frontiers | Frontiers in Sustainable Food Systems

TYPE Original Research
PUBLISHED 27 June 2025
DOI 10.3389/fsufs.2025.1595161

OPEN ACCESS

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RECEIVED 17 March 2025
ACCEPTED 10 June 2025
PUBLISHED 27 June 2025

CITATION
Liao R, Wei Y, Bai Y and Liu J (2025) Bridging the divide: how agricultural technological innovation narrows the urban–rural income gap in China.
Front. Sustain. Food Syst. 9:1595161.
doi: 10.3389/fsufs.2025.1595161

Bridging the divide: how agricultural technological innovation narrows the urban–rural income gap in China

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Introduction: Agricultural modernization and sustainable development face significant challenges from persistent urban-rural income disparities, which constrain agricultural transformation and rural revitalization. This study investigates the comprehensive impact mechanism of agricultural technological innovation on urban-rural income disparities through a multi-dimensional analytical framework integrating productivity enhancement, structural transformation, and spatial heterogeneity effects.

Methods: Using panel data from 280 Chinese cities during 2008 - 2021, we employ two-way fixed effects panel regression models to examine the relationship between agricultural technological innovation (measured by patent applications) and urban–rural income gaps (measured by the Theil index). The analysis includes robustness tests, heterogeneity analysis across regions and institutional contexts, mechanism testing through mediation analysis, and threshold effect analysis using Hansen's threshold regression technique.

Results: The integrated analysis reveals that agricultural technological innovation serves as a fundamental driver for narrowing urban-rural income gaps through interconnected pathways of employment structure optimization, factor allocation improvement, and production efficiency enhancement. Agricultural technological innovation effectively reduces the urban-rural income gap, with invention patents showing particularly significant effects. Heterogeneity analysis indicates stronger effects in eastern and western regions, and in cities with higher administrative levels, greater innovation vitality, stronger intellectual property protection, and better information accessibility. The empirical evidence reveals non-linear threshold effects, where innovation impact strengthens systematically as urbanization rates, education attention, and information accessibility increase.

Discussion: The findings form a cohesive framework for understanding innovation-driven rural development and validate agricultural technological innovation as a critical mechanism for achieving income convergence. Policy recommendations include strengthening agricultural technological innovation support, optimizing rural labor structure, promoting urbanization and information infrastructure development, and enhancing policy coordination to maximize the equalizing effects of agricultural innovation across diverse regional contexts.

KEYWORDS

agricultural technological innovation, urban–rural income gap, employment structure, resources allocation, productivity

1 Introduction

The innovation of agricultural technology is of crucial significance in driving the sustainable development of agriculture and addressing income inequality challenges in the con-temporary world. Globally, the adoption of advanced agricultural technologies has been uneven, with significant disparities between developed and developing countries. According to the World Bank (2023), developed countries allocate an average of 2.5% of agricultural GDP to agricultural R&D investment, which has significantly enhanced agricultural productivity and narrowed the urban–rural income gap. For instance, the United States achieved a 1.5:1 urban–rural income ratio through precision agriculture adoption (United States Department of Agriculture (USDA), 2022), while EU countries report a 1.2:1 ratio (Eurostat, 2023). In contrast, developing countries typically invest less than 1% of agricultural GDP in R&D (e.g., 0.6% in India, 0.7% in South Africa and 1% in Brazil), resulting in limited technology adoption, sluggish productivity growth, and substantial urban–rural income disparities. For example, sub-Saharan Africa reports a 3:1 urban–rural income ratio, India's ratio stands at 2.1:1 and Brazil has an urban–rural income ratio of 2.2:1 (World Bank, 2023).

China has achieved substantial advancements in agricultural technology innovation, with emerging technologies serving as a key catalyst for productivity growth. DJI agricultural drones have reached cumulative deployment of more than 200,000 units operating across 164.7 billion acres annually, enhancing water efficiency by 30–50% (DJI Agriculture, 2023), while MARD data confirms drone irrigation coverage has attained 65% penetration in precision agriculture pilots across 23 provinces. Blockchain implementation has expanded to more than 50 agricultural product origins, with the market growing to 1.23 billion yuan at 45% annually. AI-driven disease prediction models have demonstrated 95% accuracy, reducing pesticide application by 20% across more than 500 counties (Chinese Academy of Agricultural Sciences (CAAS), 2022). Agricultural research investment has increased consecutively for five years, reaching 86.2 billion yuan in 2023, with technology diffusion contributing 10–15% to grain yield improvements (International Food Policy Research Institute (IFPRI), 2023). These technological innovations provide an empirical foundation for analyzing the economic impacts of agricultural technological progress. The contribution rate of agricultural technological advancement to agricultural growth (defined as the ratio of the growth rate of TFP in agriculture to the growth rate of agricultural output) in China has notably increased from 54.5% in 2012 to over 63% at present, indicating significant progress in China's agricultural technological innovation system (Huang and Ping, 2024). This underscores substantial advancements in China's agricultural technological innovation system. The technological transformation has not only enhanced agricultural productivity but also created new opportunities to address persistent urban–rural development disparities, reflecting the critical role of innovation in driving sustainable agricultural growth.

However, income disparity remains a significant challenge in China's development process, particularly the gap between urban and rural areas. According to the China Development Report 2023, despite improvements in income distribution pat-terns and the alignment of resident income growth with economic growth, the Gini coefficient for disposable income in China remains high at 0.466. Notably, the income gap between urban and rural residents accounts for 40–60% of the overall income disparity (Development Research Center of the State Council, 2023). This substantial urban–rural income gap poses a critical challenge to China's pursuit of common prosperity and sustainable development. Agricultural technological innovation could serve as a crucial lever for transforming traditional agricultural production modes and potentially narrowing the urban–rural income gap through enhanced productivity and improved resource allocation efficiency (Davis et al., 2024).

