.488*** (0.178)	0.203** (0.093)	0.489*** (0.178)	0.208** (0.094)
TIE	–0.327*** (0.061)		–0.328*** (0.061)	
TIE#DE	–0.735*** (0.241)		–0.736*** (0.242)	
ATE		–0.416*** (0.051)		–0.415*** (0.051)
ATE#DE		–0.486** (0.201)		–0.496** (0.203)
Control			Yes	Yes
City F.E.	Yes	Yes	Yes	Yes
Province-year F.E.	Yes	Yes	Yes	Yes
N	2760	2760	2760	2760
F	74.884	76.486	30.041	30.796
R2	0.306	0.310	0.307	0.311

5.3.2. PSM-DID

Influenced by the "Broadband China" initiative, the development of network infrastructure is pivotal for increasing the number of broadband users, enhancing network reach, and accelerating broadband speeds. This initiative serves as a vital foundation for fostering the growth of

DE and facilitating digital transformation (Zhou, 2024). To examine the causal link between DE and city innovation convergence, the "Broadband China" policy pilot implemented in prefecture-level cities from 2011 to 2021 is utilized as a quasi-natural experiment. Furthermore, to address potential omitted variable bias, the Propensity Score Matching with Difference-in-Differences (PSM-DID) technique is employed, following the methodology proposed by Heyman et al. (2007). Specifically, in alignment with Lyu et al. (2023), a Logit model is initially used to determine the propensity scores, employing control variables as independent variables, followed by a one-to-one nearest neighbor matching process for sample alignment.

The analysis of absolute convergence concerning technological research and achievements transformation phases, is presented in Columns (1) and (2) of Table 4. The findings indicate that the interaction terms involving the "Broadband China" policy with TIE and ATE are –0.139 and –0.069, respectively. This indicates that the "Broadband China" initiative could improve the convergence trends seen in both technological research and achievements transformation phases. Furthermore, Columns (3) and (4) provide the conditional convergence analysis for the same efficiencies. The findings indicate interaction values of –0.139 and –0.068 between the "Broadband China" initiative and the associated efficiencies, further strengthening the idea that this policy may facilitate the convergence trends of both TIE and ATE. Additionally, this finding implies that, when accounting for the exclusion of endogeneity interference and emphasizing causality, the positive influence of DE on innovation during China's city technological research and achievements transformation phases, remains robust.

Table 4. Endogeneity test: PSM-DID

	Test for absolute convergence		Test for relative convergence	
	(1)	(2)	(3)	(4)
	DTIE	DATE	DTIE	DATE
policy	0.089* (0.049)	0.028* (0.016)	0.089* (0.049)	0.027* (0.016)
TIE	–0.527*** (0.034)		–0.529*** (0.034)	
TIE#policy	–0.139** (0.071)		–0.139** (0.070)	
ATE		–0.552*** (0.038)		–0.555*** (0.038)
ATE#policy		–0.069* (0.036)		–0.068* (0.036)
Constant	0.375*** (0.024)	0.247*** (0.016)	0.376*** (0.031)	0.253*** (0.019)
Control			Yes	Yes
City F.E.	Yes	Yes	Yes	Yes
Province-year F.E.	Yes	Yes	Yes	Yes
N	2755	2747	2755	2747
F	80.773	70.414	34.204	28.870
R2	0.530	0.531	0.531	0.532

5.4. Robustness test

5.4.1. Changing sample

Chinese cities are classified into three tiers: those directly controlled by the central government, cities at the sub-provincial level, and cities of the prefecture level. Compared to the numerous prefecture-level cities, municipalities under direct central authority and sub-provincial cities demonstrate greater economic development and benefit from more favorable policy advantages (Shi & Xi, 2018). This research focuses on the extensive impact of DE on the innovation efficiency within Chinese cities, intentionally omitting samples from both municipalities and sub-provincial cities to center solely on prefecture-level cities. The results of the analysis for the prefecture-level city samples are presented in Table 5. According to Columns (1) and (2), when considering absolute convergence, the interaction terms between DE and TIE, as well as those between DE and ATE, are recorded at –0.768 and –0.574, respectively. Furthermore, Columns (3) and (4) illustrate that, regarding conditional convergence, the interaction terms between DE and TIE, along with those between DE and ATE, stand at –0.775 and –1.131, respectively. In conclusion, by focusing exclusively on prefecture-level cities, DE continues to enhance the city innovation convergence in both technological research and achievements transformation phases.

