frontiers | Frontiers in Sustainable Food Systems

TYPE Original Research
PUBLISHED 03 February 2026
DOI 10.3389/fsufs.2026.1762008

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OPEN ACCESS

EDITED BY
Xiuwu Zhang,
Huaqiao University, China

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Dingde Xu,
Sichuan Agricultural University, China
Songyu Jiang,
Rajamangala University of Technology Rattanakosin, Thailand

*CORRESPONDENCE
Jun Zhao
✉ zhaojun2021@hbut.edu.cn

RECEIVED 06 December 2025
REVISED 11 January 2026
ACCEPTED 15 January 2026
PUBLISHED 03 February 2026

CITATION
Wu R, Feng D, Zhao J and Cui X (2026) Resource endowments and entrepreneurial environment matter: how digital infrastructure shapes agricultural technology innovation in China.
Front. Sustain. Food Syst. 10:1762008.
doi: 10.3389/fsufs.2026.1762008

Resource endowments and entrepreneurial environment matter: how digital infrastructure shapes agricultural technology innovation in China

Runyu Wu[1], Dongfa Feng[2,3], Jun Zhao[4]* and Xufeng Cui[5]

[1]Department of Finance, First Affiliated Hospital of Zhengzhou University, Zhengzhou, Henan, China, [2]School of Economics and Management, Nanchang University, Nanchang, China, [3]Institute of Digital Finance, Peking University, Beijing, China, [4]School of Innovation and Entrepreneurship, Hubei University of Technology, Wuhan, Hubei, China, [5]School of Business Administration, Zhongnan University of Economics and Law, Wuhan, China

Digital technology is profoundly reshaping traditional agricultural production, presenting new opportunities to promote agricultural technology innovation. This study aims to elucidate the enhancing effect of digital infrastructure development on agricultural technological innovation and its underlying mechanisms. It regards the "Broadband China" pilot city policy as a quasi-exogenous shock to the development of digital infrastructure. This study employs a panel dataset covering 281 Chinese prefecture-level and above cities from 2011 to 2021. Using a staggered difference-in-differences model, it investigates the impact of digital infrastructure on agricultural technology innovation and its underlying mechanisms. The results indicated that digital infrastructure significantly promotes agricultural technology innovation. This effect exhibits heterogeneity across regions with different resource endowments, entrepreneurial environments, and legal environments. Mechanism analysis reveals that digital infrastructure can accelerate the digital transformation of innovative entities and reduce the cost of legal rights protection, thereby expanding agricultural product sales, increasing innovation revenues, and ultimately stimulating agricultural technology innovation through a "revenue enhancement and cost reduction" effect. Further analysis reveals, on one hand, the positive spatial spillover effects of digital infrastructure construction, and on the other hand, enhancing the level of agricultural technological innovation can strengthen food security capabilities. This study offers a new perspective on understanding the in-depth integration of digital technology with the agricultural industry chain and stimulating agricultural innovation.

KEYWORDS

agricultural technology innovation, Broadband China policy, digital infrastructure, innovation benefits, rights protection costs

1 Introduction

China feeds nearly 20% of the world's population with 9% of the world's arable land, which is one of the important achievements of the long-term exploration and practice of the Chinese people under the leadership of the Party. However, China's food security still faces some risks and challenges. Figure 1a shows that China's soybean import volume rose steadily from 2003 to 2022, while the average integration of digital technology with the agricultural industry chain and stimulating agricultural innovation import price also trended upward, accelerating after

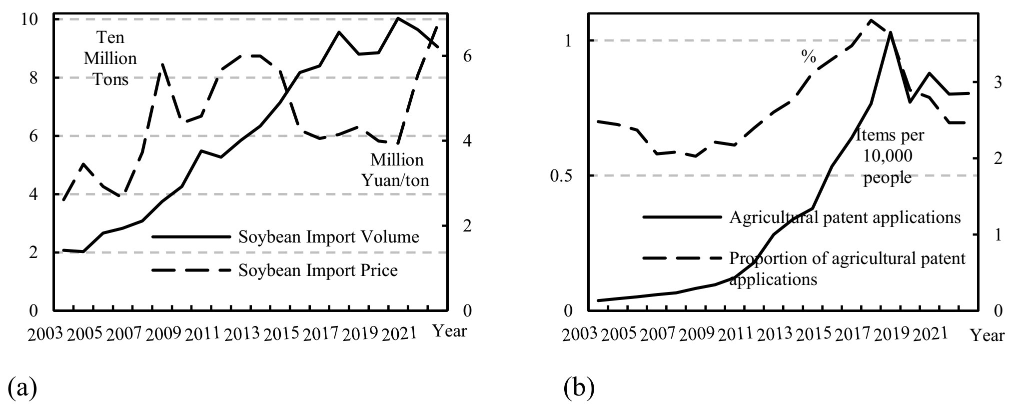

FIGURE 1
Typical stylized facts on China's food security and agricultural technology innovation. **(a)** China's annual soybean imports and import prices. **(b)** China's annual per capita agricultural patent applications and their ratios.

the COVID-19 shock. This simultaneous increase in both price and quantity reveals the growing vulnerability of international agri-food supply chains amid rising geopolitical tensions and market uncertainty, thereby accumulating additional threats to national food security. Yet Figure 1b indicates that per-capita agricultural patent applications peaked in 2018 and have since declined, while the share of agricultural patents in total applications has fallen continuously since 2017, signaling a weakening of agricultural technology innovation momentum. Against this backdrop, it is undoubtedly of great theoretical value and practical significance to explore the relevant measures to consolidate and enhance the level of agricultural technology innovation in China and the mechanism behind it.

Although agricultural technology innovation is theoretically regarded as an effective means of raising agricultural productivity, developing rural economies and improving farmers' welfare (Macours, 2019), in reality it is characterized by high costs and thin returns, so that its equilibrium level falls short of the social optimum (Marenya and Barrett, 2009). On the cost side, first, R&D outlays are high. For example, lettuce produced in vertical farms needs a selling price of USD 1.11 per ounce to break even when the market price is only USD 0.16 per ounce (Howitt and Rausser, 2022). Second, rights protection costs are high. Because crops are biological and seasonal, infringement can begin with seed theft, yet the infringer usually detects it only after harvest, leaving the infringer ample time to conceal the act. Collecting evidence on the infringer's premises is difficult and rarely cooperated with. On the return side, first, most agricultural prices are administratively controlled, preventing innovators from extracting high mark-ups (Houck, 1974). Second, innovative entities often lose control over their creations. Before hybrid seeds, for instance, farmers needed to buy elite seed only once and could then multiply it indefinitely (Dixon, 1980). Hybrids lose heterosis after self-pollination, giving breeders stronger control, but because cultivation is decentralized, farmers can still select, save and exchange seed, forming open-innovation networks that even select superior variants from hybrids (Clancy and Moschini, 2017). Gene-edited "terminator" seeds could block this leakage, yet transgenic seeds face strong legal and social resistance worldwide. It can be seen that the key to promoting agricultural technology innovation lies in 'cost reduction gain', that is, reducing the cost of agricultural technology innovation and improving the income of agricultural technology innovation, so as to improve the net income of agricultural technology innovation.

Whether and how construction of the digital infrastructure can foster agricultural technology innovation therefore merits special attention. Theoretically, on the one hand, construction of digital infrastructure enriches the information-access channels of innovative entities (Shen et al., 2023), strengthens traceability and anti-counterfeiting of farm products (Xia et al., 2019), and helps identify infringements and fix evidence, thus lowering rights protection costs for agricultural technology innovation. On the other hand, it facilitates matching between buyers and sellers (Laurina, 2018) and, via the "long-tail" principle, opens the sales of agricultural products for regional niche varieties, thereby increasing innovation benefits when farm-gate prices are sticky.

In practice, however, solid evidence that construction of digital infrastructure raises agricultural technology innovation is still scarce. Existing work focuses largely on how general digitalization affects the broad "agriculture, rural areas, and farmers" agenda. Lu et al. (2023), using household data from typical pastoral areas, find that higher digital ability raises herders' willingness to adopt advanced production techniques. Wang et al. (2023), with prefecture-level data from the Yellow River Basin, show that digital-economy development transforms farming methods, an effect stronger in cities with higher green-technology innovation. Zhang et al. (2023), combining national rural fixed-site survey data with Alibaba research data, find that rural e-commerce improves the local innovation environment and stimulates grassroots creativity. Qiu and Qiao (2021), using World Bank survey data, show that farmers with better digital skills gain more from e-commerce technologies.

Two main reasons explain why the nexus between construction of digital infrastructure and agricultural technology innovation remains under-explored. First, the current national statistical system does not supply high-granularity data on agricultural technology innovation. Second, potential endogeneity contaminates any simple correlation: unobserved factors may simultaneously shape broadband rollout and inventive activity (omitted-variable bias), while counties with stronger agricultural technology innovation could themselves demand more digital infrastructure to facilitate knowledge exchange (reverse causality). This research identifies the causal impact of construction of digital infrastructure on agricultural technology innovation and dissects its mechanisms and heterogeneity across regions. To overcome the data constraint, the approach of Feng et al. (2023a) has been extended by mapping agricultural patents through International Patent Classification (IPC) codes released by the China National Intellectual Property Administration. The database has then been web-scraped, and city-level granted agricultural patents per 10,000 residents have been constructed as the proxy for agricultural technology innovation. To address the identification strategy issue, this research uses the "Broadband China" pilot policy as a quasi-natural experiment (Zhao et al., 2020; Tian and Zhang, 2022; Jiao et al., 2023) and employs a staggered difference-in-differences model based on city-level panel data in China to analyze the impact of digital infrastructure construction on agricultural technological innovation.

The study found that the construction of digital infrastructure significantly raises agricultural technology innovation. The finding proves robust to a battery of validity checks and robustness tests. Mechanism analysis shows that pilots promote innovation by "increasing revenue and reducing cost": they accelerate the digital transformation of innovative entities, improve infringement detection and evidence collection, and thereby lower rights protection costs; they also expand the sales of agricultural products via rural e-commerce, raising innovation benefits. Heterogeneity analyses indicate that the innovation effect is stronger in cities with poor brand recognition but good transport infrastructure, rich entrepreneurial ecosystems, and weak legal institutions. Further results reveal positive spatial spillovers to neighboring non-pilot cities and that higher patenting translates into increased output of eggs, pork and beef, thereby helping to strengthen food security capabilities. Against this backdrop, this paper employs a rigorous causal identification strategy to systematically examine the impact of digital infrastructure development on agricultural technological innovation. It further delves into the underlying mechanisms, heterogeneous effects, and extended implications of this relationship. The study aims to provide new empirical evidence and theoretical insights for understanding how digital technology enables agricultural innovation and contributes to food security.

The marginal contributions of this research are three-fold. First, the research frontier on the innovation and entrepreneurship effects of the construction of digital infrastructure has been extended. Existing studies have focused on its impacts on regional innovation quantity and quality (Wang and Wang, 2024), regional entrepreneurial activity and attractiveness (Zhao et al., 2020; Jiao et al., 2023), firm-level innovation boundaries (Shen et al., 2023), and corporate green-technology innovation (Tang et al., 2021), but have paid relatively little attention to agricultural technology innovation. Particularly in the agricultural sector, the existing literature still lacks systematic evidence based on high-granularity data and rigorous causal identification strategies. Using patent-based measures of city-level agricultural innovation, the first quasi-experimental evidence on the causal effect of digital infrastructure on agricultural technology innovation is provided, thereby offering a novel perspective for evaluating the innovation and entrepreneurship consequences of construction of digital infrastructure. Second, the mechanisms through which the construction of digital infrastructure fosters agricultural technology innovation are unpacked. It is argued that raising net innovation returns is the fundamental driver of agricultural innovation. Empirically, it is shown that digital infrastructure accelerates the digital transformation of innovative entities, improves their ability to collect infringement evidence and enforce IP rights, and thus lowers rights protection costs; it also boosts rural e-commerce, stimulates agri-entrepreneurship, and expands the sales of agricultural products, thereby increasing innovation benefits. In short, construction of digital infrastructure promotes agricultural technology innovation by "increasing revenue and reducing cost." The validation of this mechanism not only clarifies the specific pathways through which digital technology enables agricultural innovation, but also deepens our understanding of the dual constraints of costs and benefits within the incentive structure for agricultural innovation. Third, the findings carry rich policy implications. At present, boosting agricultural technology innovation is a national strategy for safeguarding food security, and strengthening such innovation is vital for national security. It is demonstrated that the construction of digital infrastructure enhances agricultural technology innovation through "increasing revenue and reducing cost," thereby strengthening food security capabilities. Therefore, continued expansion of digital infrastructure in rural areas and deeper integration between digital technologies and the agricultural industry chain can serve as feasible levers for invigorating agricultural technology innovation vitality and mitigating food-security risks. These findings provide direct empirical support for the formulation and optimization of relevant policies.

2 Typical stylized facts, policy background and theoretical analysis

The selection criteria for pilot cities under the "Broadband China" initiative are based on a set of clearly defined establishment standards. These standards primarily cover four dimensions: first, broadband access capacity; second, broadband penetration levels; third, broadband application levels; fourth, the level of local government support and policy environment. This implies that pilot cities are typically regions with relatively strong information infrastructure, robust economic strength, and high policy implementation capacity. This non-random "selection by merit" approach may introduce systematic differences between pilot and non-pilot cities at the baseline period, potentially leading to "selection bias." To visually observe these differences, this paper compares the main macroeconomic characteristics of the two groups of cities before policy implementation (the 2011 baseline period).