The relationship between agricultural technological innovation and urban–rural income disparities represents a complex, multi-layered phenomenon that operates through interconnected economic, social, and spatial mechanisms. The impact of agricultural technological innovation on urban–rural income disparities appears to be contingent upon multiple factors, including economic development levels, agricultural structures, and technological diffusion capacities across nations (Foster and Rosenzweig, 2022; Manta et al., 2024; Suri, 2011). As the world's largest developing economy, China's exploration of the relationship between agricultural technological innovation and urban–rural income inequality has significant implications. These insights not only contribute to achieving China's rural revitalization and common prosperity goals but also inform global strategies for agricultural development and urban–rural economic balance.

Scholars have systematically examined the mechanisms driving the urban–rural income gap, with existing research primarily focusing on macroeconomic policies. These studies highlight the role of key factors such as economic policy regulation, business environment optimization, and industrial structure upgrading (Yu et al., 2019; Li et al., 2021; Hou and Yuan, 2023). Notably, agricultural technological innovation has emerged as a crucial regulatory force in the dynamic evolution of the urban–rural economic system. Recent studies indicate that agricultural technological progress not only enhances agricultural production efficiency by improving total factor productivity (TFP) but also facilitates the optimization and reallocation of production factors, thereby driving structural transformation within the agricultural sector (Restuccia and Rogerson, 2008; Gollin et al., 2021). From a productivity perspective, technological innovations in agriculture have been shown to significantly increase crop yields and reduce input requirements (Barrett et al., 2022; Liu et al., 2022). Moreover, agricultural technological advancement promotes factor reallocation effects through multiple channels, including labor migration from agricultural to non-agricultural sectors (Bustos et al., 2016), capital flow optimization across rural enterprises (Caunedo and Keller, 2020), and improvements in land use efficiency (Adamopoulos and Restuccia, 2020). These technological improvements ultimately contribute to broader structural transformation by accelerating the shift of resources toward higher-productivity activities and reducing sectoral misallocation (Gollin et al., 2021; Swinnen and Kuijpers, 2019).

However, current research primarily emphasizes the economic effects of agricultural technological innovation, with limited exploration of its role in promoting urban–rural integration, particularly lacking quantitative analyses of its impact on the urban–rural income gap. Several critical research gaps emerge from this literature review. First, while existing studies examine individual aspects of agricultural innovation's impact, there is insufficient understanding of how these multiple dimensions—productivity enhancement, structural transformation, and spatial differentiation—interact systematically to influence urban–rural income disparities. Second, city-level studies that systematically integrate agricultural innovation and urban–rural income disparity within a unified analytical framework are notably absent. Third, the non-linear threshold effects and conditional mechanisms through which agricultural technological innovation influences income distribution under varying developmental contexts require comprehensive empirical investigation.

The main aim of this study is to enhance comprehension of how agricultural technological innovation influences urban–rural income disparities, with a focus on identifying the key transmission channels and threshold effects. To achieve this, we utilize panel data from 280 Chinese cities covering 2008 to 2021, offering a robust empirical foundation for our analysis.

The structure of this paper is outlined below. Section 2 presents literature review and theoretical analysis, then proposes research hypotheses. Section 3 describes the empirical model design and data sources. Section 4 reports and analyzes the empirical results, including benchmark regression, robustness tests, and heterogeneity analysis. Section 5 conducts mechanism testing and further analysis to explore the transmission channels and threshold effects. Section 6 summarizes the re-search conclusions and puts forward policy suggestions. Finally, Section 7 summarizes the limitations of this study and provides an outlook for future research.

2 Theoretical analysis and empirical review

2.1 Theoretical analysis

The analysis of agricultural innovation's impact on urban–rural disparities integrates three theoretical lenses. Neoclassical growth theory posits that technological advancement stimulates economic expansion through productivity gains and resource optimization (Alston et al., 2009; Davis et al., 2024)—in agrarian contexts, this manifests as cost-reducing efficiency improvements that directly elevate farm incomes. The technology diffusion perspective extends this analysis by underscoring how knowledge dissemination channels shape innovation adoption (Scholtz, 2018). Regions with robust information infrastructure experience accelerated transfer of agricultural technologies, empowering rural producers to modernize operations and align with market needs. This dual theoretical framework crucially informs both productivity enhancements and the structural transformations driving rural revitalization.

This integrated theoretical framework collectively elucidates how agricultural innovation reshapes urban–rural income dynamics: neoclassical principles emphasize productivity-driven wealth generation, diffusion mechanisms govern technological permeation patterns, while distributional effects capture the spatial reallocation of economic benefits across geographical and sectoral divides.

Agricultural innovation's influence on urban–rural income disparities unfolds through three interconnected pathways. The workforce restructuring mechanism—where automation displaces field workers—aligns with Lewis's dual-economy model (Lewis, 1954). As agricultural mechanization reshapes labor dynamics (de Janvry and Sadoulet, 2001), surplus agricultural workers transition toward higher-productivity sectors, creating both displacement risks and economic mobility opportunities. This structural shift mirrors historical industrialization patterns but introduces modern challenges in skills retraining and regional job market absorption capacities. This structural transformation helps narrow the urban–rural income gap by enabling rural workers to access higher-paying employment opportunities. The transfer of surplus labor from farming to manufacturing and service not only increases the income of rural workers but also fosters economic expansion by reallocating labor to more productive uses.

Second, concerning factor allocation improvement, from the perspective of new institutional economics, agricultural technological innovation reduces transaction costs and promotes more efficient distribution of production factors such as land, capital, and labor. Pingali notes that the promotion of land-intensive management and mechanized production has enhanced the efficiency of resource utilization in rural areas (Pingali, 2007). This optimization of resource allocation leads to increased agricultural productivity and, consequently, higher rural incomes. By lowering the costs associated with information asymmetry and contractual enforcement, technological innovations enable more effective coordination and utilization of resources, further enhancing the overall efficiency of the agricultural sector.