Table 5. Robustness test: changing sample

	Test for absolute convergence		Test for relative convergence	
	(1)	(2)	(3)	(4)
	DTIE	DATE	DTIE	DATE
DE	0.517*** (0.192)	0.240** (0.104)	0.519*** (0.192)	0.468** (0.211)
TIE	–0.333*** (0.065)		–0.336*** (0.065)	
DE#TIE	–0.768*** (0.262)		–0.775*** (0.262)	
ATE		–0.403*** (0.056)		–0.821*** (0.115)
DE#ATE		–0.574** (0.231)		–1.131** (0.469)
Constant	0.245*** (0.048)	0.184*** (0.026)	0.247*** (0.049)	0.374*** (0.052)
Control			Yes	Yes
City F.E.	Yes	Yes	Yes	Yes
Province-year F.E.	Yes	Yes	Yes	Yes
N	2620	2620	2620	2620
F	78.204	80.079	31.538	32.629
R2	0.536	0.539	0.538	0.540

5.4.2. Remove extremes

This study employs a 1% Shrink tail method to mitigate the influence of outliers on the results of the regression analysis. The findings are presented in Table 6. The results indicate the coefficient of the interaction term passed significance test, with only minimal changes compared to the original value. This further enhances the robustness of the conclusions.

Table 6. Robustness test: remove extremes

	Test for absolute convergence		Test for relative convergence	
	(1)	(2)	(3)	(4)
	DTIE	DATE	DTIE	DATE
DE	0.488*** (0.178)	0.203** (0.093)	0.489*** (0.178)	0.208** (0.094)
TIE	–0.327*** (0.061)		–0.328*** (0.061)	
DE#TIE	–0.734*** (0.241)		–0.735*** (0.241)	
ATE		–0.417*** (0.051)		–0.415*** (0.051)
DE#ATE		–0.484** (0.200)		–0.495** (0.202)
Constant	0.243*** (0.046)	0.191*** (0.024)	0.245*** (0.046)	0.195*** (0.024)
Control			Yes	Yes
City F.E.	Yes	Yes	Yes	Yes
Province-Year F.E.	Yes	Yes	Yes	Yes
N	2770	2770	2770	2770
F	74.918	76.571	30.076	30.840
R2	0.529	0.532	0.530	0.532

5.4.3. Placebo test

To exclude the influence of certain unobservable characteristics on the results, this Section conducts a placebo test based on the "Broadband China" policy, which is highly correlated with the development of DE in Chinese cities. The results are presented in Table 7 and Figure 1. Table 7 illustrates the temporal placebo test conducted by resetting the start date of the "Broadband China" policy. The results indicate that during the fictitious policy implementation period, the interaction terms between DE and both TIE and ATE show no statistical significance. This finding demonstrates that the development of DE, as represented by the 'Broadband China' policy, contributes to promoting city innovation convergence.

Figure 1 illustrates the individual placebo tests conducted for the technological research phase (Figure 1) and the achievements transformation phase (Figure 2) using randomly generated experimental groups. The results show that the distribution of the randomly generated erroneous regression coefficients is centered around zero and follows a normal distribution. Moreover, the vast majority of erroneous regression results fail to pass the significance test at the 10% level. These findings align with the expectations of the placebo test, indicating that the conclusion regarding the DE's role in promoting city innovation convergence is robust.