2.1 Agricultural technology innovation and food security

Agricultural technological innovation serves as a core driving force for enhancing land productivity, strengthening risk resilience, and improving the sustainability of resource utilization. It plays a critical role in safeguarding national food security. Since the launch of reform and opening-up, China has gradually built a modern patent system aligned with global standards, providing strong impetus for technological progress and economic growth. The patent system serves two core functions: protection and disclosure. It confers on inventors an exclusive intellectual-property right for a limited period, while simultaneously publishing the technical content worldwide. Once the protection term expires, the patent falls into the public domain. Consequently, agricultural innovative entities may prefer trade secrets rather than patents to safeguard their inventions (Clancy and Moschini, 2017), implying that patent counts do not capture the full spectrum of technological progress. Nevertheless, patents remain the most comprehensive and objective data source available for tracking innovation trends and have been widely used in the literature (Shen et al., 2023; Wu et al., 2021; Tian and Xu, 2022). In China, the patent application process is divided into three stages: application, review and grant. The types of patents mainly include invention patents, utility model patents, and design patents. Among them, invention patents require applicants to pay more intellectual contribution, higher value and longer protection period.

The key to measuring agricultural technology innovation lies in the accurate identification of agricultural patents. In 2015, the China National Intellectual Property Administration (CNIPA) released the Reference Table for the Correspondence between International Patent Classification and National Economic Industry Classification (Trial Version), which systematically mapped IPC codes to economic sectors. This was updated in 2018 as the Reference Table (2018) (hereafter referred to as the Reference Table), and has since served as a key benchmark for official statistics and technology evaluation. The Reference Table lists IPC codes corresponding to agriculture, forestry, animal husbandry and fishery. Beyond the conventional A01 (agriculture, forestry, animal husbandry), it also includes B27J (rattan processing), C12N15 (gene editing), D01C1 (plant material processing), and other categories closely related to modern agriculture, aligning well with current strategic priorities in agricultural development. Drawing on the PatSnap Global Patent Database, agricultural patents are identified by filtering for applicant address, application date, and IPC code.

This study aims to reveal the fundamental patterns of China's agricultural innovation dynamism and its implications for food security underpinnings. This is done by constructing city-level annual counts based on aggregated agricultural patent data. Agricultural patents are aggregated to construct city-level annual counts. Figure 2a presents the per capita agricultural patent applications across China's eastern, central and western regions. The data reveal a clear coastal-to-inland gradient in agricultural technology innovation vitality, with the east maintaining and widening its lead over the central and western regions throughout the sample period. By 2021, the number of agricultural patent applications per capita in the eastern region is 1.012 per ten thousand people, more than twice that of the central region (0.481 per ten thousand people) and the western region (0.458 per ten thousand people). This geographical imbalance mirrors a spatial misallocation of innovation resources. More critically, it harbors the risk of creating disparities in regional food security, revealing a latent fragility in its technological foundations. In terms of temporal trends, all three macro-regions experienced steady growth in per capita agricultural patent applications until 2017. Thereafter, the eastern region continued its upward trajectory, while the central and western regions plateaued or fluctuated. The COVID-19 pandemic led to a noticeable decline in innovation activity across all regions in 2021.

Figure 2 shows a statistically significant positive spatial autocorrelation: cities with high agricultural technology innovation vitality tend to be surrounded by neighbors that also exhibit high innovation vitality. Overall, China's agricultural technology innovation displays a marked spatial divide. This pattern may hamper the holistic improvement of overall technological capabilities and the balanced development of comprehensive food security capacity across all regions. Particularly the lagging performance of the central and western regions constrains national progress. Given the presence of spatial spillovers, linking the eastern, central and western regions through construction of digital infrastructure and accelerating knowledge diffusion from the east toward the inland may constitute a viable route to boost national agricultural technology innovation vitality. In addition, the levels and trends in Figure 2a closely mirror those in Figure 1b, indicating that the sampled cities are highly representative and the underlying patent data are reliable.

2.2 Digital infrastructure and agricultural technological innovation

Digital infrastructure serves as a critical cornerstone for contemporary agricultural technological innovation. Although China began to build its digital infrastructure later than many developed economies, the pace of expansion has been rapid. The country officially introduced Internet technology only in the late 1980s,

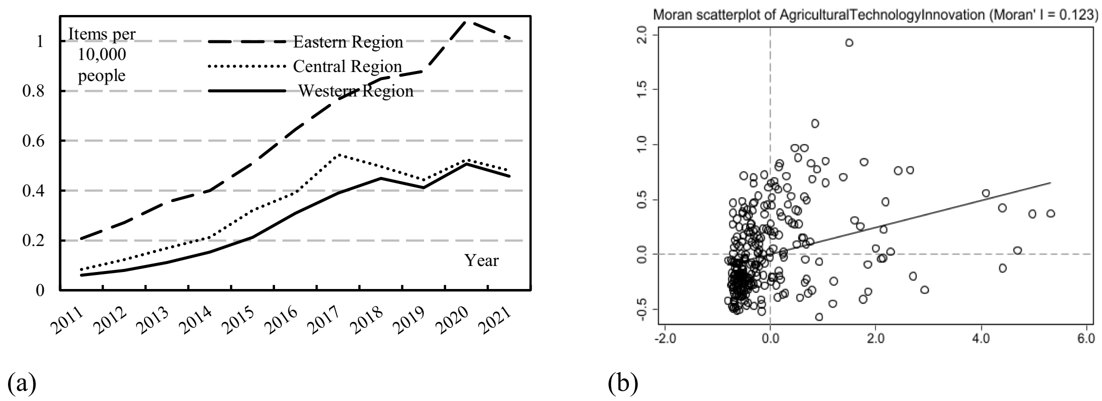

FIGURE 2
The Moran scatterplot of per-capita agricultural patent applications in 2021 based on a geographic-distance matrix. **(a)** Changes in the per capita number of agricultural technology patent applications. **(b)** Spatial correlation of per capita agricultural patent applications.

connected to the global network in 1994, opened public access in 1995 and established a nationwide backbone by 1996. Early users relied on dial-up lines with low speeds, yet subscriptions leapt from 0.62 million in 1997 to 22.5 million in 2000, ushering China into the digital era. After 2000, broadband technologies diffused quickly and were upgraded repeatedly. In 2005 the number of broadband subscriptions surpassed that of dial-up accounts for the first time, making broadband the principal form of construction of digital infrastructure. In 2008, the number of broadband users in China surpassed the United States to become the world's first, but the average network downlink rate is less than 4 trillion, far less than the average level of 17.4 trillion in developed countries. Moreover, urban–rural imbalances, thin application ecosystems and limited indigenous technological capacity persisted. To close these gaps, the Ministry of Industry and Information Technology (MIIT) proposed the "Broadband China" concept in 2011; the State Council elevated it to a national strategy in 2013.

The 2013 "Broadband China Strategy and Implementation Plan" set targets for raising urban and rural coverage, household penetration, transmission capacity of fixed and mobile broadband, and depth of use across society, calling for "active regional pilot demonstrations." Years of sustained investment have met most quantitative targets. Figure 3a shows that total broadband subscriptions accelerated after 2015, with rural subscribers' share rising steadily; by 2022 the nation had 589.6 million broadband accounts, 29.9 per cent in rural areas. Figure 3b shows that the overall size of China's online shopping users and online payment users have risen steadily during the sample period, reaching 845.3 billion and 911.4 billion, respectively, by 2022, accounting for 79.2 and 85.4% of the netizens, respectively.

The "Broadband China" pilot program is an important component of the "Broadband China" strategy. In 2014, the Ministry of Industry and Information Technology (MIIT) and the National Development and Reform Commission (NDRC) jointly issued the "Management Measures for the Creation of "Broadband China" Pilot Cities (City Clusters)," aiming to "significantly enhance the local broadband development level" in the pilot cities. It was proposed that "cities (city clusters) applying to create "Broadband China" demonstration zones should have a solid foundation for broadband development," and required that the six indicators of the pilot cities, including broadband access capability, broadband penetration rate, and other key metrics, "should all reach a national leading level by the end of the creation period." The two ministries announced three batches of pilot cities in September 2014, October 2015, and July 2016. Pilot cities are required to incorporate broadband development into various development plans, ensure sufficient investment in network construction, user popularization, and application development, and regularly report progress to the MIIT. Looking at the current situation, the "Broadband China" pilot cities have achieved the pilot objectives well and have built a domestic leading broadband network. To more clearly illustrate this point, this research uses the total volume of telecommunications services, the number of mobile phone users, the number of international Internet users, and the text-based measurement indicators of Chao et al. (2021) as proxies for the level of digital infrastructure construction in cities. Regression analysis is employed to examine the correlation between these indicators and the "Broadband China" pilot program, with the regression results reported in Table 1. The information indicates that there is a significant positive correlation between the "Broadband China" pilot program and the level of digital infrastructure construction. The findings indicate that the pilot policy has effectively enhanced urban digital infrastructure levels, thereby providing a more favorable foundation for a wide range of innovation and entrepreneurial activities.

The spatial and temporal distribution characteristics of the "Broadband China" pilot cities are reported in Figure 4a. It can be seen that the pilot cities show no significant clustering characteristics in terms of time and space, indicating that the pilot policy has a relatively exogenous nature. At the same time, the pilot policy significantly promotes the level of digital infrastructure construction in the local area. Therefore, the "Broadband China" pilot policy can be regarded as a "quasi-exogenous shock" to the construction of digital infrastructure, constituting an ideal "quasi-natural experiment." Figure 4b reports the comparison of the per capita number of agricultural technology patents granted between the first batch of pilot cities and non-pilot cities. The information shows that before 2014, the difference in per capita agricultural technology patents between pilot and non-pilot cities remained relatively stable, and began to gradually widen after 2014. It can be seen that pilot and non-pilot cities have similar growth patterns in

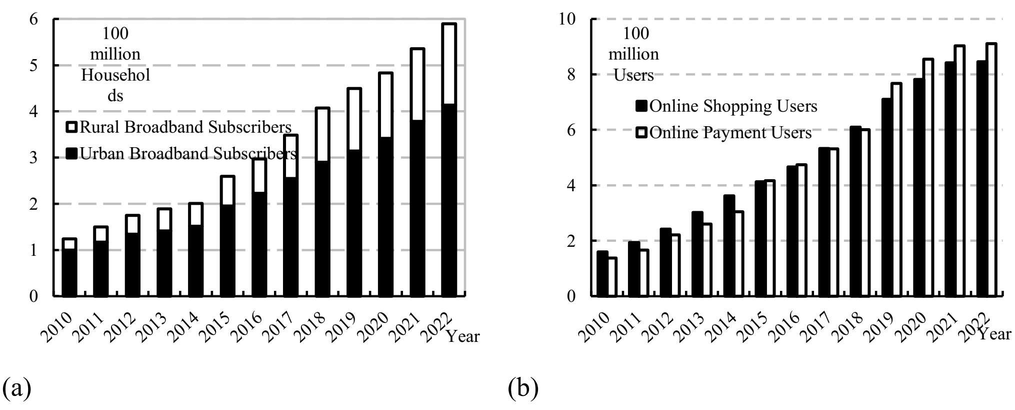

FIGURE 3
The achievements of the "Broadband China" strategy. **(a)** Changes in the number of urban and rural broadband subscribers. **(b)** Changes in the number of online shopping and online payment users.

TABLE 1 The impact of the "Broadband China" pilot policy on the level of digital infrastructure construction.

Variable	Telecommunications business volume	Number of mobile phone users	Number of international internet users	Textual indicator of digital infrastructure
	Regression 1	Regression 2	Regression 3	Regression 4
"Broadband China" pilot	0.100** (0.042)	0.039** (0.016)	0.032*** (0.008)	0.246*** (0.070)
City fixed effects	Controlled	Controlled	Controlled	Controlled
Time fixed effects	Controlled	Controlled	Controlled	Controlled
Observations	3,091	3,091	3,091	2,798
Adjusted R^2	0.772	0.973	0.846	0.832

Note: * P<0.1, ** P<0.05, *** P<0.01; standard errors are robust and shown in parentheses.

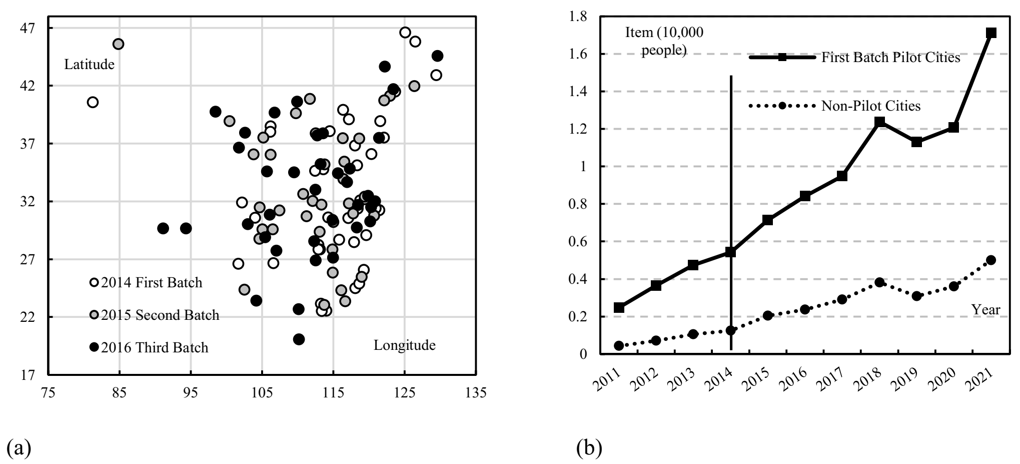

FIGURE 4
The spatial distribution of "Broadband China" pilot cities and their impact on agricultural technology innovation. **(a)** Spatial distribution of "Broadband China" pilot cities. **(b)** Impact of "Broadband China" pilot on agricultural technology innovation.

agricultural technology innovation. Therefore, it is appropriate to identify the causal relationship between digital infrastructure and agricultural technology innovation based on the difference-in-differences model.