Third, in terms of production efficiency enhancement, from the total factor productivity (TFP) theory perspective, modern agricultural technologies, including advanced equipment, superior crop varieties, and information management systems, significantly boost agricultural productivity (Huang and Rozelle, 2004). These innovations enable more efficient resource utilization, reduce production risks, and increase output value, thereby improving farmers' income levels and contributing to the reduction of urban–rural income disparities. Specifically, agricultural technological innovation enhances TFP through three pathways: (1) optimizing the production function to increase output with the same level of inputs; (2) altering the combination of input factors to raise marginal output; and (3) reducing production risks, thereby minimizing output fluctuations caused by natural disasters and market volatility.

From the preceding theoretical framework, we draw the mechanism path diagram and propose the following research hypotheses (see Figure 1): first, regarding the overall effect, agricultural technological innovation can directly bridge the divide between urban and rural areas through two channels: cost reduction and output enhancement. Through advanced agricultural technologies such as biotechnology and precision farming, production costs can be effectively reduced while crop yields are improved. Additionally, technological innovation enhances the quality and market competitiveness of agricultural products, leading to higher market prices. Therefore, we propose:

> Hypothesis 1: Agricultural technological innovation can directly narrow the urban–rural income gap.

The transmission mechanisms through which agricultural technological progress affects urban–rural income disparities operate through three distinct indirect channels. First, drawing upon Lewis's dual-economy structural framework, agricultural mechanization fundamentally alters rural labor markets by diminishing labor requirements in farming operations, thereby facilitating the migration of surplus agricultural labor toward non-agricultural sectors characterized by higher productivity and wages. This sectoral labor reallocation represents a critical pathway for rural income enhancement. Second, technological innovation in agriculture catalyzes the optimization of production factor allocation within rural economies. Through the adoption of advanced technologies, rural producers achieve more efficient utilization of

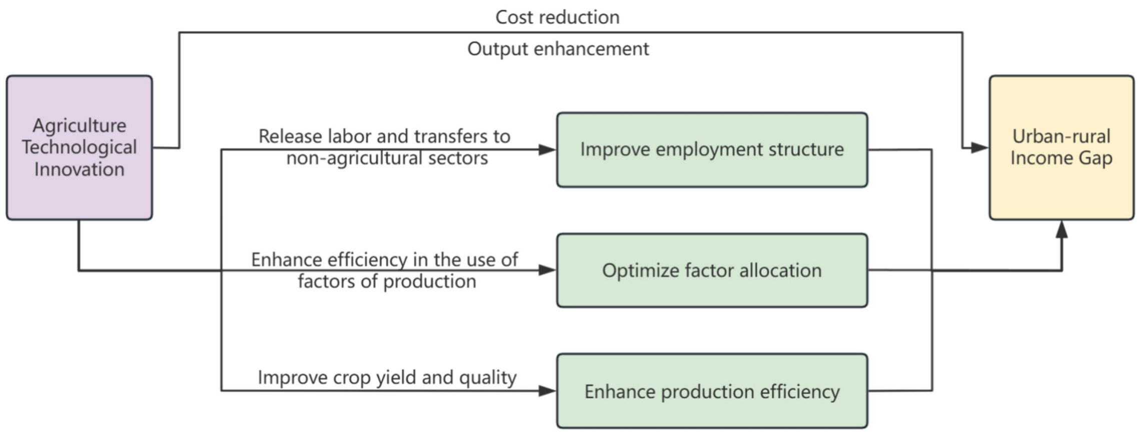

FIGURE 1
Mechanism path diagram.

natural resources and capital inputs, thereby increasing total factor productivity. As Pingali (2007) empirically demonstrates, the transition toward land-intensive management systems and mechanized production methods significantly enhances the efficiency coefficient of resource utilization across various agricultural contexts. Third, modern agricultural technological systems substantially elevate production efficiency through an integrated matrix of advanced equipment deployment, genetically improved crop varieties, and sophisticated information management systems. Davis et al. (2024) provide robust evidence that precision agriculture techniques and smart farming technologies enable significantly more efficient resource allocation decisions and yield substantial increases in crop productivity, thus amplifying rural income-generating capacity. Therefore, we propose:

> Hypothesis 2: Agricultural technological innovation indirectly narrows the urban–rural income gap by improving the rural employment structure, optimizing regional resource allocation and enhancing agricultural productivity.

These hypotheses form the foundation for our subsequent empirical analysis, which will test both the direct effects and transmission mechanisms of agricultural technological innovation on the urban–rural income gap.

2.2 Empirical review

2.2.1 The effect of agricultural technological innovation

Agricultural technological innovations exhibit the dual attributes of both driving and tearing. Empirical studies demonstrate that precision agriculture tools (such as soil sensor-based systems and smart irrigation) have boosted rice yields to unprecedented levels in digitally advanced regions like the Yangtze and Pearl River Deltas (Huang and Wang, 2024). Studies show digitization-driven farming systems fundamentally transform production functions, linking operational efficiency directly to export competitiveness and supply chain agility to reshaped trade dynamics (Chen and Zhang, 2023; Liu et al., 2021). However, technology adoption exhibits a Matthew effect: urban hubs with superior infrastructure capture disproportionate returns, whereas rural areas face adoption barriers due to limited capital and technical capacity. Peripheral villages confront prohibitive maintenance costs and fragmented knowledge transfer, creating self-reinforcing exclusion. This polarization reveals a critical mechanism in innovation diffusion: technological adoption trajectories are shaped by regional economic conditions, as innovation resources concentrate in high-return zones—undermining the role of natural resource endowments in equitable technology implementation.