Table 7. Robustness test: time placebo test

	Test for absolute convergence		Test for relative convergence	
	(1)	(2)	(3)	(4)
	DTIE	DATE	DTIE	DATE
policy	0.032 (0.043)	0.010 (0.017)	0.031 (0.043)	0.009 (0.017)
TIE	–0.526*** (0.036)		–0.528*** (0.036)	
TIE#policy	–0.075 (0.064)		–0.073 (0.063)	
ATE		–0.549*** (0.039)		–0.551*** (0.038)
ATE#policy		–0.046 (0.041)		–0.044 (0.042)
_cons	0.378*** (0.025)	0.249*** (0.016)	0.377*** (0.030)	0.253*** (0.019)
Control			Yes	Yes
City F.E.	Yes	Yes	Yes	Yes
Province-year F.E.	Yes	Yes	Yes	Yes
N	2770	2770	2770	2770
F	71.860	69.289	30.161	28.882
r2	0.526	0.531	0.527	0.531

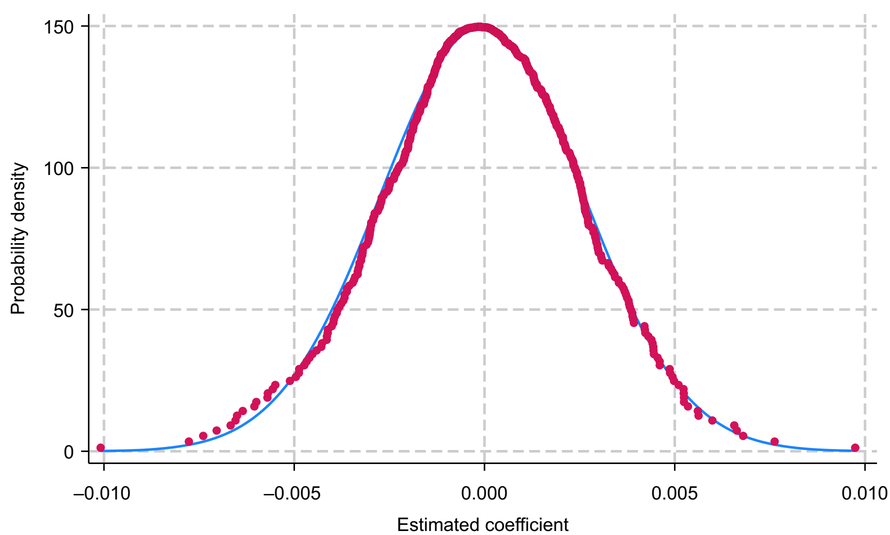

Figure 1. Robustness test: Individual placebo test – technological research phase

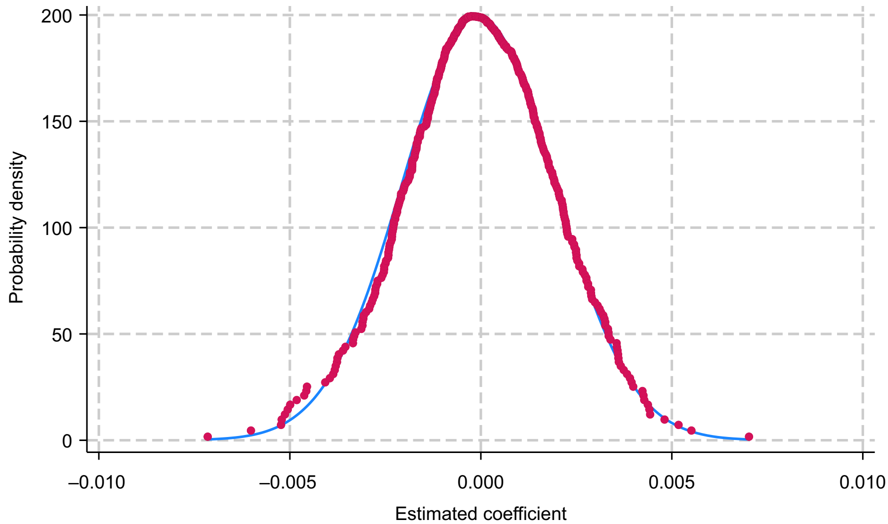

Figure 2. Robustness test: Individual placebo test – achievements transformation phase

5.5. Spatial effect analysis

5.5.1. Spatial correlation analysis

This paper initially employs global Moran's I index to examine the spatial autocorrelation of city innovation. The methodology for calculating the Moran's I index is as follows:

$$\text{Moran's} = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2}, \tag{17}$$

where x_i is the observed value, $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$, and ω_{ij} is the spatial weight matrix.