2.3 Digitalization, e-commerce, and agricultural upgrading

Agriculture is the foundation of the national economic system. Agricultural technology innovation plays a positive role in agricultural production and economic development. Stimulating the vitality of agricultural technology innovation is one of the important goals of countries around the world. However, due to the fragmented nature of agricultural production and management, the randomness of biological experimental results, and the regional nature of crop cultivation (Pardey and Alston, 2021), agricultural technology innovation is characterized by low returns and high costs. It is prone to market failure due to insufficient incentives (Marenya and Barrett, 2009), necessitating government intervention. The government primarily intervenes in the innovation behavior of micro entities through two approaches: one is direct guidance through increased public research funding, and the other is market incentives through the optimization of the innovation environment (Pardey and Alston, 2021). Direct guidance measures can channel substantial resources into the specialized fields desired by the government and achieve results in the short term (Masters, 2021), but they may lead to government failure and resource waste. Market incentive measures enable micro entities to gain competitive advantages through innovation, thereby allowing innovative outcomes to emerge spontaneously throughout society. For example, Clancy and Moschini (2017) found that the allowance of crop patenting in the United States in 1980 significantly stimulated the development of life sciences and gave rise to revolutionary innovations such as gene editing. Howitt and Rausser (2022) pointed out that since Singapore first approved the public sale of lab-grown meat globally in 2020, related enterprises have had greater profit margins, and the variety and taste of lab-grown meat have significantly improved with technological advancements. This research argues that digital infrastructure can enhance the innovation capabilities of micro entities and optimize the innovation environment (Shen et al., 2023), which is a type of market incentive measure. It can reduce innovation costs and increase innovation benefits, thereby stimulating the vitality of agricultural innovation. By promoting the digital transformation of the entire industry chain and the vigorous development of e-commerce, it effectively reduces the cost of agricultural technological innovation while enhancing innovation returns, thereby stimulating innovation dynamism and driving agricultural upgrading. Specifically:

On the one hand, digital infrastructure can accelerate the digital transformation of innovative entities, enhance their ability to monitor infringement, and reduce the cost of protecting innovation rights through better use of legal tools. It establishes a systematic mechanism for cost reduction. First, the construction of digital infrastructure increases the total number of broadband network users, improves information transmission speed, and enhances the overall value of the network (Liu and Hu, 2010). This gives enterprises a strong incentive to connect to the network and accelerate digital transformation through organizational restructuring and process reengineering, thereby better utilizing digital technology and gaining competitive advantages. Digital technology reduces the information search costs of enterprises (Goldfarb and Tucker, 2019), enhances their information accessibility (Shen et al., 2023), and strengthens their ability to perceive competitor's dynamics and market changes. This enables better monitoring of infringement in the market and timely warnings to reduce infringement losses. Second, digital technologies such as blockchain enhance the traceability and anti-counterfeiting capabilities of agricultural products (Xia et al., 2019), which can better protect brand value and reduce the likelihood of counterfeiting. Third, cutting-edge digital technologies such as machine learning and neural networks can help innovative entities quickly identify infringement and fix evidence of infringement once detected (Luo and Mortimer, 2016). This improves the evidence chain and increases the success rate of rights protection. These digital means collectively function to mitigate the risks and execution costs faced by innovators across multiple aspects, including information acquisition, intellectual property protection, and judicial evidence presentation, and thereby increase the level of agricultural technology innovation by reducing the cost of rights protection.

On the other hand, digital infrastructure can promote the development of rural e-commerce, open up sales channels for agricultural products, and enhance the value of the industrial chain, thereby increasing the market returns of agricultural technology innovation. It establishes effective channels for increasing returns. First, the continuous popularization of digital infrastructure in rural areas enhances the ability of small farmers to connect with large markets, giving rise to rural e-commerce models such as "WeChat business" and "TikTok business." This allows regional agricultural products to be sold nationwide and enables farmers to maintain close contact with customers, accurately grasp market trends, and adjust production plans in a timely manner (Xia et al., 2019), thereby increasing the commercial value of agricultural technology innovation through expanded sales channels and increased sales volume. Second, the development of rural e-commerce increases rural employment opportunities and the probability of labor returning to rural areas for entrepreneurship and employment (Qiu and Qiao, 2021), which can attract more human capital to rural areas. This helps to increase farmer's innovation capabilities and their willingness to adopt advanced technologies through scale and network effects. Third, the development of rural e-commerce drives the growth of many related industries, including cold chain transportation and storage of vegetables and fruits, effectively extending the agricultural product-related industrial chain and value chain (Zhang et al., 2023). This attracts more people to engage in agricultural-related activities and greatly enriches the pool of agricultural innovation entities in the market. Finally, the development of rural e-commerce can increase farmer's income, narrow the economic and social gaps between farmers and between urban and rural areas (Qiu and Qiao, 2021), and enable them to establish more stable cooperative relationships with agricultural research institutions. This ensures that the direction of agricultural technology innovation better meets the actual needs of farmers (Macours, 2019), thereby improving the innovation achievement transformation chain and motivating researchers to work more actively. This series of e-commerce-driven changes, encompassing market expansion, talent attraction, industrial extension, and income growth, systematically enhances the expected returns and broadens the scope of returns for agricultural technological innovation, thereby enhancing the level of agricultural technology innovation in cities.

2.4 Conceptual framework and hypotheses

The preceding analysis identifies a spatially heterogeneous pattern in China's agricultural technological innovation, characterized by a coastal-to-inland gradient decline. The "Broadband China" pilot policy, serving as a quasi-natural experiment, provides a critical exogenous shock for identifying the causal effect of digital infrastructure. Theoretical discussion further indicates that agricultural innovation suffers from market failure due to high costs and narrow profit margins, while digital technology demonstrates potential to address this dilemma by enhancing intellectual property protection and market connectivity. Integrating these empirical observations, the policy context, and theoretical insights, this paper constructs an overarching conceptual framework to guide the subsequent analysis and formulates research hypotheses accordingly.

The theoretical framework established in this study is illustrated in Figure 5. Its core aim is to elucidate how digital infrastructure shapes agricultural technological innovation through specific pathways, moderated by key contextual conditions such as resource endowment and entrepreneurial environment. The framework's logical starting point is the exogenous shock to digital infrastructure induced by the "Broadband China" policy. Its central mechanism operates through two parallel pathways. The first is "reducing cost," where digital technologies empower innovators by enhancing the availability and verifiability of infringement evidence, thereby lowering the transaction costs of intellectual property protection. The second is "increasing revenue," where digital platforms expand market boundaries by connecting fragmented demand and stimulating agricultural entrepreneurship, thereby increasing the market returns to innovation activities. These two pathways

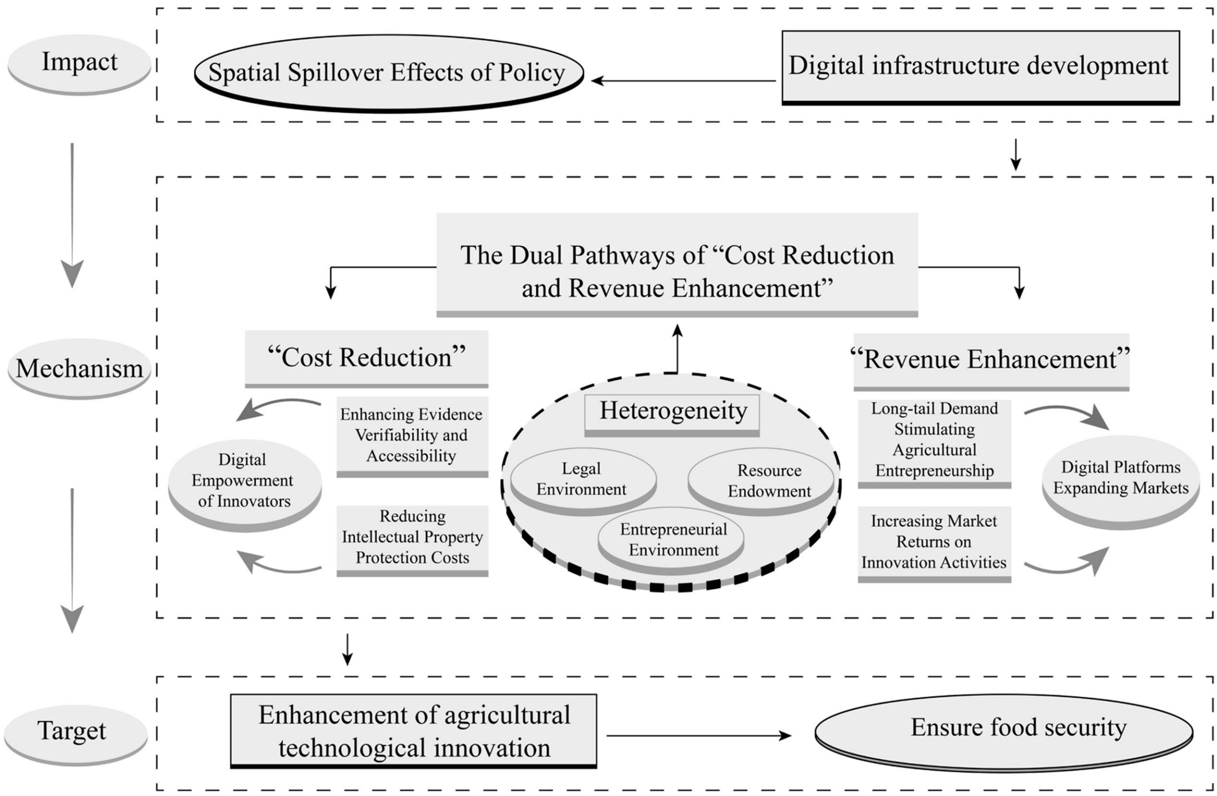

FIGURE 5
Mechanism of digital infrastructure in shaping agricultural technological innovation.

jointly act to raise the net expected return on agricultural technological innovation, constituting the primary channels of influence, which are tested through mediating variables.

The framework further emphasizes that the strength of these “increasing revenue and reducing cost” effects is not homogeneous but is significantly shaped by heterogeneity, moderated by factors including regional resource endowment, entrepreneurial environment, and legal environment. Additionally, the framework extends the chain of influence in both directions: considering potential spatial knowledge spillovers from digital infrastructure at the upstream end, and the subsequent strengthening of food security capacity resulting from enhanced agricultural technological innovation at the downstream end. Therefore, this framework is not an isolated schematic but serves as a comprehensive blueprint that organically connects the aforementioned phenomena, theory, and policy with the subsequent empirical design, testing, and extended analysis, precisely addressing the core concern highlighted in the title regarding “the importance of resource endowment and entrepreneurial environment.”

Based on this framework, this paper takes into account the observed correlative changes between digital infrastructure levels and agricultural patent output in pilot cities following the policy implementation. It also draws on systematic theoretical analysis, which argues that digital infrastructure acts as a market-based incentive and can stimulate micro-level actors by optimizing the innovation environment. On this basis, the paper posits that the development of digital infrastructure can directly promote agricultural technological innovation. Accordingly, Research Hypothesis 1 is proposed.

> *H1*: The construction of digital infrastructure can promote the level of agricultural technology innovation in cities.

Concurrently, theoretical analysis suggests that the key to promoting agricultural technological innovation lies in “increasing revenue and reducing costs.” Digital infrastructure achieves this critical effect precisely by empowering two specific application scenarios: “rights protection” and “sales.” It lowers the costs of rights protection by facilitating digital transformation and increases innovation returns by fostering rural e-commerce development. Therefore, “increasing revenue and reducing costs” serves as the core transmission channel linking digital infrastructure to agricultural technological innovation. Testing this mediating mechanism is crucial for understanding “how digital infrastructure shapes agricultural technological innovation.” Based on this, the paper proposes Research Hypothesis 2.

> *H2*: The construction of digital infrastructure can promote agricultural technology innovation through increasing revenue and reducing cost, that is, by promoting the digital transformation of innovative entities and reducing the cost of innovation rights protection, and by expanding the sales of agricultural products to increase the benefits of agricultural technology innovation.

3 Methodology

3.1 Econometric models

In order to explore the causal relationship between digital infrastructure construction and agricultural technology innovation, this research regards the "Broadband China" pilot as a "quasi-exogenous shock" to the local digital infrastructure stock, and constructs the following staggered difference-in-difference model:

$$AgriInnov_{it} = \alpha + \beta \times BroadBand_{it} + \sum_k z_{ik}\varphi'(t)\delta_k + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

Among them, the explanatory variable $AgriInnov_{it}$ is the agricultural technology innovation level of city i in the t period, which is measured by the number of agricultural patents granted per 10,000 people; the core explanatory variable $BroadBand_{it}$ is a dummy variable representing the processing state. When the city i enters or has entered the "Broadband China" pilot list in the t period, the value is 1, otherwise the value is 0; μ_i is the urban fixed effect, which controls the unobservable but time-invariant individual heterogeneity; λ_t is the time fixed effect, which controls the macroeconomic fluctuations that affect all cities to the same extent; ε_{it} is a random disturbance term; z_{ik} is the kth previously determined variable that affects whether city i is processed. Since this variable does not have time-varying characteristics, this research takes it as a control variable after interacting with the abstract function $\varphi(t)$ of time trend t, and δ_k is the corresponding parameter vector. α is the intercept term of the model; this research mainly focuses on the parameters β, which is significantly that the positive representative treatment group pilot city has a higher level of agricultural technology innovation than the control group after receiving treatment. Because the core explanatory variables fluctuate at the city level, this research will be robust.