Agricultural innovation exerts a dual influence on rural development from an environmental perspective. Zhang et al. (2023) indicated that technological advancements could promote green agricultural practices by reducing chemical inputs and optimizing resource allocation. However, the ecological outcomes remain complex. Burgess and Morris (2009) and Gras and Cáceres (2020) highlighted a persistent paradox, noting that machinery intended to enhance productivity may instead increase emissions by intensifying land use and fossil fuel dependency, particularly in agricultural regions. This contradiction is especially pronounced in agriculture-dependent economies, where environmental pressures resulting from excessive mechanization can negatively affect rural livelihoods. Moreover, ineffective management of these ecological pressures can lead to a feedback loop that further exacerbates spatial inequality.

Government subsidies and rural financial systems also play a critical role in facilitating agricultural innovation (Liu et al., 2021; Wu et al., 2022). These resources effectively stimulate research and development activities, contributing to ecologically sustainable development and enhanced agricultural productivity. However, the effectiveness of such policies largely depends on their specific implementation mechanisms. Empirical evidence indicates that large-scale agricultural operators near urban areas typically enjoy superior access to financial support and advanced technological resources through institutional channels, creating spatial disparities in technology adoption. Although smallholders dominate agricultural production in many developing countries, they frequently encounter systemic barriers to accessing modern agricultural technologies. Consequently, technology diffusion patterns influenced by existing spatial hierarchies may intensify, rather than mitigate, the urban–rural development gap.

Small-scale farmers encounter several economic barriers to participating in agricultural technological innovation. Gras and

Cáceres (2020) indicate that the substantial initial investments required for modern agricultural equipment typically limit its accessibility to commercially oriented producers connected to urban markets, inadvertently exacerbating existing wealth disparities. This accessibility paradox generates self-reinforcing cycles, intensifying the divide between those who possess modern technology and those who do not, thereby reinforcing established economic inequalities. Furthermore, the economic viability of rural areas is closely tied to local ecological conditions, making harmony with the natural environment essential. Thus, it is imperative to balance productivity improvements with ecological preservation, ensuring technological advancements do not compromise environmental sustainability.

2.2.2 Factors affecting the urban–rural income gap

There is a wide gap between the incomes of urban and rural residents in China. Exploring the root causes of this gap requires an analysis of the interplay of multiple and complex factors, such as the process of urbanization, differences in production efficiency, the formulation of relevant policies and the allocation of human capital. Clarifying these intertwined influences is a prerequisite for the development of effective interventions to alleviate spatial inequalities between economies in different regions.

Interestingly, the impact of urbanization is closely related to the methods employed to measure income disparities. Yuan et al. (2020) indicate that varying measurement approaches yield significantly different conclusions. Specifically, indicators based on income or consumption suggest a widening urban–rural gap, whereas inequality indices, such as the Theil index and the Gini coefficient, imply that the gap is narrowing, revealing a notable contradiction. Additionally, regional heterogeneity should not be overlooked. Su et al. (2015), employing Granger causality tests, demonstrated that accelerated urbanization in eastern China has intensified income inequality, emphasizing that institutional factors play a crucial moderating role in this process.

Empirical studies have examined the differential impact of productivity gains on rural–urban disparities. Yao and Jiang (2021) indicate that rural productivity enhancements—particularly through agricultural modernization and industrial diversification—significantly boost rural incomes and reduce urban–rural inequality. Conversely, urban productivity growth tends to exacerbate regional disparities, as the agglomeration effect during technology dividend absorption amplifies cities' inherent advantages. Zhao (2024) highlights that the urban–rural dichotomy is closely tied to economic restructuring pathways. For instance, Zhang and Yang (2019) demonstrate how the transition from traditional agriculture to urban-specialized industries drives economic resource concentration in core cities, leading to increasingly asymmetric regional development trajectories.

Government policies significantly influence the extent of the rural–urban income gap. Yao and Jiang (2021) highlight that interventions, such as reforms of the hukou system, effectively narrow the urban–rural income gap, albeit with a time lag. Hu (2023) underscores the importance of agricultural support policies in enhancing rural economic conditions, demonstrating that mechanisms for price stabilization and targeted investments significantly benefit rural areas, contributing to the reduction of regional disparities.

Regional economic prosperity, industrial restructuring, and government macroeconomic policies significantly influence the income disparity between urban and rural areas (Chen and Shen, 2021). Industrial restructuring and macroeconomic interventions, as directed by governmental policies, form critical determinants of urban–rural income inequality. According to Li et al. (2021), although natural factors such as climatic conditions, topography, and landscape play moderating roles, socio-economic determinants remain dominant in shaping regional income disparities. Additionally, disparities in information accessibility and uneven regional development further exacerbate the persistence of the urban–rural income gap (Hou and Yuan, 2023; Piketty et al., 2019).

Educational attainment is another critical determinant of the urban–rural income gap. Sicular et al. (2007) emphasize that higher levels of education significantly reduce this disparity. Specifically, their analysis demonstrates that increased educational attainment facilitates the narrowing of income inequality by equipping rural populations with enhanced skills, thus influencing income through a dual mechanism. This mechanism includes both facilitating labor mobility toward urban labor markets and enhancing productivity within rural industries. Consequently, education fosters greater participation by rural residents in urban employment opportunities and simultaneously boosts productivity in rural sectors.

2.2.3 Related research on the impact of agricultural technological innovation on urban–rural income gap

Wordofa et al. (2021) demonstrate that agricultural technology adoption significantly influences household income. Their study reveals that the high initial investment associated with modern agricultural equipment often limits adoption to commercial producers with urban market linkages, inadvertently widening wealth disparities. This finding highlights the potential of agricultural technology to improve household welfare and underscores the necessity of strengthening technology generation, diffusion, and adoption. Agricultural innovations directly contribute to increased farmer incomes primarily by reducing production costs and enhancing crop yields. Technologies such as biotechnology and precision agriculture exemplify this by simultaneously lowering production costs and increasing outputs (Tang et al., 2022).