The findings presented in Table 8 detail the Moran's I indices related to regional innovation efficiency from 2011 to 2021. The findings suggest a notable positive trend in the indices of Moran's I for both TIE and ATE over the years. Furthermore, the data in Table 7 suggest a strong positive spatial correlation in city innovation. In turn, this strengthens the relevance of the spatial econometric model in examining the efficiency of regional innovation.

5.5.2. Spatial regression analysis

Table 9 showcases the results of the analysis that investigates the impact of DE on city innovation convergence, employing a geographical distance matrix approach. Columns (1) and (3) present findings that demonstrate how DE influences the spatial absolute convergence related to TIE and ATE. Notably, the interaction term coefficient between DE and TIE is –0.610, while the corresponding coefficient for ATE is –0.445. Both coefficients have undergone validation via a significance test at the 1% threshold. These results indicate that, under the concept of spatial absolute convergence, DE could promote an upward trend in TIE, along with ATE. Similarly, Columns (2) and (4) display the effects of DE on the spatial conditional city innovation convergence in technological research and achievements transformation phases.

Table 8. Analysis of spatial correlation

	TIE		ATE	
	Moran's I	Z	Moran's I	Z
2011	0.094***	19.04	0.097***	19.45
2012	0.098***	19.67	0.100***	20.07
2013	0.086***	17.38	0.089***	17.89
2014	0.076***	15.40	0.078***	15.87
2015	0.060***	12.39	0.076***	15.46
2016	0.033***	7.163	0.057***	11.69
2017	0.033***	7.160	0.064***	13.11
2018	0.031***	6.700	0.072***	14.72
2019	0.027***	6.008	0.070***	14.22
2020	0.047***	9.894	0.083***	16.80
2021	0.044***	9.226	0.078***	15.73

Table 9. Spatial convergence analysis of innovation efficiency in DE – geographical distance matrix

	Test for absolute convergence		Test for relative convergence	
	(1)	(2)	(3)	(4)
	DTIE	DATE	DTIE	DATE
DE	0.407*** (0.141)	0.186*** (0.066)	0.412*** (0.141)	0.194*** (0.066)
TIE	–0.306*** (0.057)		–0.313*** (0.058)	
TIE#DE	–0.610*** (0.192)		–0.603*** (0.192)	
ATE		–0.364*** (0.047)		–0.368*** (0.048)
ATE#DE		–0.445*** (0.141)		–0.450*** (0.141)
rho	0.417*** (0.111)	0.421*** (0.109)	0.406*** (0.115)	0.416*** (0.111)
sigma	0.002*** (0.000)	0.000*** (0.000)	0.002*** (0.000)	0.000*** (0.000)
Control			Yes	Yes
W × Variable	Yes	Yes	Yes	Yes
City F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	2830	2830	2830	2830
R2	0.305	0.179	0.186	0.096

The results reveal that the interaction term coefficient linking DE with TIE is –0.603, whereas for ATE, it is –0.450. Once again, both coefficients have successfully passed the significance test at the 1% level. These findings suggest that in the realm of spatial conditional convergence, DE can further facilitate an improved convergence pattern for both technological research and for achievements transformation phases.

Table 10 presents the findings from the analysis of how city innovation convergence is influenced by DE, employing an adjacency distance matrix approach. The findings presented in columns (1) and (3) illustrate how DE influences the absolute spatial convergence associated with TIE and ATE. The findings reveal that the coefficient associated with the interaction term relating to DE and the TIE stands at –0.724, whereas the coefficient linked to ATE is –0.539. Both results have successfully passed the significance test at the 1% level. The results indicate, under the concept of spatial absolute convergence, DE promotes tendencies toward convergence in both TIE and ATE. In contrast, columns (2) and (4) present the results concerning the influence of DE on the spatial conditional convergence. The interaction term has coefficients of –0.708 for TIE and –0.535 for ATE, with both findings reaching significance at the 1% level. The results suggest that, under the concept of spatial conditional convergence, DE may further improve the convergence trends associated with both the effectiveness of technological research and the application of innovations. Furthermore, an examination of the spatial spillover impacts associated with various spatial matrices reveals that the spillover effects of DE can significantly promote city innovation convergence. This further substantiates the substantial spatial spillover impacts that DE has in facilitating city innovation convergence.