The difference-in-differences model cannot naturally give the parameters β an explanation of the causal effect, and the following key prerequisites should be met:

$$\mathrm{cov}\left(BroadBand_{it}, \varepsilon_{it}\right) = 0 \quad (2)$$

Where $\mathrm{cov}(\cdot,\cdot)$ represents the covariance between random variables. Since Equation 2 cannot be fully verified by means of measurement, this research sorts out four main reasons that will lead to the failure of Equation 2 and excludes them one by one, so as to discuss the effectiveness of the identification strategy. These four types of problems include: First, the violation of the parallel trend hypothesis. The parallel trend hypothesis requires that the difference between the treatment group and the control group remains stable in the counterfactual state, otherwise the two groups are essentially incomparable. Second, the control variables fail to make the choice of the treatment group city and the choice of the specific treatment time point relatively exogenous, that is, the core explanatory variables are related to the random disturbance term. Thirdly, there may be other policy shocks during the sample period that also affect the level of agricultural innovation, resulting in parameter estimates that cannot accurately reflect the causal relationship. Fourth, there are some unobservable unknown factors that interfere with the regression results.

For the first type of problem, because the parallel trend hypothesis cannot be fully tested, this research refers to La Ferrara et al. (2012), discusses the ex-ante parallel trend of the treatment group and the control group based on the event analysis method, and studies the dynamic effect of policy shocks. The model is as follows:

$$AgriInnov_{it} = \alpha + \sum_{-5 \le s \le 7, s \ne -1} D_{i,s}\theta_s + \sum_k z_{ik}\varphi'(t)\delta_k + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

Here, $D_{i,-s}$ and $D_{i,+s}$ are dummy variables representing the s years before and after the city i became a pilot city, and θ_s is the regression coefficient corresponding to $D_{i,s}$. In this research, the ex-ante 1 period is used as the base period of the ex-ante parallel trend test, eliminating $D_{i,-1}$ and avoiding complete collinearity. If all prior dummy variables are not significant and their joint tests are also not significant, the null hypothesis that there is a prior parallel trend cannot be rejected. However, Sun and Abraham (2021) proved that the traditional estimate of θ_s is the weighted average of a series of relative time-point dynamic processing effects including their own s. In the staggered difference-in-differences model, the time points processed by different rounds of treatment groups are not the same. If there is a heterogeneous processing effect, θ_s will no longer represent the dynamic processing effect of the Year s, and the test results based on the two-way fixed effect model are not reliable. Therefore, this research uses the robust estimation method of heterogeneity treatment effect proposed by Sun and Abraham (2021) to re-implement the prior parallel trend test, so as to improve the robustness of the test results.

For the second issue, if the selection process of the treatment group cities is relatively exogenous, then after controlling for the predetermined variables, the differences between the treatment and control groups should be relatively small. Referring to Li et al. (2016), the following balance test is conducted:

$$Other_i = \alpha + \gamma \times Treat_i + \sum_k z_{ik}\delta_k + \varepsilon_{it} \quad (4)$$

Where $Other_i$ is an economic variable contemporaneous with z_{ik}, and $Treat_i$ is a dummy variable indicating whether city i receives the treatment, taking a value of 1 if it does and 0 otherwise. If the coefficient $Treat_i$ corresponding to γ is not significant, it indicates that after controlling for the predetermined variable z_{ik}, $Other_i$ shows no significant difference between the treatment and control groups, thereby passing the balance test.

If the timing of treatment for the treatment group cities is relatively exogenous, then the innovative entities cannot anticipate the specific timing of policy implementation and will not form anticipatory effects that change the level of agricultural technology innovation through behavioral adjustments. Theoretically, since the international Internet entered China in 1994 and the first round of the "Broadband China" pilot program was implemented

20 years later, it can be considered that the implementation of the pilot policy in any year during this period is relatively random. To exclude anticipatory effects in the econometric test, the following model is constructed:

$$AgriInnov_{it} = \alpha + \beta \times BroadBand_{it} + D_{i,-s}\theta_{-s} + \sum_k z_{ik}\varphi'(t)\delta_k + \mu_i + \lambda_t + \varepsilon_{it} \quad (5)$$

Equation 5 adds a dummy variable $D_{i,-s}$ representing the period s years before treatment to Equation 1, with $D_{i,-s}$ generally taking values of 1 or 2. The corresponding model coefficient θ_{-s}represents the size of the anticipatory effect. If θ_{-s} is not significant, it indicates that there is no anticipatory effect in the period s years before treatment.

Regarding the third issue, since the benchmark regression model represented by Equation 1 includes time fixed effects λ_t, which can control for macro policies implemented at the national level, this research mainly focuses on pilot-type policies that may affect agricultural technology innovation. First, to accelerate the implementation of an innovation-driven development strategy, the Chinese government began to list 78 cities in batches as pilot cities for innovation-driven development starting in 2008. By gathering innovation factors, cultivating innovative enterprises, building innovation carriers, and incentivizing innovative talents, the innovation and entrepreneurship environment of cities has been optimized (Bai et al., 2022), which may stimulate innovation enthusiasm and promote agricultural innovation. Second, to achieve coordinated development between urbanization and new rural construction, the National Development and Reform Commission and nine other ministries began to establish 341 pilot areas for returning entrepreneurship in three batches starting in 2016. By implementing targeted tax reductions, universal fee reductions, subsidizing new types of agricultural business entities, and guiding increased agricultural funding, these policies attract migrant workers, college students, and retired soldiers to return to their hometowns for entrepreneurship (Huang et al., 2022), which may promote agricultural innovation through technology diffusion. Finally, to actively explore a Chinese-characteristic agricultural modernization path, the Ministry of Agriculture and Rural Affairs began to recognize 283 national modern agricultural demonstration zones in three batches starting in 2010. By scaling up, mechanizing, and industrializing, these zones have significantly increased land output and labor productivity, which may induce agricultural technology innovation as new equipment and systems are rolled out. This research adds dummy variables representing these policy shocks as new control variables to Equation 1. If the key explanatory variable remains significant and the changes in the estimated values are relatively small, it can be concluded that these policies do not interfere with the benchmark regression results.

Regarding the fourth issue, this research refers to Kong and Qin (2021) and uses two methods to mitigate the impact of unobservable time-varying unknown factors. The first method is to introduce the interaction term between provincial fixed effects and time fixed effects into the regression model to control for some time-varying factors, such as various agricultural development policies or innovation incentive policies implemented independently by provinces. The second method is a placebo test, which involves randomly selecting a number of cities equal to the treatment group from the sample cities as a false treatment group, and then randomly selecting a year within the sample period as the false treatment time. Finally, the false treatment variable obtained is substituted for the key explanatory variable in Equation 1 and re-regressed. If unobservable factors do not cause systematic biases in the estimation results, then the coefficient corresponding to the newly generated false treatment variable should be insignificant and close to zero. In empirical research, to reduce the randomness of a single random draw, the above random drawing process is generally repeated 500 times to observe the overall performance of all estimation results.

To explore the potential mechanisms through which the construction of digital infrastructure affects agricultural technology innovation, this research constructs the following regression model for the mechanism variables on the key explanatory variable Equation 6:

$$Mechanism_{it} = \alpha + \theta \times BroadBand_{it} + \sum_k z_{ik}\varphi'(t)\delta_k + \mu_i + \lambda_t + \varepsilon_{it} \quad (6)$$

Where $Mechanism_{it}$ is the mechanism variable, and θ is the estimated coefficient corresponding to the key explanatory variable. A significant positive value of θ implies that the construction of digital infrastructure can promote the level of agricultural technology innovation in cities by enhancing $Mechanism_{it}$.

To analyze the potential spatial spillover effects of the "Broadband China" pilot cities, this research refers to Tian and Xu (2022) and constructs the following regression model for the control group samples that never became "Broadband China" pilot cities during the sample period:

$$AgriInnov_{it} = \alpha + \gamma \times Distance_i \times BroadBand_{it}^{i} + \sum_k z_{ik}\varphi'(t)\delta_k + \mu_i + \lambda_t + \varepsilon_{it} \quad (7)$$

Where $Distance_i$ represents the logarithm of the inverse of the geographical distance from city i to the nearest "Broadband China" pilot city; $BroadBand_{it}^{i}$ is a dummy variable indicating the treatment status of the nearest pilot city to city i. If the policy shock has a significant positive spatial spillover effect on the spatial neighbors of the pilot cities, this research expects γ to be significantly positive.

3.2 Variable description

(1) Dependent Variable: Level of Agricultural Technology Innovation.

Measuring innovation levels based on patent data is a common practice in academia, with common indicators including the number of patents granted, the number of patent applications, and the number of invention patents granted. This research argues that the number of patents granted, compared to the number of applications, better reflects a city's true level of innovation. To eliminate the impact of city size, this research uses the number of agricultural patents granted per ten thousand people as a proxy for the level of agricultural technology innovation in the baseline regression. The rationality of utilizing patent data to measure agricultural innovation lies in its precision and objectivity. First, the use of International Patent Classification (IPC) codes allows for the accurate filtering of "pure" agricultural technologies, effectively excluding non-agricultural interference. Second, patents are granted by the CNIPA based on unified national legal standards, ensuring that the data is less susceptible to local administrative interference compared to other regional innovation metrics. Finally, the distinction between invention and utility model patents provides a quantifiable measure of innovation quality. To ensure the reliability of the baseline regression results, this research replaces the original dependent variable with two indicators in the robustness test: the number of agricultural invention patents granted per ten thousand people and the number of agricultural patent applications per ten thousand people.

(2) Key Explanatory Variable: Construction of Digital Infrastructure.

This research manually constructs a dummy variable based on the three batches of "Broadband China" pilot lists published by the Ministry of Industry and Information Technology (MIIT) and the National Development and Reform Commission (NDRC) as the key explanatory variable. The variable takes a value of 1 in the year a city enters the pilot list and in subsequent years, and 0 otherwise. In the robustness test, this research uses two alternative measurement methods. The first method adjusts the value in the pilot year based on the original dummy variable, considering the impact of monthly differences. Specifically, the three batches of pilot lists were released in September, October, and July of the respective years. The values for the pilot year are adjusted to 4/12, 3/12, and 6/12, respectively. The second method follows the approach of Chao et al. (2021), which posits that local governments are the core force in investing in and constructing digital infrastructure. The frequency of terms related to digital infrastructure in government work reports can reflect the intensity of digital infrastructure construction. This research multiplies this frequency by the proportion of information and communication technology (ICT) employees in the total population to measure the development level of digital infrastructure in cities. A higher value indicates a higher level of development.

(3) Control Variables.

The selection of "Broadband China" pilot cities is not random, and the parallel trends assumption may be violated, meaning that the post-treatment differences between the treatment and control groups may not be due to policy shocks but rather pre-existing trend changes. This could render the identification strategy ineffective. To enhance the reliability of the identification strategy, this research refers to Li et al. (2016) and includes variables that determine a city's selection into the pilot list as control variables to achieve relative randomness in the treatment group selection. As indicated by the policy background, the existing broadband development foundation and the future difficulty of broadband construction are key factors in determining city selection. For the existing broadband development foundation, this research selects four indicators: the proportion of international Internet users, the proportion of mobile phone users, the proportion of ICT employees, and the per capita total volume of telecommunications services. For the difficulty of broadband construction, this research selects four indicators: per capita real gross domestic product (GDP), population density, topographic slope, and per capita fiscal expenditure, totaling eight indicators as predetermined variables. Predetermined variables can only be selected as cross-sectional data before the treatment. Referring to Li et al. (2016), this research uses data from the year before the first round of pilots (2013) as predetermined variables, and in the robustness test, data from the first period of the sample (2011) are used as predetermined variables. Predetermined variables must be interacted with time-varying indicators to serve as control variables. This research uses two interaction methods in the baseline regression. One is interaction with time fixed effect dummy variables, and the other is interaction with a cubic polynomial of the time trend term. The latter assumes that the impact of predetermined variables on agricultural technology innovation has some time trend, while the former does not have this restriction.

In the test to exclude the interference of other contemporaneous policies, this research includes dummy variables representing national innovative city pilots, returnee entrepreneurship pilots, and national modern agricultural demonstration zones as new control variables in the empirical model based on the relevant pilot area lists. The specific construction method for the dummy variables is as follows: First, cities or their subordinate districts and counties that are on the pilot lists are marked as treatment groups. Second, the earliest year the treatment group receives treatment is recorded as the treatment time point. Third, the corresponding dummy variable takes a value of 1 in the year the treatment group receives treatment and in subsequent years, and 0 otherwise.

(4) Mechanism Variables.

This research explores the mechanisms through which the construction of digital infrastructure affects agricultural technology innovation from two aspects: facilitating intellectual property rights (IPR) protection and expanding the sales channels for agricultural products. In terms of facilitating IPR protection, following Wu et al. (2021), the frequency of terms related to "digital transformation" mentioned in the annual reports of listed companies is used to depict the degree of digital transformation. Drawing on Jiang and Liang (2022), the total number of publicly available judicial documents related to intellectual property and competition disputes, as well as the number of judgments among them, are used to measure the legal protection efforts of innovative entities, with higher values indicating greater protection efforts. Regarding expanding the sales channels for agricultural products, following Zhang et al. (2021), the sum of the per capita Internet search volumes for keywords such as "rural e-commerce," "rural electronic commerce," and "agricultural electronic commerce" is used as a proxy for the development level of rural e-commerce in cities. Referring to Feng et al. (2023a), the per capita number of newly established enterprises with business scopes including "agriculture" is used as a proxy for the activity level of agriculture-related entrepreneurship. Agriculture-related enterprises cover the entire agricultural industry chain, including the production, processing, transportation, and sales of agricultural products. Higher values of these two indicators suggest broader sales channels for local agricultural products.