Agricultural technological innovations exhibit a dual role in economic development: exacerbating income inequality while driving aggregate income growth. Tan et al. (2022) demonstrate that technological adoption intensifies income disparities in 73 countries, though public expenditure interventions mitigate this effect. Key factors such as the level of public spending, the employment rate in agriculture and export diversification moderate the relationship between technological innovation and inequality. Technological progress also generates indirect effects through multiple channels, such as optimizing employment structures, enhancing resource allocation efficiency, and boosting productivity (Munshi and Rosenzweig, 2013).

The relationship between agricultural technological innovation and income distribution reveals nuanced dynamics across socioeconomic contexts. Zhao and Zhou (2021) investigation identifies three primary mechanisms—labor productivity enhancement, product quality optimization, and workforce migration—through which farm technologies influence rural incomes. Their findings nevertheless indicate paradoxical outcomes in China, where technological adoption occasionally suppresses income growth, revealing how local implementation frameworks can reverse anticipated benefits. This context-dependent effectiveness underscores how regional development disparities, innovation capacities, and digital infrastructure quality mediate technological impacts (Wu et al., 2022).

Distributional consequences prove equally complex. While Giller et al. (2021) document disproportionate benefits accruing to commercial farms and urban consumers, Lowder et al. (2021) bring up policy-technological synergies to redirect advantages toward smallholders. Barrett et al. (2022) macroeconomic modeling confirms that technology selection inherently shapes inequality trajectories, with Ruzzante et al. (2021) advocating labor-intensive innovations to harmonize efficiency and equity. Input–output analyses further reveal how farm-level consumption patterns amplify or dampen broader economic effects.

In summary, while the existing literature on this field is extensive, it still exhibits certain limitations. First, existing scholarship predominantly examines macroeconomic or endogenous factors in urban–rural inequality, largely overlooking innovation's mediating role. Second, while agricultural innovation's economic impacts receive attention, its potential for fostering urban–rural integration remains underexplored. Third, rigorous quantitative investigations into prefecture-level mechanisms linking agricultural technology and income disparities remain scarce, particularly analyses disentangling direct and spillover effects.

This study offers three significant advancements to the field. First, it combines agricultural tech innovation and urban–rural income inequality within a cohesive analytical framework, using panel data from 280 Chinese cities (2008–2021) to empirically demonstrate that agricultural technological innovation significantly narrows the urban–rural income gap. This provides new evidence for understanding its role in integrated urban–rural development.

Second, the paper identifies three key mechanisms through which agricultural technological innovation reduces the income gap: employment structure optimization, factor allocation improvement, and production efficiency enhancement. These findings enrich theoretical research and offer practical insights for policy-making, such as facilitating rural labor transfer and improving resource allocation efficiency.

Third, the paper reveals threshold effects in the relationship between agricultural technological innovation and the income gap. The moderating effect strengthens with higher urbanization levels, government support, and information accessibility, providing precise guidance for policy formulation.

Overall, this study addresses critical gaps in the literature and offers valuable insights for promoting urban–rural integration through agricultural technological innovation.

3 Research design

3.1 Data declaration

The sample of this paper comprises panel data from 280 Chinese prefecture-level cities spanning 2008–2021. The construction of agricultural technological innovation indicators follows a rigorous three-step procedure using Python-based web scraping to systematically collect patent application records from the China National Intellectual Property Administration database.

The selection of the broad A01 International Patent Classification category as the agricultural innovation proxy reflects careful methodological considerations. While A01 encompasses agriculture, forestry, animal husbandry, hunting, and fishing, this choice aligns with established research conventions (Fuglie and Toole, 2014; Galasso and Schankerman, 2015) that prioritize cross-study comparability over narrow sectoral boundaries. Moreover, modern agricultural innovation increasingly involves technological convergence across traditional sector boundaries—precision agriculture systems integrate sensor networks, drone applications, and data analytics-making the A01 framework particularly suitable for capturing these cross-sectoral spillovers.

Spatial attribution was achieved through advanced natural language processing of inventor addresses, enabling precise municipal-level geocoding, with patents involving multiple applicants proportionally allocated across participating regions. The core dependent variable (urban–rural income gap) was operationalized through the Theil index using granular income data from the China City Statistical Yearbook. Control variables describing economic development and structure, policy and resource allocation structure, and sustainable development were systematically extracted from several statistical yearbooks to ensure temporal and spatial consistency. This multi-source integration approach creates a unique panel dataset capturing both technological and institutional dimensions of regional development.

To comprehensively reveal the relationship between agricultural technological innovation and urban–rural income disparity, this study not only employs panel regression analysis using agricultural patent applications and urban–rural income gap data from 280 prefecture-level cities nationwide between 2008 and 2021, but also conducts visual exploration of the temporal evolution trends and spatial distribution characteristics of the data.

Figure 2 displays the time series changes of national agricultural patent applications and urban–rural Theil index. We observe rapid growth in agricultural patents after 2014, while urban–rural income disparity shows a steady declining trend. The two variables exhibit negative correlation in the temporal dimension, providing preliminary support for the hypothesis that agricultural technological innovation may help narrow urban–rural income gaps. However, relying solely on national averages may mask regional heterogeneity in technological innovation capacity and income distribution structures.

To reveal this spatial heterogeneity, Figure 3 presents the spatial distribution of cumulative agricultural patents across prefecture-level cities during the study period. Agricultural technological innovation is clearly concentrated in eastern coastal regions (such as Jiangsu, Shandong, and Zhejiang) and certain central provinces (such as Henan and Hubei), while most western and northeastern regions lag relatively behind. This spatially uneven distribution suggests that regional heterogeneity in agricultural technological innovation may lead to differential impacts on urban–rural income disparity across regions. Therefore, in subsequent empirical analysis, this paper will introduce fixed effects models and further consider regional heterogeneity to more accurately identify the dynamic mechanisms through which agricultural technological progress affects urban–rural income gaps.