Table 10. Spatial convergence analysis of innovation efficiency in DE – Adjacency Matrix

	Test for absolute convergence		Test for relative convergence	
	(1)	(2)	(3)	(4)
	DTIE	DATE	DTIE	DATE
DE	0.494*** (0.140)	0.227*** (0.073)	0.484*** (0.142)	0.226*** (0.074)
TIE	–0.281*** (0.055)		–0.287*** (0.055)	
TIE#DE	–0.724*** (0.191)		–0.708*** (0.194)	
ATE		–0.332*** (0.050)		–0.337*** (0.050)
ATE#DE		–0.539*** (0.158)		–0.535*** (0.159)
rho	0.181*** (0.026)	0.169*** (0.027)	0.181*** (0.026)	0.171*** (0.027)
sigma	0.002*** (0.000)	0.000*** (0.000)	0.002*** (0.000)	0.000*** (0.000)
Control			Yes	Yes
W × Variable	Yes	Yes	Yes	Yes
City F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	2830	2830	2830	2830
R2	0.286	0.216	0.239	0.181

5.6. Regulating effect

5.6.1. Financial pressure

Table 11 illustrates the moderating influence of government fiscal pressure on the ability of DE to enhance city innovation convergence. The findings in columns (1) and (2) reveal that, when examining absolute and conditional convergence, the coefficients for the interaction term related to fiscal pressure during the technological research phase are 0.1 and 0.097, both significant at the 5% level. This indicates that fiscal pressure exerted by local governments diminishes the positive influence of DE on city innovation convergence within the technological research phase. Conversely, the results from columns (3) and (4) demonstrate that, regarding absolute and conditional convergence, the coefficients for the interaction term concerning fiscal pressure during the achievements transformation phase are not statistically significant. This implies that local government fiscal pressure does not influence or lessen the DE's capacity to facilitate city innovation convergence at this phase. Thus, Hypothesis 2 is supported.

Table 11. Regulatory role of financial pressure

	Technological research phase		Achievements transformation phase	
	(1)	(2)	(3)	(4)
	DTIE	DTIE	DATE	DATE
DE	0.570*** (0.180)	0.553*** (0.180)	0.185** (0.081)	0.185** (0.083)
Fpower	–0.008 (0.005)	–0.009* (0.005)	–0.007*** (0.002)	–0.008*** (0.002)
DE#Fpower	–0.054* (0.028)	–0.052* (0.027)	–0.003 (0.012)	–0.005 (0.011)
TIE (ATE)	–0.337*** (0.067)	–0.349*** (0.066)	–0.424*** (0.058)	–0.431*** (0.058)
TIE (ATE)#DE	–0.873*** (0.255)	–0.844*** (0.255)	–0.463** (0.185)	–0.463** (0.188)
TIE (ATE)#Fpower	0.004 (0.009)	0.005 (0.009)	0.016** (0.007)	0.016** (0.007)
TIE(ATE)#DE#Fpower	0.100** (0.043)	0.097** (0.043)	0.018 (0.029)	0.022 (0.029)
rho	0.185*** (0.026)	0.185*** (0.026)	0.166*** (0.028)	0.169*** (0.027)
sigma	0.002*** (0.000)	0.002*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Control		Yes		Yes
W × Variable	Yes	Yes	Yes	Yes
City F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	2830	2830	2830	2830
R2	0.285	0.230	0.235	0.203

The primary factors contributing to this disparity can be summarized as follows: firstly, in technological research phase, increased fiscal pressure on local governments may lead to a reduction in investment in digital infrastructure, thereby hindering the DE's effectiveness in promoting knowledge and information exchange among cities and influencing the output of innovative results. Secondly, once innovation activities progress into achievements transformation phase, market mechanisms assume a more critical role. This phase increasingly depends on established market dynamics and a robust industrial chain to drive the transformation and application of scientific and technology advancements. Consequently, despite government experiencing financial constraints, the effect on the commercial utilization of groundbreaking innovations remains quite minimal.