The impact of digital infrastructure construction on the economy and society is extensive. In addition to expanding the sales channels for agricultural products and reducing the costs of IPR protection, it may also promote agricultural technology innovation through other channels. One possible competing mechanism is the promotion of agricultural development. Wang et al. (2023) pointed out that the construction of digital infrastructure can effectively reduce the cost of information transmission and expand the scope of information dissemination, helping farmers to more conveniently learn various advanced agricultural knowledge, effectively improving agricultural production efficiency and expanding production scale. This objectively helps to develop an open agricultural innovation network and stimulate agricultural technology innovation. Moreover, the information effect of digital infrastructure will subtly change farmers' awareness, enhance their recognition and participation in modern agricultural production methods, and encourage them to participate in agricultural innovation more actively. Another possible competing mechanism is the alleviation of financing constraints. Digital technology can help commercial banks better assess the repayment ability and willingness of borrowers (Fuster et al., 2019), enhancing their willingness to provide loans to micro-innovative entities and creating a favorable financial environment for agricultural technology innovation. Digital infrastructure strengthens the ability of innovative entities to convey positive market signals to the outside world, such as the market potential of existing patents and the success rate of technology research and development. Higher information transparency is also more likely to win the trust of financial institutions. This research uses the per capita number of newly established enterprises in agriculture, forestry, animal husbandry, and fishery to depict the activity level of agricultural enterprise entrepreneurship and the logarithm of per capita value added in the primary industry to depict agricultural output. Higher values of these two indicators indicate a higher level of agricultural development. The ratio of financial institution loan balance to GDP and the ratio of loan balance to deposit balance are used to measure financing constraints, with higher values indicating lower financing constraints.

(5) Grouping Variables.

In the heterogeneity analysis section, this research divides cities into different groups from three dimensions: resource endowments, entrepreneurial environment, and legal environment. Regarding resource endowments, this research examines the differences in agricultural brands among cities. If a city was selected as one of the national advanced cities (prefectures, leagues, or alliances) for grain production by 2012 or earlier, it is considered to have a certain national reputation in agricultural production; otherwise, it is considered to have a lower agricultural brand endowment. This research also examines the differences in transportation infrastructure among cities. If the per capita road freight volume of a sample city exceeds the median of the pre-treatment mean of the entire sample, it is considered to have better transportation endowments; otherwise, it is considered to have poorer transportation endowments. In terms of the entrepreneurial environment, this research examines the differences in agricultural knowledge reserves among cities. If the pre-treatment mean of agricultural science and technology core journal papers published in the province where the city is located exceeds the median of the pre-treatment mean of the entire sample, it is considered to have a better agricultural entrepreneurial environment; otherwise, it is considered to have a poorer agricultural entrepreneurial environment. This research also examines the differences in economic uncertainty among cities. If the pre-treatment mean of the economic policy uncertainty index of the province where the city is located is lower than the median of the entire sample, it is considered to have a better entrepreneurial environment; otherwise, it is considered to have a poorer entrepreneurial environment. Regarding the legal environment, this research examines the differences in intellectual property protection among cities. If the pre-treatment mean of the intellectual property protection sub-index of the China Marketization Index of the province where the city is located exceeds the median of the entire sample, it is considered to have a better legal environment; otherwise, it is considered to have a poorer legal environment. This research also examines the differences in government information opacity among cities. It is believed that the "negotiated transfer" method in the transfer of state-owned land is less transparent than the methods of public listing, bidding, or auction (Li et al., 2016). Therefore, the proportion of land transferred through negotiated transfer is calculated for each region and year. Cities with a pre-treatment mean value of this indicator lower than the median of the full sample are considered to have a better legal environment, while others are considered to have a poorer one.

(6) Other Variables.

In the balance test, this research selects the per capita railway freight volume, per capita road freight volume, degree of opening up to the outside world, industrial structure, and carbon emission intensity of each city in 2013 as test variables. In further analysis, this research uses car navigation distance to measure the geographical distance between cities (Feng et al., 2023b), to test the spatial spillover effects of the pilot policy; and selects the production of poultry eggs, pork, beef, etc., as downstream variables of agricultural technology innovation, to test the impact of the pilot policy on food security.

3.3 Data sources

The patent data used in this research are sourced from the Zhihuiya Patent Database; entrepreneurial data are obtained from the official website of Tianyancha; topographic slope, local government work reports, and annual reports of listed companies are retrieved from the CNRDS database; internet search data are taken from the Baidu Index official website; the number of judicial documents and judgments is scraped from the China Judgements Online; the volume of agricultural science and technology core journal papers is sourced from the China National Knowledge Infrastructure (CNKI) Academic Evaluation Support Platform; the provincial economic policy uncertainty index is obtained from Yu et al. (2021); the China Marketization Index is sourced from the China Marketization Index database; state-owned land transfer data are retrieved from the China Land Market Network; car navigation distance is obtained from the Baidu Map Open Platform; other data are sourced from the China City Statistical Yearbook, official websites of provinces and cities, and statistical yearbooks. The raw data are processed as follows: First,

TABLE 2 Definitions and descriptive statistics of main variables.

Variable Name	Variable Description	Mean	Standard deviation	Minimum	Maximum
Agricultural Technology Innovation Level	Total number of agricultural patents granted in the city / total population (items per ten thousand people)	0.364	0.548	0	5.508
Construction of Digital Infrastructure	Takes a value of 1 in the year the city enters the "Broadband China" pilot program and in subsequent years, and 0 otherwise	0.262	0.440	0	1
Proportion of International Internet Users	Number of international Internet users / total population (households per person)	0.172	0.145	0.036	0.975
Proportion of Mobile Phone Users	Number of mobile phone users at year-end / total population (households per person)	0.205	0.125	0.080	0.764
Proportion of ICT Employees	Number of employees in information transmission, computer services, and software / total population	0.002	0.005	0.000	0.044
Per Capita Total Volume of Telecommunications Services	Total volume of telecommunications services / total population (ten thousand yuan per person)	0.094	0.110	0.005	1.180
Per Capita Real GDP	Regional gross domestic product / total population (ten thousand yuan per person)	5.244	4.909	0.979	46.595
Population Density	Total population / administrative area land area (ten thousand people per square kilometer)	0.046	0.034	0.001	0.262
Geographical Slope	Average slope of the city	10.245	5.471	1.592	27.139
Per Capita Fiscal Expenditure	Local fiscal general budget revenue / total population (ten thousand yuan per person)	0.784	0.559	0.187	5.446
Rural E-commerce	Natural logarithm of the per capita internet search volume for keywords such as "rural e-commerce," "rural electronic commerce," and "agricultural electronic commerce"	-1.655	2.874	-8.115	3.066
Agriculture-related Entrepreneurship	Natural logarithm of the number of newly established enterprises with business scopes including the keyword "agriculture" divided by the total population	1.690	0.802	-0.823	6.112
Enterprise Digitalization	Natural logarithm of the frequency of terms related to "digital transformation" mentioned in the annual reports of listed companies plus 1	0.648	1.034	0	6.011
Judicial documents	Ln (Number of IP and competition-dispute judicial documents + 1)	1.397	1.713	0	7.589
Judgment documents	Ln (Number of IP and competition-dispute judgments +1)	1.288	1.611	0	7.586

based on the availability of specific mechanism variables, the initial year of the sample is set to 2011. Second, according to the availability of urban statistical data, the final year of the sample is set to 2021. Third, cities with a relatively high number of missing values are removed. Fourth, the K-nearest neighbors algorithm is used to fill in a small number of missing values in the dataset. Ultimately, a balanced panel dataset for 281 prefecture-level and above cities in China from 2011 to 2021 is obtained, comprising a total of 3,091 city-year observations. The specific forms of the main variables entering the regression model and the corresponding descriptive statistical results can be seen in Table 2.

4 Results

4.1 Baseline regression

Table 3 reports the baseline regression results. Regression 1 controls for city fixed effects and time fixed effects. Regression 2 introduces the interaction terms of predetermined variables and time fixed effects on the basis of Regression 1. Regression 3 adds the interaction terms of predetermined variables and the first, second, and third powers of the time trend to Regression 1. The results show that the coefficient of the key explanatory variable is significantly positive at the 1% level in all model specifications. Since the introduction of interaction terms between predetermined variables and time fixed effects implies fewer assumptions, this research interprets the economic significance of the coefficient estimates based on Regression 2. It is believed that the "Broadband China" pilot program has increased the per capita number of agricultural patents granted in cities by 0.117 items per ten thousand people compared with non-pilot cities. This value accounts for 13.60% of the per capita agricultural patent grants (0.860 items per ten thousand people) in the full sample in 2021, which is economically significant. In conclusion, this research argues that the construction of digital infrastructure can promote local agricultural technology innovation, which preliminarily verifies Research Hypothesis H1.

TABLE 3 The impact of digital infrastructure construction on agricultural technology innovation: baseline regression.

Variable	Dependent variable: agricultural technology innovation level					
	Regression 1		Regression 2		Regression 3	
	Coefficient	Robust standard error	Coefficient	Robust standard error	Coefficient	Robust standard error
Digital infrastructure construction	0.194***	0.040	0.117***	0.035	0.115***	0.034
City fixed effects	Controlled		Controlled		Controlled	
Time fixed effects	Controlled		Controlled		Controlled	
Pre-determined variables × Time fixed effects	Not controlled		Controlled		Not controlled	
Pre-determined variables × Time trend (1st order)	Not controlled		Not controlled		Controlled	
Pre-determined variables × Time trend (2nd order)	Not controlled		Not controlled		Controlled	
Pre-determined variables × Time trend (3rd order)	Not controlled		Not controlled		Controlled	
Observations	3,091		3,091		3,091	
Adjusted R^2	0.718		0.799		0.789	

Note: * P<0.1, ** P<0.05, *** P<0.01; standard errors are robust and shown in parentheses.

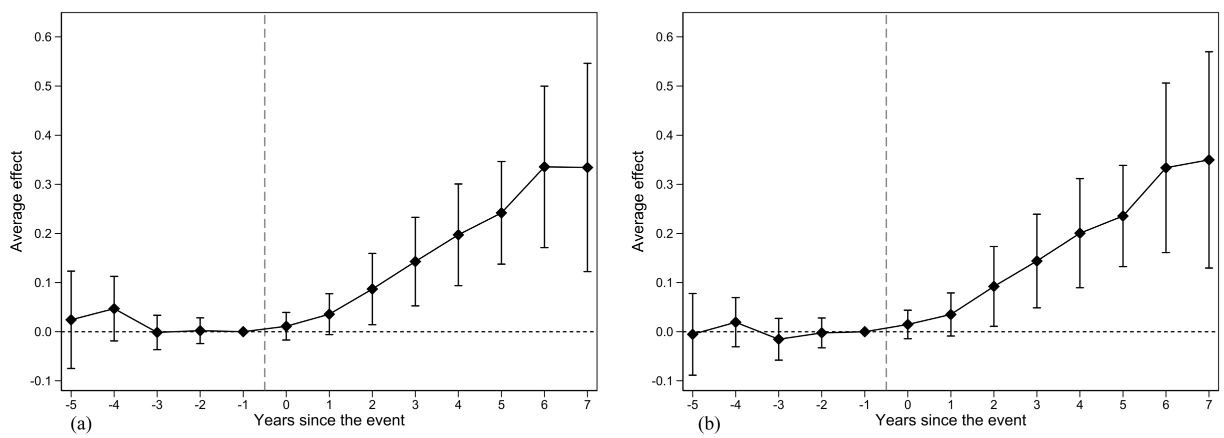

FIGURE 6
Pre-treatment parallel trend test. **(a)** Test results based on the two-way fixed effects model. **(b)** Test results based on the heterogeneous treatment effect robust estimation method.

4.2 Validity test of identification strategy

(1) Pre-treatment Parallel Trend Test.

Figure 6a reports the regression results based on the two-way fixed effects model estimation of Equation 3. It can be seen that none of the coefficients corresponding to the pre-treatment dummy variables are significant at the 5% level. The joint test F-statistic for these coefficients is 1.120 (p-value 0.348), and there is no clear time trend in the coefficients corresponding to the pre-treatment dummy variables. This indicates that before the implementation of the "Broadband China" pilot policy, there was no significant change in the difference in agricultural technology innovation levels between the treatment and control groups, thereby passing the pre-treatment parallel trend test. Further examination of the post-treatment coefficients shows that the coefficients corresponding to the pilot year and the first post-treatment period are not significant, while the coefficients for the second post-treatment period and thereafter are significant at the 5% confidence level and continue to rise. This suggests that digital infrastructure needs to go through a time lag before it can begin to promote agricultural technology innovation, but the impact is relatively sustained and profound. The post-treatment dynamic effects show such a pattern, which is consistent with economic intuition. This is because, whether digital infrastructure truly plays a role in the innovation process or a patent takes time from application to grant, its role in reducing the information acquisition threshold for innovators is undoubtedly lasting and stable. To further enhance the robustness of the test results, Figure 6b reports the test results based on the robust estimation method for heterogeneous treatment effects proposed by Sun and Abraham (2021). The revealed information is similar to that in Figure 3a, that is, none of the pre-treatment dummy variables are significant at the 5% level, and there is no clear time trend. The post-treatment effects strengthen continuously after a time lag. In summary, this research cannot reject the null hypothesis of pre-treatment parallel trends, and the baseline regression can reflect the causal relationship between the construction of digital infrastructure and agricultural technology innovation. The necessity of the second method (Sun and Abraham, 2021) arises from the potential bias of traditional TWFE in staggered DID designs. While Method 1 offers a baseline trend visualization, recent econometric literature suggests that if treatment effects are heterogeneous across different cohorts, traditional TWFE may assign "negative weights" to certain observations, leading to biased estimates. Method 2 provides a robust estimator that accounts for this heterogeneity, ensuring that the parallel trend assumption holds even when the timing of policy implementation is dispersed.

(2) Test for the Relative Exogeneity of Treatment Group Selection and Treatment Timing.