3.2 Model setup

To assess the impact of agricultural technological innovation on China's urban–rural income gap, we construct the following two-way fixed effects panel data model (Equation 1):

$$Theil_{it} = \beta_0 + \beta_1 ATC_{it} + \lambda Control_{it} + \delta_i + \eta_t + \varepsilon_{it} \tag{1}$$

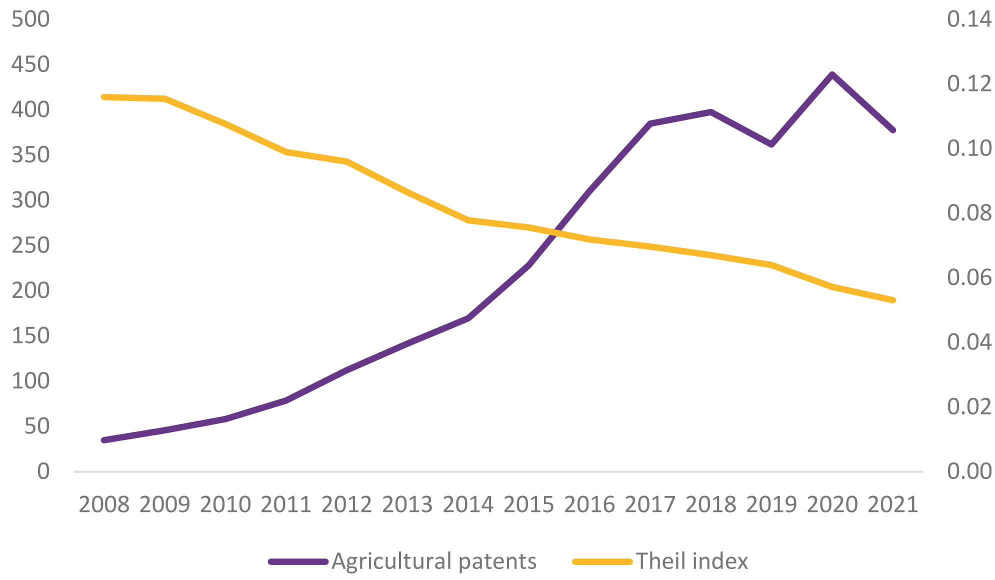

FIGURE 2
Time trend graph of core variables.

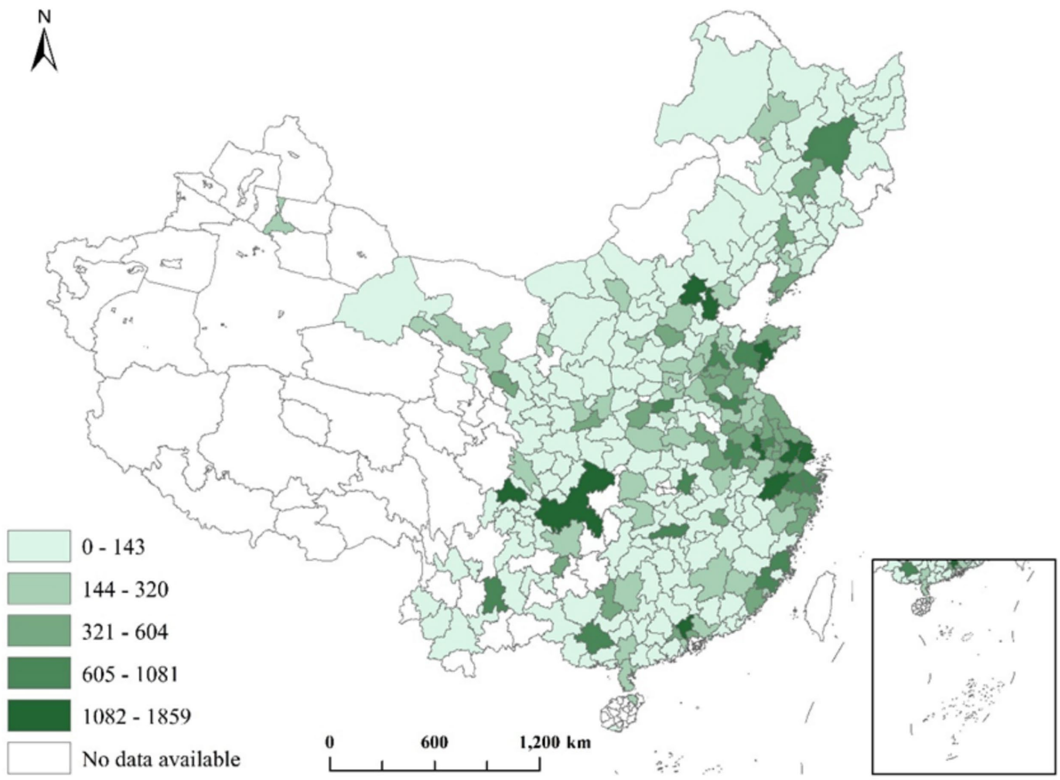

FIGURE 3
Spatial distribution of samples. The map is based on the standard map no. GS (2022) 1873 downloaded from the website of standard map service of the ministry of natural resources of China.

where the subscripts i and t stand for city and year, respectively. $Theil_{it}$ represents urban–rural income gap of the i city in China within t year(s). ATC_{it} is the key explanatory variable reflecting the level of agricultural technological innovation, proxied by the natural logarithm of the number of agricultural patent applications. The model also incorporates a set of control variables to account for additional influencing factors. $Controls_{it}$ is a vector of control variables that account for other potential determinants of income disparity, as detailed later in Variable Selection.

To address unobserved heterogeneity, we adopt a two-way fixed effects (TWFE) approach, which includes both city fixed effects (δ_i) and year fixed effects (η_t) to control for time-invariant regional characteristics and time-specific national shocks, respectively (Wooldridge, 2010; Baltagi, 2021). Specifically, δ_i is implemented using a full set of city dummy variables (excluding one to avoid perfect multicollinearity), accounting for factors such as geographic endowment, institutional legacy, and long-term development path (Stock, 2020). η_t is included via year dummies, capturing common temporal shocks such as policy changes or macroeconomic trends (Angrist and Pischke, 2009).