5.6.2. City innovation and entrepreneurship vitality

Table 12 illustrates moderating influence of city innovation and entrepreneurship vitality on the role of DE in enhancing city innovation convergence. The findings presented in columns (1) and (2) indicate that, when examining absolute and conditional convergence, the coefficients for the interaction term of city innovation vitality during the technological research phase are 0.271 and 0.273, both statistically significant at the 1% level. This suggests that city innovation vitality diminishes the effect of DE on the convergence of city innovation during the technological research phase. Similarly, the results in columns (3) and (4) demonstrate that, in the context of both absolute and conditional convergence, the interaction term coefficients for city innovation vitality during the achievements transformation phase are 0.150 and 0.152, also significant at the 1% level. This suggests that the dynamism of city innovation equally diminishes the beneficial effects of digital entrepreneurship on city innovations convergence during the phase of transformative achievement. Thus, Hypothesis 3 is supported. The reasons for this phenomenon are twofold: firstly, cities with high levels of innovation and entrepreneurial vitality are better positioned to attract greater amounts of capital, talent, and technology, facilitating faster progress in new technological research. This ultimately results in innovation outputs that surpass those of other cities, contributing to an increased disparity in city innovation during the technological research phase. Conversely, cities characterized by robust innovation and entrepreneurial dynamism tend to experience significant economic vitality and a greater willingness to experiment with emerging technologies. This facilitates the rapid application of innovative outcomes toward economic productivity, thereby exacerbating the city innovation disparity during the achievements transformation phase and diminishing the positive influence of DE on city innovation convergence in both phases. A deeper examination reveals that, regardless of whether the analysis focuses on absolute or conditional convergence, the dampening impact of city entrepreneurial vigor during the technological research phase is more pronounced than in achievements transformation phase. Given that the costs associated with the inter-regional movement of factors relevant to technological research are substantially higher than those for the cross-regional implementation of innovation outcomes, the diminishing effect of city entrepreneurial vigor in technological research phase exceeds that observed in achievements transformation phase.

Table 12. Regulatory role of city innovation and entrepreneurship vitality

	Technological research phase		Achievements transformation phase	
	(1)	(2)	(3)	(4)
	DTIE	DTIE	DATE	DATE
DE	0.664*** (0.158)	0.659*** (0.160)	0.282*** (0.083)	0.283*** (0.083)
Ivitality	0.117*** (0.015)	0.116*** (0.015)	0.044*** (0.012)	0.044*** (0.012)
DE#Ivitality	–0.185*** (0.027)	–0.186*** (0.027)	–0.067** (0.027)	–0.067*** (0.026)
TIE(ATE)	–0.128* (0.066)	–0.132** (0.066)	–0.250*** (0.057)	–0.252*** (0.057)
TIE(ATE)#DE	–0.989*** (0.224)	–0.985*** (0.229)	–0.685*** (0.182)	–0.685*** (0.184)
TIE(ATE)#Ivitality	–0.169*** (0.022)	–0.168*** (0.023)	–0.094*** (0.019)	–0.094*** (0.019)
TIE(ATE)#DE#Ivitalty	0.271*** (0.047)	0.273*** (0.050)	0.150*** (0.043)	0.152*** (0.042)
rho	0.180*** (0.026)	0.173*** (0.027)	0.179*** (0.026)	0.174*** (0.026)
sigma	0.002*** (0.000)	0.000*** (0.000)	0.002*** (0.000)	0.000*** (0.000)
Control		Yes		Yes
W × Variable	Yes	Yes	Yes	Yes
City F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
N	2830	2830	2830	2830
R2	0.315	0.301	0.238	0.228