Selected indicators such as per capita railway freight volume, per capita road freight volume, degree of opening up to the outside world, industrial structure, and carbon emission intensity for each city prior to treatment as dependent variables, regression analysis was conducted based on Equation 4 and the results are reported in Table 4. The information shows that under the control of predetermined variables, the regression coefficients corresponding to the treatment group dummy variables are not significant at the 10% level, indicating that the differences of these test variables between the treatment and control groups are relatively small. The treatment group cities can be regarded as conditionally randomly selected to some extent, which means that the selection of the treatment group has relative exogeneity. Based on Equation 5, this research tests for anticipatory effects and reports the regression results in regressions 1–2 of Table 5. It is found that the regression coefficients corresponding to the dummy variables for 1 period before and 2 periods before the treatment are not significant at the 10% confidence level, indicating that the innovative entities did not form anticipatory effects before the "Broadband China" pilot program. This suggests that the timing of the policy shock has relative exogeneity. In summary, it can be concluded that this research has reasonably selected predetermined variables, so that there is no obvious correlation between the key explanatory variable and the random disturbance term.

(3) Exclusion of Interference from Other Contemporary Policies.

This research successively introduces dummy variables representing national innovative city pilots, returnee entrepreneurship pilots, and national modern agricultural demonstration zones as new control variables into Equation 1, and reports the regression results in regressions 3–5 of Table 5. The results show that the coefficients corresponding to the key explanatory variable remain significant at the 1% level, and the changes in the values relative to the baseline regression results are relatively small. This indicates that after excluding the interference of other contemporary policy shocks, the construction of digital infrastructure still promotes agricultural technology innovation.

(4) Exclusion of Interference from Unobservable Time-Varying Factors.

First, this research introduces the interaction terms between provincial fixed effects and time fixed effects into the baseline regression and reports the results in regression 6 of Table 5. The results show that the key explanatory variable remains significantly positive, indicating that the baseline regression results remain robust after considering policy changes at the provincial level. Then, this research conducts a placebo test and reports the results in Figure 7. The information shows that the estimated values corresponding to the false treatment variables are mostly concentrated around the zero point, with a mean value of 0.0004 very close to zero. The kernel density curve is similar in shape to the probability density curve of a normal distribution. Most of the estimated coefficients have p-values exceeding 0.05, meaning they are not significant at the 5% confidence level. The baseline regression result of 0.117 is significantly to the right of the kernel density curve and is distinct from the placebo test estimates. These findings indicate that the placebo test is passed. In summary, this research is confident in excluding the potential adverse effects of unobservable time-varying factors on the baseline regression results.

4.3 Robustness tests

(1) Instrumental Variable Regression.

Although the previous tests have fully demonstrated the validity of the identification strategy and the baseline regression results can reflect the causal relationship between the construction of digital infrastructure and agricultural technology innovation, to further enhance the reliability of the estimation results, this research continues to use instrumental variables to address potential endogeneity issues. A valid instrumental variable needs to meet the relevance condition and the exogeneity condition, that is, it is correlated with the key explanatory variable but not with the random disturbance term. Referring to Zhao et al. (2020), the number of post offices per capita and the number of fixed telephones per capita in 1984 are used as instrumental variables for digital infrastructure. The rationale is as follows: First, after the founding of New China, postal and telecommunications services were long under the same organization. Areas with higher post office density would have more fixed

TABLE 4 The test for the relative exogeneity of treatment group selection.

Variable	Per capita railway freight volume	Per capita road freight volume	Degree of opening to the outside world	Industrial structure	Carbon emission intensity
	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
Treatment group dummy variable	−1.055	1.304	0.002	−0.091	−0.123
	(0.876)	(3.069)	(0.002)	(0.077)	(0.180)
Pre-determined variables	Controlled	Controlled	Controlled	Controlled	Controlled
Observations	281	281	281	281	281
Adjusted R^2	0.183	0.278	0.206	0.151	0.107

TABLE 5 The validity test of identification strategy.

Variable	Dependent variable: agricultural technology innovation level					
	Excluding anticipation effects		Excluding other policy interferences		Excluding unobservable factors	
	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5	Regression 6
Digital infrastructure construction	0.117***	0.114***	0.108***	0.116***	0.117***	0.096***
	(0.038)	(0.035)	(0.034)	(0.034)	(0.035)	(0.029)
Pre-treatment Period 1	0.001					
	(0.018)					
Pre-treatment Period 2		−0.013				
		(0.011)				
National innovative city pilot			0.222***			
			(0.061)			
Returnee entrepreneurship pilot				0.011		
				(0.030)		
National modern agricultural demonstration zone					−0.006	
					(0.027)	
Province fixed effects × Time fixed effects	Not controlled	Not controlled	Not controlled	Not controlled	Not controlled	Controlled
City fixed effects	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Time fixed effects	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Pre-determined variables × Time fixed effects	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Observations	3,091	3,091	3,091	3,091	3,091	3,025
Adjusted R^2	0.799	0.799	0.804	0.799	0.799	0.820

Note: * P<0.1, ** P<0.05, *** P<0.01; standard errors are robust and shown in parentheses.

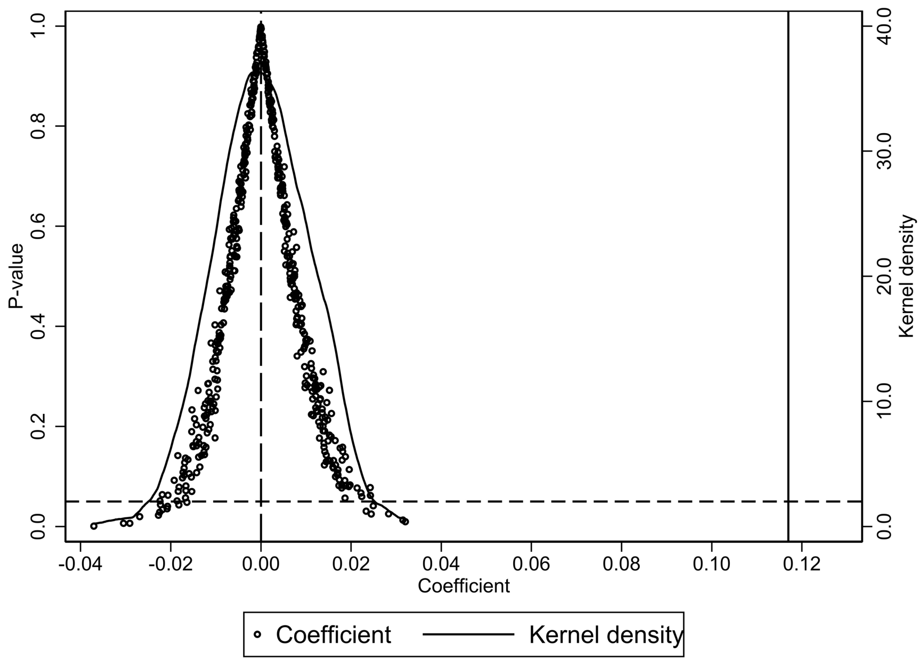

FIGURE 7
The placebo test.

telephones installed. The historical inertia brought better telecommunications infrastructure, which increased the likelihood of a city being selected as a "Broadband China" pilot city, thereby satisfying the relevance condition. Second, in terms of the time span, 1984 is quite distant from the initial period of the sample and is unlikely to affect current agricultural innovation. In terms of the nature of the indicators, post offices and fixed telephones have become less influential in contemporary socio-economic activities with the rise of mobile internet, thereby satisfying the exogeneity condition. Since historical postal and telecommunications development levels do not vary over time, to make them feasible instrumental variables, following Tian and Zhang (2022), they are interacted with the "Broadband China" time dummy variable before being included in the empirical model.

This research implements instrumental variable regression based on two-stage least squares estimation and reports the results of the first-stage regression in regression 1 of Table 6. The results show that both instrumental variables are significantly positively correlated with the key explanatory variable. The F-test rejects the null hypothesis that the instrumental variables are not correlated with the key explanatory variable, indicating that cities with higher historical postal and telecommunications development levels are more likely to become "Broadband China" pilot cities, thereby verifying the relevance condition of the instrumental variables. Regression 2 reports the results of the second-stage regression. All test statistics exceed the commonly used threshold values, rejecting the null hypotheses of insufficient identification and weak instrumental variables, further verifying the relevance condition of the instrumental variables. Since this research has designed two different instrumental variables for one endogenous variable, it meets the prerequisite for conducting an over-identification test. The obtained Hansen J statistic is not significant at the 10% confidence level, indicating that the null hypothesis that both instrumental variables are simultaneously exogenous cannot be rejected. It can be seen that the instrumental variables used in this research are quite reasonable. From the parameter estimation results, the coefficient corresponding to the key explanatory variable is significantly positive at the 5% confidence level, indicating that the construction of digital infrastructure can promote the level of agricultural technology innovation, which once again verifies the robustness of the baseline regression.

(2) Adjusting the Measurement of Variables.

First, the measurement of the dependent variable is adjusted. This research uses the number of agricultural invention patents granted per ten thousand people and the number of agricultural patent applications per ten thousand people as new dependent variables, and reports the estimation results in regressions 1–2 of Table 7. The coefficients corresponding to the key explanatory variable are significant at the 1% level in both cases. This indicates that digital infrastructure can simultaneously increase both the quantity and quality of agricultural technology innovation in cities, and the baseline regression results are robust. Second, the measurement of the key explanatory variable is adjusted. This research replaces the key explanatory variable with an intensity indicator that considers the differences in pilot months and a continuous indicator based on the frequency of terms in government work reports, and reports the results in regressions 3–4 of Table 7. Both are significant at the 1% level, indicating that different measurement methods of the key explanatory variable do not affect the reliability of the baseline regression results. Third, the setting of control variables is adjusted. Considering that the choice of year for predetermined variables may affect the regression results, this research replaces the original 2013

TABLE 6 Robustness test: Instrumental variable regression.

Variable	Digital infrastructure		Agricultural technology innovation level	
	Regression 1		Regression 2	
	Coefficient	Robust standard error	Coefficient	Robust standard error
Per capita number of post offices × "Broadband China" time dummy variable	1.486***	0.258		
Per capita number of fixed telephones × "Broadband China" time dummy variable	0.004***	0.001		
Digital infrastructure construction			0.147**	0.060
City fixed effects	Controlled		Controlled	
Time fixed effects	Controlled		Controlled	
Pre-determined variables × Time fixed effects	Controlled		Controlled	
First-stage regression F-statistic for all instruments	104.411***			
Kleibergen-Paap rk LM Statistic			74.524***	
Kleibergen-Paap rk Wald F statistic			104.411*	
Hansen J statistic			0.261	
Observations	2,519		2,519	

Since the adjusted R^2 in Regression 2 is negative and does not have a reasonable statistical meaning, it is not reported in the current table. Note: * $P<0.1$, ** $P<0.05$, *** $P<0.01$; standard errors are robust and shown in parentheses.

data with cross-sectional data from the initial period of the sample in regression 5 of Table 7, and includes both in the empirical model in regression 6. The results show that the coefficients corresponding to the key explanatory variable are significant at the 1% level, and the estimated values are relatively close to the baseline values, indicating that the impact of choosing different years is relatively small. In summary, this research believes that after various adjustments to the measurement of variables, the basic conclusions remain robust.

(3) Adjusting the Sample Selection Scope.

First, removing certain city samples. Infrastructure has strong scale and network effects and may produce spatial spillover effects on neighboring areas (Liu and Hu, 2010). To exclude the potential interference of this spillover effect on causal identification, this research refers to Li et al. (2016) and successively removes cities that border "Broadband China" pilot cities but are not pilot cities themselves from the sample and re-regresses. The results of regression 1 in Table 8 show that the coefficient of the impact of digital infrastructure on agricultural technology innovation is significantly positive, indicating that the baseline regression results remain robust after excluding the spillover effects of bordering cities. Considering that municipalities directly under the central government and sub-provincial cities have higher administrative levels than other cities and are more likely to benefit from national strategies, this research first removes the four municipalities and reports the results in regression 2 of Table 8, and then removes the 15 sub-provincial cities and reports the results in regression 3. The information shows that the key explanatory variable is significant at the 1% level, indicating that the baseline regression results remain robust after excluding differences in administrative levels.

Second, re-estimation using matching methods. Since there are certain differences in sample size and observable values between the treatment and control groups, to enhance the robustness of the estimation results, matching methods are used to select more similar control groups for the treatment group and re-estimate. This research uses propensity score matching to match each pilot city with the most similar control group city and reports the estimation results based on the new sample after matching in regression 4 of Table 8. The coefficient corresponding to the key explanatory variable is significantly positive, indicating that after balancing the basic characteristics of each city, the construction of digital infrastructure still has a significant positive impact on agricultural technology innovation. Since propensity score matching reduces the sample size for regression analysis, this research re-matches the sample using entropy balancing matching and reports the estimation results in regression 5 of Table 8. The results show that the construction of digital infrastructure has a significant innovation-promoting effect.

Third, adjusting the sample period. To avoid a long sample period that may mix other policy factors and cause biased estimation results, this research adjusts the sample period to 2011–2019 and re-regresses, reporting the estimation results in regression 6 of Table 8. The reason for choosing this time period is that it is 3 years from the start of the

TABLE 7 Robustness test: adjusting the measurement of variables.

Variable	Invention patent grants	Patent applications	Agricultural technology innovation level			
	Adjusting dependent variable		Adjusting core explanatory variable		Adjusting control variables	
	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5	Regression 6
Digital infrastructure construction	0.046***	0.131***			0.105***	0.104***
	(0.017)	(0.036)			(0.035)	(0.036)
Digital infrastructure intensity indicator			0.150***			
			(0.041)			
Textual indicator of digital infrastructure				0.055***		
				(0.014)		
Initial pre-determined variables × Time fixed effects	Not controlled	Not controlled	Not controlled	Not controlled	Controlled	Controlled
City fixed effects	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Time fixed effects	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Pre-determined variables × Time fixed effects	Controlled	Controlled	Controlled	Controlled	Not controlled	Controlled
Observations	3,091	3,091	3,091	2,798	3,091	3,091
Adjusted R^2	0.724	0.812	0.800	0.806	0.789	0.802

Note: * P<0.1, ** P<0.05, *** P<0.01; standard errors are robust and shown in parentheses.