Estimation is carried out using the within transformation method (Cameron and Trivedi, 2005), which demeans the data along both cross-sectional and time dimensions to eliminate fixed effects. The error term ε_{it} captures idiosyncratic shocks and is assumed to be independently and identically distributed with zero mean and constant variance (Hsiao, 2014). This specification helps reduce omitted variable bias and improves causal inference regarding the effect of agricultural technological innovation on the urban–rural income gap (Imai and Kim, 2021; Cunningham, 2021).

The dependent variable $Theil_{it}$ is calculated using the Theil Index, which quantifies income disparity between urban and rural areas of various cities in China. The specific calculation method is shown in Equation 2:

$$Theil = \sum_{n}^{2}\left[\frac{p_n}{p}\right]\ln\left[\frac{p_n}{p}/\frac{z_n}{z}\right] \tag{2}$$

where $n = 1,2$ represents the urban and rural area within the city, respectively. z_n represents the population. p_n represents the total income, and z, p represent the total population and total income of the city, respectively.

3.3 Estimation procedure

The empirical analysis employs a two-way fixed effects panel data model estimated using Stata 16.0. The Hausman test confirms the appropriateness of fixed effects over random effects specification. The model is estimated using the within-group estimator with year dummies to account for temporal effects. Standard errors are clustered at the city level to correct for potential serial correlation and heteroscedasticity. Diagnostic tests for multicollinearity using variance inflation factors show a mean VIF of 2.84, indicating no significant multicollinearity concerns. Potential endogeneity issues are addressed through lagged explanatory variable models as detailed in Section 4.2.4. For threshold effect analysis, Hansen's (1999) threshold regression technique is applied, using bootstrap procedures with 300 replications to test threshold significance.

3.4 Variable selection

3.4.1 Explained variable: urban–rural income gap

Currently, scholars primarily employ several factors to measure the urban–rural income gap, including the Theil Index, Gini Coefficient, and Urban–Rural Income Ratio. Each of these indicators possesses distinct advantages and disadvantages when analyzing income disparity issues.

While the Gini coefficient is widely used to measure the degree of inequality, its diagnostic limitations become apparent in urban–rural analyses. The metric's aggregated nature masks geographical blind spots and demonstrates limited capacity to detect income extremes—particularly problematic when assessing impoverished populations. By compressing spatial disparities into singular values and smoothing distribution tails, it inadvertently obscures nuanced fluctuations in vulnerable groups' earning trajectories.

As for the Urban–Rural Income Ratio, it is easy to calculate and based on simple principles, which makes it frequently utilized in policy discussions and media reports. However, the Urban–Rural Income Ratio merely reflects the average level of income distribution and is prone to overlook the internal income inequality present within urban and rural areas.

In contrast, the Theil Index is adept at capturing differences in extreme values (Oancea and Pirjol, 2019) and exhibits greater sensitivity in measuring inequality (Qu et al., 2023). It is particularly suitable for analyzing income inequality in rapidly changing economies (Jorgenson and Timmer, 2011). In order to ensure the scientificity and rationality of variable selection, this paper did the test based on Bayesian Information Criterion for the three indicators, Theil index, *RUIR*, and Gini index, and found that $bic\_Theil < bic\_RUIR < bic\_Gini$, which indicates that the Theil index is more capable of identifying causality in the regression analysis of this paper. Therefore, this paper uses Theil as the dependent variable in the baseline regression and includes *RUIR* as an alternative indicator of the dependent variable in the robustness test.

3.4.2 Core explanatory variable: agricultural technological innovation

In this study, the natural logarithm of the quantity of agricultural patents is employed as a proxy variable for agricultural technology innovation ($ATC_{i,t}$), notwithstanding the recognized limitations of this indicator. While patent counts primarily capture formal, patentable innovations and fail to account for informal innovations and non-patentable incremental improvements, they remain the most viable metric for measuring technological innovation in the extant literature, given considerations of data availability and indicator comparability. The *ATC* index is calculated as the natural logarithm of the total number of granted invention patents classified under the International Patent Classification (IPC) A01 category. This metric aligns with prior studies measuring innovation through patent output (Griliches, 1990; Hall et al., 2005). It should be noted that the patent count used in this study specifically refers to valid patents that have been granted and are maintaining normal annual fee payments, indicating that these patents remain within their validity period and are legally protected. This approach ensures that our innovation measure captures economically meaningful technological advances rather than dormant or abandoned patents.

The utilization of patent data as an innovation metric is justified by three principal considerations. First, patent statistics provide an objective and quantifiable measure of innovation output. The volume of patent applications serves as a direct indicator of the innovative activities undertaken by enterprises and research institutions (Griliches, 1990). Second, the legal protection mechanism inherent in the patent system enhances the reliability of this metric. Given the complexity and substantial costs associated with patent application procedures, economic agents typically pursue patent protection only for innovations with significant market potential and commercial value. This self-selection mechanism consequently improves the validity of patents as innovation indicators (Hall et al., 2005).

Furthermore, the systematic documentation and public accessibility of patent data facilitate robust cross-temporal and cross-regional comparative analyses, thereby providing a reliable empirical foundation for this research. In the context of China's economic transition towards an innovation-driven growth model, patent statistics have gained particular significance as a crucial indicator of technological innovation capacity. The aforementioned characteristics collectively substantiate the appropriateness of employing patent data as a proxy for agricultural technology innovation in this analysis.

3.4.3 Control variables

China's urban–rural income disparities are shaped by multiple socioeconomic forces, necessitating rigorous control of confounding variables to isolate agricultural technology's unique effects. Regional development imbalances, labor mobility patterns, and fiscal transfer mechanisms particularly require statistical normalization when assessing how farming innovations influence this economic divide.