6. Conclusions and policy recommendations

6.1. Conclusions

Innovation is a multifaceted process that encompasses various stages, including technological research and achievement transformation. Each of these phases is interconnected, forming a cohesive system known as the IVCT. From the perspective of this value chain, the present study conducts an empirical analysis utilizing data from 283 cities across China, covering the years 2011 to 2021. The objective is to examine the influence of DE on city innovation convergence. While also examining how local government fiscal pressure and urban entrepreneurial vitality moderate this relationship. The results of the research are as follows:

DE primarily noted for its substantial spillover effects associated with knowledge and information, promotes the interconnectedness of CIES, fosters the creation of city innovation ecological networks, and is essential in furthering the city innovation convergence in China throughout both the technological research and achievements transformation phases. This impact remains consistent even when accounting for spatial spillover effects. Furthermore, the fiscal pressures faced by governments influence the configuration of CIES and serve as a significant moderating factor in how DE facilitates city innovation convergence. Subsequent analysis demonstrates significant differences in how fiscal pressure moderates the technological research phase compared to the achievements transformation phase. During technological research phase, fiscal pressures diminish the positive influence of DE on city innovation convergence; conversely, in the achievements transformation phase, fiscal pressure does not significantly affect DE's ability to promote city innovation convergence. Additionally, city innovation and entrepreneurial vitality represent another key moderating element that impacts the CIES, significantly influencing the capacity of DE to encourage city innovation convergence. Variations in city innovation and entrepreneurial vitality reduce the positive influence of DE on city innovation convergence, regardless of whether it is during technological research and achievements transformation phases, with this effect being more pronounced during the technological research phase.

Admittedly, this study has certain limitations. The conclusions drawn are entirely based on an in-depth analysis of the innovation convergence phenomenon in Chinese cities. As China is a rapidly developing and relatively mature economy, the findings in this specific context may not fully apply to countries with less developed economies. Therefore, future research on innovation convergence should broaden its international perspective, aiming to conduct comparative analyses of innovation convergence in both developed and underdeveloped economies. This would enable the formulation of targeted and practical policy recommendations tailored to the specific conditions of each country.

6.2. Policy recommendations

Based on the findings presented in this paper, several policy suggestions are proposed. First, the importance of DE in promoting city innovation convergence must be clearly emphasized, establishing it as the primary catalyst for this convergence and defining its strategic significance within urban development. Furthermore, a targeted development strategy for DE should be formulated to facilitate its deep integration with city innovation convergence.

The government plays a vital part in the advancement of CIES. It is important to create sustained growth plans that outline the goals and routes for incorporating urban innovation. By utilizing policy structures and market forces, the government ought to encourage the smooth incorporation of DE with CIES. It is vital for the government to bolster its strategic commitment and, despite facing significant fiscal challenges, enhance structural fiscal support for innovative research organizations. This includes introducing various favorable initiatives, such as fiscal subsidies, tax incentives, and financial assistance aimed at stimulating technological research efforts by innovative organizations. Concurrently, efforts to strengthen innovation and entrepreneurship within DE sector must be intensified, facilitating a more substantial impact of DE on city innovation integration. Local authorities should proactively invest in developing digital infrastructure to maximize DE's contribution to city innovation. Furthermore, the government should take the lead in creating public innovation and research platforms, establishing funds for innovation and entrepreneurship, and providing financial support and incubation services for new ventures. Collaboration among businesses, universities, and research institutions should be encouraged to facilitate the conversion and application of innovative outcomes.

To optimize the business environment and invigorate city innovation and entrepreneurial vitality, it is crucial to consider the city's historical, geographical, and cultural context. Organizing events such as innovation competitions and entrepreneurship forums can enhance the city's reputation and influence within the innovation sector. It is important to cultivate an inclusive, open, and innovative cultural setting to raise citizens' awareness of both innovation and entrepreneurship. Additionally, policies aimed at attracting and retaining top-tier talent should be developed, including housing subsidies and favorable arrangements for children's education. Strengthening partnerships with universities and research institutions will be essential for introducing and nurturing professionals in DE. This strategy will enhance the city's research capabilities and drive city technology development. Furthermore, initiatives to promote innovation achievement should be expanded, and demonstration zones established to facilitate the experimental application of these innovations, ultimately fostering their implementation and utilization.

Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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