TABLE 8 Robustness test: adjusting the sample selection scope.

Variable	Dependent variable: agricultural technology innovation level					
	Removing some city samples			Matching method re-estimation		Adjusting sample period
	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5	Regression 6
Digital infrastructure construction	0.093*	0.118***	0.106***	0.108***	0.147***	0.079**
Robust standard error	(0.051)	(0.035)	(0.037)	(0.037)	(0.041)	(0.032)
City fixed effects	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Time fixed effects	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Pre-determined variables × Time fixed effects	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Observations	1,254	3,047	2,882	2,794	3,091	2,529
Adjusted R^2	0.812	0.784	0.719	0.746	0.827	0.799

Note: * P<0.1, ** P<0.05, *** P<0.01; standard errors are robust and shown in parentheses.

sample to the first round of the "Broadband China" pilot and also 3 years from the end of the sample to the last round of the pilot, which can achieve a good balance between sample size and time span. The information shows that digital infrastructure can significantly promote agricultural technology innovation, and the baseline regression results are robust.

10.3389/fsufs.2026.1762008

4.4 Mechanism analysis

(1) Facilitating Rights Protection and Reducing Innovation Costs.

Regressions 1–3 in Table 9 report the results of the impact of digital infrastructure construction on enterprise digital transformation, the number of judicial documents, and the number of judgment documents, respectively. The results show that the construction of digital infrastructure promotes the digital transformation of enterprises, enabling them to conveniently use various cutting-edge digital technologies such as public opinion monitoring, content fingerprinting, and traceability blockchain to identify infringement by competitors. They can collect a sufficient amount of key evidence in the early stages of infringement and take legal action as soon as possible, effectively reducing the cost of protecting technological innovation. Specifically, digital infrastructure addresses the "evidence collection difficulty" inherent in agricultural innovation. For instance, in the crop breeding sector, where infringement often involves "clandestine reproduction" of protected varieties, digital infrastructure enables the integration of DNA "digital fingerprinting" with blockchain-based traceability systems. Innovative seed enterprises can now store variety genetic data in digital databases and use IoT-enabled field monitoring to detect unauthorized cultivation in real-time. This digital evidence chain significantly lowers the evidentiary threshold and shortens the duration of judicial identification in intellectual property litigation. By providing higher granularity and immutability of evidence, digital infrastructure effectively reduces the "rights protection cost" that previously deterred agricultural innovators, thereby fostering a more secure environment for long-term R&D investment. In China, the main avenues for resolving intellectual property disputes through legal means include negotiation, mediation, arbitration, and litigation. The first three emphasize the voluntary participation of both parties, with faster processes and lower costs, while litigation is the last resort when the first three fail, requiring the involvement of state enforcement power. Infringers tend to settle out of court when faced with a complete chain of infringement evidence to avoid expanding the social impact of civil disputes. The comparison between regressions 2 and 3 shows that the increase in judgment documents is slightly less than the overall increase in judicial documents, indicating that new intellectual property disputes are less likely to resort to the ultimate means, indirectly confirming the important role of digital technology in collecting infringement evidence.

(2) Expanding Sales Channels and Increasing Innovation Benefits.

Regressions 4–5 in Table 9 report the results of the impact of digital infrastructure construction on rural e-commerce and agriculture-related entrepreneurship. The results show that the construction of digital infrastructure can significantly promote the development of rural e-commerce, enhance the connection between agricultural product origins and markets, expand sales channels for various agricultural products, thereby enriching agricultural market opportunities and increasing the potential benefits of agricultural technology innovation. A concrete example is the promotion of niche regional agricultural technologies through digital branding and live-streaming e-commerce. Previously, high-value agricultural innovations, such as specific regional organic cultivation techniques or specialty varieties, were often confined to local markets due to information asymmetry and high search costs. With the expansion of digital infrastructure, agricultural entrepreneurs can now bypass traditional intermediaries and directly connect with premium urban consumer segments through platforms like TikTok or WeChat Business. By leveraging big data to match innovative, high-quality products with specific consumer preferences, digital platforms help realize the price premium of agricultural technology. This revenue enhancement effect, driven by the long-tail market access, ensures that the economic returns on agricultural innovation are both realizable and substantial, thereby incentivizing further technological upgrading. At the same time, the rich agricultural market opportunities can also encourage more people to engage in agriculture-related

TABLE 9 Mechanism analysis.

Variable	Enterprise digitalization	Judicial documents	Judgment documents	Rural e-commerce	Agriculture-related entrepreneurship
	Reducing innovation costs			Increasing innovation benefits	
	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
Digital infrastructure construction	0.115***	0.303**	0.262**	0.224***	0.081**
Robust standard error	(0.037)	(0.131)	(0.127)	(0.079)	(0.034)
City fixed effects	Controlled	Controlled	Controlled	Controlled	Controlled
Time fixed effects	Controlled	Controlled	Controlled	Controlled	Controlled
Pre-determined variables × Time fixed effects	Controlled	Controlled	Controlled	Controlled	Controlled
observations	22,604	3,091	3,091	3,091	3,091
Adjusted R^2	0.650	0.807	0.792	0.952	0.883

Since regression 1 is based on data from listed companies, it has a relatively larger number of observations. Note: * P<0.1, ** P<0.05, *** P<0.01; standard errors are robust and shown in parentheses.

entrepreneurship, perfecting the entire industry chain and supply chain of agricultural products from the field to the dining table. Whether it is new market entrants or incumbent enterprises with a first-mover advantage, in order to stand out in the fierce market competition, they need to continuously increase R&D investment to strengthen their technological capabilities, thereby bringing about more agricultural technology innovation. In summary, this research verifies Hypothesis H2.

(3) Excluding Other Possible Mechanisms.

To exclude the competing mechanisms of agricultural development and financing constraints, this research uses the per capita number of new agricultural enterprises and the per capita value added of the primary industry to measure the level of agricultural development, and the ratio of financial institution loan balance to GDP and the ratio of financial institution loan balance to deposit balance to measure the degree of financing constraints. First, the regression results with these variables as dependent variables are reported in Panel A of Table 10. The coefficients corresponding to the key explanatory variable are not significant at the 10% level, indicating that the construction of digital infrastructure has not directly affected the level of agricultural development and the status of financing constraints. Then, the aforementioned variables are successively included as control variables in the baseline regression, and the estimation results are reported in Panel B of Table 10. The coefficients corresponding to the key explanatory variable remain significant at the 1% level, and the estimated values are relatively close to the baseline regression results, indicating that the conclusions of this research still hold after controlling for the level of agricultural development and the degree of financing constraints. Therefore, this research excludes the two competing mechanisms of promoting agricultural development and alleviating financing constraints.

4.5 Heterogeneity analysis

(1) Heterogeneity in Resource Endowments.

This research argues that the construction of digital infrastructure can increase the benefits of agricultural technology innovation by promoting the development of rural e-commerce and enriching the sales channels for agricultural products. On the one hand, when a city has a high level of agricultural product notoriety, it has already formed a systematic, complete, and unobstructed offline sales network and holds a dominant position in the domestic agricultural product market competition. Therefore, the marginal benefits it gains from the expansion of sales channels are relatively small. Conversely, the entry of more niche and regionally distinctive agricultural products into the national unified market will create a substitution effect, weakening their profitability. To verify this hypothesis, this research divides the full sample into two subsamples based on the differences in agricultural production brand endowments of cities and conducts grouped regressions. The corresponding regression results are reported in regressions 1–2 of Table 11. It can be seen that in cities with relatively low national notoriety of agricultural products, the coefficient corresponding to the construction of digital infrastructure is significantly positive, while in cities with higher notoriety, it is not significant. Moreover, the difference between the estimated coefficients of the two subsamples is relatively significant, thereby verifying the current hypothesis. On the other hand, although rural e-commerce provides a convenient online trading matching platform for both parties in agricultural product transactions, the transactions themselves still rely on the transportation, storage, and delivery of physical goods offline, especially when the transaction objects are perishable agricultural products. An efficient and rapid logistics system is a crucial link in the transaction process. This research expects that good transportation infrastructure is a prerequisite for the effectiveness of digital infrastructure. Slow logistics speed will put agricultural producers at a disadvantage. To verify this hypothesis, this research divides the full sample into two subsamples based on differences in transportation infrastructure endowments of cities and conducts grouped regressions. The corresponding regression results are reported in regressions 3–4 of Table 11. It can be seen that in cities with better transportation infrastructure, the coefficient corresponding to the construction of digital infrastructure is significantly positive, while in the other subsample, it is not significant. Moreover, the difference between the estimated coefficients of the two groups is relatively significant, thereby also verifying this hypothesis. In summary, the construction of digital infrastructure can to some extent compensate for the disadvantages in brand endowments of cities, but it still relies on good transportation infrastructure endowments when exerting its innovative effects.

(2) Heterogeneity in Entrepreneurial Environment.

This research argues that the construction of digital infrastructure can extend the agricultural product industry chain, enhance the value chain of agricultural products, and improve the supply chain of agricultural products by promoting entrepreneurship in agriculture-related enterprises. Meanwhile, these newly emerged micro and small innovative and entrepreneurial entities will also activate the vitality of agricultural technology innovation in the entire city. Since entrepreneurship is a high-risk business activity and is sensitive to the entrepreneurial environment of a city, entrepreneurial spirit only shines when entrepreneurs expect to realize their business models and obtain stable and lasting income. This research expects that in cities with a relatively poor entrepreneurial environment, the construction of digital infrastructure will have a smaller promoting effect on agricultural technology innovation. On the one hand, when a city has published a relatively large number of core agricultural science and technology journal papers, it should have more numerous, larger-scale, and higher-quality agricultural and forestry colleges and scientific research institutes, and a richer reserve of agricultural knowledge, which can provide agricultural intellectual capital to agriculture-related enterprises at a lower cost, thereby increasing the probability of successful entrepreneurship in agriculture-related enterprises, that is, having a better entrepreneurial environment. On the other hand, rational entrepreneurs, when choosing the timing of entrepreneurship, are essentially making a choice between quickly obtaining entrepreneurial benefits through current

TABLE 10 Excluding other possible mechanisms.

Panel A: Direct tests				
Variable	Agricultural development		Financing constraints	
	Agricultural enterprise entrepreneurship	Per capita value added of the primary industry	Loan-to-GDP Ratio	Loan-to-Deposit Ratio
	Regression 1	Regression 2	Regression 3	Regression 4
Digital infrastructure construction	−0.058	−0.029	−0.002	0.021
Robust standard error	(0.046)	(0.022)	(0.027)	(0.016)
City fixed effects	Controlled	Controlled	Controlled	Controlled
Time fixed effects	Controlled	Controlled	Controlled	Controlled
Pre-determined variables × Time fixed effects	Controlled	Controlled	Controlled	Controlled
Observations	3,069	3,091	3,091	3,091
Adjusted R^2	0.732	0.981	0.887	0.458

Panel B: Adding control variables				
Variable	Dependent variable: agricultural technology innovation level			
	Regression 1	Regression 2	Regression 3	Regression 4
Digital infrastructure construction	0.123***	0.117***	0.117***	0.116***
	(0.035)	(0.035)	(0.035)	(0.035)
Agricultural enterprise entrepreneurship	0.020			
	(0.021)			
Per capita value added of the primary industry		0.016		
		(0.055)		
Loan-to-GDP ratio			0.010	
			(0.036)	
Loan-to-deposit ratio				0.033
				(0.022)
City fixed effects	Controlled	Controlled	Controlled	Controlled
Time fixed effects	Controlled	Controlled	Controlled	Controlled
Pre-determined variables × Time fixed effects	Controlled	Controlled	Controlled	Controlled
Observations	3,069	3,091	3,091	3,091
Adjusted R^2	0.803	0.799	0.799	0.799

Note: * P<0.1, ** P<0.05, *** P<0.01; standard errors are robust and shown in parentheses.

entrepreneurship and postponing entrepreneurship to reduce uncertainty. When the economic uncertainty of a city is high, the expected benefits for entrepreneurs to choose to postpone entrepreneurship will be higher, thereby reducing current entrepreneurial behavior and manifesting as a low level of entrepreneurial activity at the macro level, indicating that the entrepreneurial environment of the city is relatively poor. To verify the aforementioned hypothesis, this research examines the heterogeneity of the entrepreneurial environment from two dimensions: agricultural knowledge reserves and economic uncertainty, and reports the regression results in Table 12. The information shows that the coefficient corresponding to the key explanatory variable is significantly positive in cities with rich agricultural knowledge reserves or low economic uncertainty, and is not significant in other cities. The differences in coefficients between groups are also relatively significant, indicating that the construction of digital infrastructure has a stronger promoting effect in cities with a better entrepreneurial environment.

(3) Heterogeneity in Legal Environment.

TABLE 11 Heterogeneity analysis I: heterogeneity in resource endowments.

Variable	Dependent variable: agricultural technology innovation level			
	Agricultural product brand		Transportation infrastructure	
	Low agricultural product brand	High agricultural product brand	Below median transportation infrastructure	Above median transportation infrastructure
	Regression 1	Regression 2	Regression 3	Regression 4
Digital infrastructure construction	0.154***	−0.011	0.070	0.140***
	(0.041)	(0.032)	(0.049)	(0.047)
Empirical *P*-value	0.015**		0.057*	
City fixed effects	Controlled	Controlled	Controlled	Controlled
Time fixed effects	Controlled	Controlled	Controlled	Controlled
Pre-determined variables × Time fixed effects	Controlled	Controlled	Controlled	Controlled
Observations	2,563	528	1,551	1,540
Adjusted R^2	0.800	0.778	0.778	0.799

The empirical *P*-values for the differences in coefficients between groups are calculated using Fisher's combined test (with 1,000 replications). The same applies to the following tables. Note: * $P<0.1$, ** $P<0.05$, *** $P<0.01$; standard errors are robust and shown in parentheses.

TABLE 12 Heterogeneity analysis II: heterogeneity in entrepreneurial environment.

Variable	Dependent variable: agricultural technology innovation level			
	Agricultural knowledge reserve		Economic uncertainty	
	Below median	Above median	Below median	Above median
	Regression 1	Regression 2	Regression 3	Regression 4
Digital infrastructure construction	0.047	0.123***	0.145***	0.031
	(0.055)	(0.047)	(0.050)	(0.042)
Empirical *P*-value	0.075*		0.005***	
City fixed effects	Controlled	Controlled	Controlled	Controlled
Time fixed effects	Controlled	Controlled	Controlled	Controlled
Pre-determined variables × Time fixed effects	Controlled	Controlled	Controlled	Controlled
Observations	1,023	2068	1793	1,298
Adjusted R^2	0.731	0.832	0.761	0.843

Note: * $P<0.1$, ** $P<0.05$, *** $P<0.01$; standard errors are robust and shown in parentheses.

This research argues that digital infrastructure can help innovative entities respond more quickly to infringement by competitors and use legal tools to protect their rights, thereby reducing their cost of rights protection, alleviating their concerns about engaging in innovative activities, and increasing their enthusiasm for applying for patents. Intellectual property rights are civil rights of civil subjects, and intellectual property and competition disputes generally fall under civil disputes. When parties to civil disputes appeal to the court, civil litigation is formed. Currently, China has essentially established a comprehensive rule-of-law governance framework. As long as the plaintiff's claims are "clear in fact and sufficient in evidence," they generally can win in civil litigation. Therefore, in theory, if innovative entities can collect enough decisive evidence, their litigation claims can be satisfied in any region of China. However, in practice, even if digital technology can effectively supplement the evidence chain for the rights protection party, it may still not completely overcome the inherent difficulties of proving agricultural technology infringement. That is, the submitted evidence chain may have certain defects. At this time, the judge's use of discretionary power can greatly affect the final litigation outcome. Discretionary power has a double-edged sword effect. On the one hand, discretionary power can to some extent make up for the shortcomings of legislative lag, allowing judges to make reasonable judgments based on local conditions, thereby better maintaining fairness and justice and promoting social welfare (Tummers and Bekkers, 2014). On the other hand, discretionary power may create some room for economic rent-seeking (Krueger, 1974). In regions that emphasize intellectual property protection, judges tend to protect the interests of innovative entities. In regions with higher government transparency, judges may face more pressure from ex-post supervision and public opinion, thereby reducing favoritism towards infringers (Epstein and O'Halloran, 1994). In these two types of regions, discretionary power is beneficial for the rights

TABLE 13 Heterogeneity analysis III: heterogeneity in legal environment.

Variable	Dependent variable: agricultural technology innovation level			
	Intellectual property protection		Government information opacity	
	Below median	Above median	Below median	Above median
	Regression 1	Regression 2	Regression 3	Regression 4
Digital infrastructure construction	0.151**	0.052	0.083**	0.174***
	(0.068)	(0.033)	(0.042)	(0.065)
Empirical *P*-value	0.017**		0.037**	
City fixed effects	Controlled	Controlled	Controlled	Controlled
Time fixed effects	Controlled	Controlled	Controlled	Controlled
Pre-determined variables × Time fixed effects	Controlled	Controlled	Controlled	Controlled
Observations	1,353	1738	1,452	1,309
Adjusted R^2	0.708	0.849	0.731	0.826

Note: * P<0.1, ** P<0.05, *** P<0.01; standard errors are robust and shown in parentheses.

protection of innovative entities. Therefore, this research expects that digital infrastructure, by providing more evidence for the rights protection party and compressing the space for the application of discretionary power, will have a relatively smaller innovation-promoting effect in the above two types of regions. To verify this hypothesis, this research divides the full sample into two subsamples based on two dimensions: intellectual property protection and government information opacity, and conducts grouped regressions. The estimation results in Table 13 show that the coefficient corresponding to the key explanatory variable has a higher estimated value and significance level in regions with weaker intellectual property protection and higher government information opacity, and the difference in coefficients between groups is also relatively significant, thereby verifying the above hypothesis.

5 Discussion

5.1 Spatial spillover effects of policy shocks

This research argues that the construction of digital infrastructure can significantly promote agricultural technology innovation. Although the robustness test section excluded the interference of spatial spillover effects on the identification results, it has not yet discussed the spatial spillover effects of digital infrastructure construction, that is, whether "Broadband China" pilot cities will affect the agricultural technology innovation level of neighboring cities. On the one hand, digital infrastructure has scale and network effects, which can alleviate information asymmetry among all cities within the network (Liu and Hu, 2010), helping neighboring cities obtain more intellectual capital and stimulating their innovation vitality. On the other hand, digital infrastructure may widen the digital divide and bring inequality in development opportunities (Qiu and Qiao, 2021), weakening the innovation potential of surrounding cities through agglomeration and suction effects. For example, Jiao et al. (2023) found that the "Broadband China" pilot program significantly increased the city's attractiveness to high-skilled entrepreneurial talent from outside. This research reports the regression results based on Equation 7 in regression 1 of Table 14. The results show that the key explanatory variable is significantly positive at the 5% level, indicating that if a city is closer to a "Broadband China" pilot city, it will have a greater increase in agricultural patent grants compared to cities that are farther away after the policy is implemented. To enhance the reliability of the conclusion, this research also replaces the original dependent variable with the per capita number of agricultural invention patents granted and the per capita number of agricultural patent applications, and reports the corresponding regression results in regressions 2–3 of Table 14. The significance of the key parameter estimates does not change. In summary, this research believes that the construction of digital infrastructure will have a positive spatial spillover effect on spatial neighbors, that is, it significantly promotes the level of agricultural technology innovation in surrounding cities.

5.2 Downstream effects of agricultural technology innovation

The fundamental way to ensure food security lies in vigorously developing agricultural technology innovation. First, agricultural biotechnologies such as genetic breeding can ensure the independent control of core seed sources, effectively consolidate and enhance the coverage of high-quality crop varieties in China, and firmly hold the Chinese people's food bowls in their own hands, thereby ensuring national food security at the source. Second, agricultural chemical technologies represented by pesticides and fertilizers can accelerate the green transformation of agricultural production, reduce the negative environmental impacts of agriculture, effectively prevent the degradation of arable land, and lay a solid foundation for national food security. Finally, intelligent technologies can accelerate the modernization of agricultural production methods, help farmers make more scientific production decisions, and improve agricultural production efficiency, providing new ideas and methods for ensuring national food security. Based on this, this research expects that the construction of digital infrastructure, while enhancing the level of agricultural technology innovation, can also alleviate food security issues to some extent. To verify this inference, this research selects the

TABLE 14 Spatial spillover effects of policy shocks.

Variable	Per capita agricultural patent grants		Per capita agricultural invention patent grants		Per Capita agricultural patent applications	
	Regression 1		Regression 2		Regression 3	
	Coefficient	Robust standard error	Coefficient	Robust standard error	Coefficient	Robust standard error
Nearest neighbor geographical distance	0.012**	0.005	0.006**	0.003	0.009**	0.005
City fixed effects	Controlled		Controlled		Controlled	
Time fixed effects	Controlled		Controlled		Controlled	
Pre-determined variables × Time fixed effects	Controlled		Controlled		Controlled	
Observations	1914		1914		1914	
Adjusted R^2	0.708		0.577		0.710	

Note: * P<0.1, ** P<0.05, *** P<0.01; standard errors are robust and shown in parentheses.

TABLE 15 Downstream effects of agricultural technology innovation.

Variable	Poultry egg production		Pork production		Beef production	
	Regression 1		Regression 2		Regression 3	
	Coefficient	Robust standard error	Coefficient	Robust standard error	Coefficient	Robust standard error
Digital infrastructure construction	0.195**	0.075	0.218***	0.075	0.321***	0.107
City fixed effects	Controlled		Controlled		Controlled	
Time fixed effects	Controlled		Controlled		Controlled	
Pre-determined variables × Time fixed effects	Controlled		Controlled		Controlled	
Observations	2,823		2,683		2,285	
Adjusted R^2	0.754		0.704		0.810	

Note: * P<0.1, ** P<0.05, *** P<0.01; standard errors are robust and shown in parentheses.

logarithm of the production of poultry eggs, pork, beef, and other agricultural products as new dependent variables in Equation 7 and reports the regression results in Table 15. The results show that the coefficients corresponding to the policy shock variables are significantly positive in all regressions, indicating that the construction of digital infrastructure can alleviate food security issues, specifically by increasing the production and supply capacity of several common agricultural products.

5.3 Policy implications

Based on the theoretical analysis and empirical results, this research proposes the following policy implications:

First, the vitality of agricultural technology innovation in China is currently in a weak period, which poses some hidden dangers to the country's ability to take the initiative in food security. It should be one of the key areas for China to focus on ensuring food security. Therefore, governments at all levels in China should continue to increase investment in the construction of digital infrastructure, accelerate the deep integration of digital technology with the entire agricultural industry chain, and improve the profit margins of various microeconomic entities in the agricultural sector. By increasing innovation returns, it can stimulate the vitality of agricultural technology innovation and thereby alleviate national food security issues.

Second, the results of agricultural technology innovation are easily pirated at a low cost, while the cost of proving rights protection is relatively high, which will gradually weaken the enthusiasm of agricultural science and technology personnel for innovation. Therefore, courts at all levels in China can subjectively and actively use discretionary power within the legal framework, appropriately leaning towards intellectual property rights holders, and more fully protecting the legitimate interests of innovative entities to encourage them to continue exploring the frontiers of science and technology.

Third, the innovation-promoting effect of the construction of digital infrastructure varies across different regions. Local governments should formulate and implement development policies in accordance with local conditions. For example, in areas with poor transportation accessibility, less agricultural intellectual capital, and higher economic policy uncertainty, local governments should quickly make up for the corresponding shortcomings to enable digital infrastructure to fully exert its positive socio-economic effects.

6 Conclusions and future research

This research identifies agricultural technology patents based on the International Patent Classification (IPC) and uses the number of agricultural technology patents granted per ten thousand people as a proxy for the level of agricultural technology innovation in 281 prefecture-level and above cities in China from 2011 to 2021. It regards the "Broadband China" pilot program as a quasi-exogenous shock to the construction of digital infrastructure and employs a staggered difference-in-differences (DID) model to study the causal relationship between the construction of digital infrastructure and agricultural technology innovation. The baseline regression results show that the construction of digital infrastructure significantly enhances the level of agricultural technology innovation. This conclusion remains valid after a series of validity tests for the identification strategy and robustness tests. The mechanism analysis indicates that the construction of digital infrastructure affects the level of agricultural technology innovation by reducing the cost of protecting innovation rights and increasing innovation benefits. On the one hand, the construction of digital infrastructure accelerates the digital transformation of enterprises, enhances their ability to collect evidence of infringement, and makes them more proactive in using legal tools to protect their rights, thereby stimulating their enthusiasm for innovation by reducing the cost of rights protection. On the other hand, the construction of digital infrastructure promotes the development of rural e-commerce, opens up online sales channels for agricultural products, enhances the value of the entire agricultural industry chain, and guides more entrepreneurial resources into agriculture-related fields, thereby promoting agricultural technology innovation by increasing the market returns on innovation.

The heterogeneity analysis finds that the construction of digital infrastructure has a more significant promoting effect in cities with lower agricultural brand notoriety and better transportation infrastructure, indicating that digital infrastructure can compensate for the disadvantages in brand endowments of cities but still needs to develop in synergy with transportation infrastructure. It also has a more significant effect in regions with richer agricultural knowledge reserves and lower economic policy uncertainty, suggesting that a good entrepreneurial environment is a basic condition for the full play of the innovation effects of digital infrastructure. Furthermore, it has a more significant promoting effect in regions with weaker intellectual property protection and higher government information opacity, indicating that the construction of digital infrastructure can eliminate the negative impact of a poor legal environment. Further analysis shows that the construction of digital infrastructure has a significant positive spatial spillover effect on neighboring cities. Enhancing the level of agricultural technology innovation can significantly increase the production and supply of several common agricultural products, thereby alleviating China's food security issues to some extent.

While this study has yielded certain findings in identifying the causal effects of digital infrastructure on agricultural technological innovation and its underlying mechanisms, several limitations remain, pointing to directions for future research. In terms of research methodology, the use of city-level panel data and a quasi-experimental design has effectively identified causal relationships. However, constrained by data availability, the analysis primarily relies on aggregated macro-level data. How innovation agents at the micro-level specifically perceive the changes in costs and benefits brought by digital infrastructure, and the heterogeneity in their internal decision-making processes and behavioral responses, still require further revelation through future research incorporating firm-level data or in-depth case studies. Regarding regional applicability, the empirical evidence of this study is mainly derived from city samples under the specific policy context of "Broadband China" initiative. The generalizability of its conclusions needs further testing in comparative studies across different national institutional frameworks, agricultural development models, and stages of digitalization. Future research could focus on constructing cross-national comparative analytical frameworks or delving into more micro-level geographical units within China, such as counties or villages, to examine the robustness and diversity of digital infrastructure's role in enabling agricultural innovation, thereby extracting more generalizable theoretical insights.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

RW: Conceptualization, Methodology, Writing – original draft. DF: Data curation, Methodology, Writing – original draft. JZ: Conceptualization, Methodology, Writing – review & editing. XC: Writing – review & editing.

Funding

The author(s) declared that financial support was not received for this work and/or its publication.

Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

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