(1) Economic development level (*Eco*), quantified by the logarithmic value of the city's per capita GDP. By controlling for the level of economic development, the direct effect of economic development on the urban–rural income gap can be ruled out to more accurately identify the independent effect of agricultural technology innovation on the urban–rural income gap.
(2) Quadratic term of economic development level (*Eco2*), which is used to control the nonlinear impact of economic development on the urban–rural income gap, avoiding the wrong model setting due to ignoring this nonlinear relationship.
(3) Level of financial development (*Fin*), evaluated by the proportion of total deposits and loans from financial institutions relative to the regional GDP. The level of financial development reflects the availability of regional financial resources and the popularity of financial services, and controlling for the level of financial development is used to exclude the impact of unequal distribution of financial resources on the urban–rural income gap.
(4) Government involvement (*Gov*), quantified by the ratio of local government fiscal spending to the regional GDP. Government intervention may affect the urban–rural income gap through infrastructure construction, public service provision, etc. It needs to be controlled to exclude the impact of government policies on the urban–rural income gap, and to ensure that the impact of agricultural technological innovation is not obscured by differences in government intervention.
(5) Primary industry structure (*Prim*), assessed by the ratio of value added of the primary industry within the local GDP. The industrial structure reflects the region's dependence on agriculture, and by controlling for the structure of the primary industry, the impact of the weight of agriculture in the economic structure on the urban–rural income gap can be ruled out.
(6) Ecological environment governance level (*Env*), represented by the rate of harmless treatment of municipal solid waste as a proxy indicator for the level of ecological environment governance. The level of ecological and environmental governance reflects regional efforts in environmental protection and sustainable development, and is also a profile of the living standards of the population, which needs to be controlled.

Table 1 presents the outcomes of the correlation analysis among different variables, specifically the correlation between Theil and the explanatory variables. *Theil* shows a significant negative correlation with *ATC*, *Eco*, and *Eco2*, indicating that economic development and technological innovation significantly contribute to reducing the urban–rural income gap. Furthermore, *Fin* is negatively correlated with Theil, suggesting that the expansion of financial markets aids in diminishing the urban–rural disparity. In contrast, *Gov* and *Prim* are significantly positively correlated with *Theil*, indicating that higher government expenditures and an increased share of agriculture may exacerbate the urban–rural income gap. Moreover, *Env* exhibits a significant negative correlation with *Theil*, suggesting that improvements in ecological governance are associated with a reduction in income disparity. Overall, the correlations among the variables reveal multiple factors influencing the urban–rural income gap, thereby demonstrating a robust explanatory capacity.

TABLE 1 Correlation analysis of main variables.

Variables	Theil	ATC	Eco	Eco2	Fin	Gov	Prim	Env
Theil	1							
ATC	−0.439***	1						
Eco	−0.675***	0.600***	1					
Eco2	−0.668***	0.600***	0.999***	1				
Fin	−0.262***	0.469***	0.283***	0.285***	1			
Gov	0.341***	−0.126***	−0.448***	−0.447***	0.196***	1		
Prim	0.348***	−0.348***	−0.708***	−0.707***	−0.270***	0.537***	1	
Env	−0.336***	0.392***	0.445***	0.439***	0.192***	−0.035**	−0.253***	1

***, **, *represent significance level at 1%, 5%, 10%, respectively.

4 Analysis of empirical results

4.1 Descriptive statistics

Table 2 presents the summary statistics of key variables, covering a total of 3,920 observations. The mean of the Theil index for the urban–rural income gap (*Theil*) is 0.08, with a standard deviation of 0.048, a minimum value of 0.0077, and a maximum value of 0.2440. This indicates that there exists a certain degree of fluctuation in the urban–rural income gap across different regions, reflecting significant differences in the gap between urban and rural income among regions. The mean value of the core explanatory variable, Agricultural Technology Innovation (*ATC*), is 4.26, with a standard deviation of 1.662 and a range from 0 to 7.7227. This indicates significant regional disparities in agricultural technology innovation capacity. The logarithm of Economic Development Level (*Eco*) has a mean value of 10.60, while the quadratic term (*Eco2*) has a mean of 112.79. This suggests that the sample regions exhibit a relatively high level of economic development and display non-linear characteristics. The mean value of Financial Development Level (*Fin*) is 2.38, indicating that the financial markets in the sample regions are relatively developed. However, significant disparities exist, with a maximum value of 6.61. The mean value of Local Government Governance Intensity (*Gov*) is 0.19, indicating a relatively low proportion of public financial expenditures and significant variations among regions. The mean value of Primary Industry Structure (*Prim*) is 0.13, indicating that its share within the urban economic structure of Chinese is relatively small. The mean value of Ecological Environment Governance Level (*Env*) is 90.00, with a maximum of 100 and a minimum of 19.44. This indicates that while most regions exhibit a high level of governance, there are still some areas where deficiencies persist.

4.2 Benchmark regression

After conducting the Hausman test, this study employs a fixed-effects model to examine the impact of agricultural innovation on the urban–rural income gap in China. By incorporating urban fixed effects and time control variables, we effectively mitigate regional heterogeneity and macroeconomic fluctuations, enabling a more precise estimation of the net effect of technological innovation on income disparity. Furthermore, a series of robustness checks help isolate the influence of confounding factors, such as infrastructure disparities and policy implementation delays, thereby strengthening the theoretical framework for analyzing the innovation-driven inequality model.

The regression results reported in Table 3 demonstrate consistent findings across multiple model specifications. Columns 1–4 present estimates using the Theil index as the dependent variable, reflecting the degree of urban–rural income disparity. Column (1) includes only city and year fixed effects, yielding a statistically significant negative coefficient for agricultural technology innovation (*ATC*) at the 1% confidence level. Specifically, a one-unit increase in *ATC* corresponds to a 0.0044 reduction in the Theil index, indicating that agricultural innovation contributes to narrowing income gaps.

In Column (2), economic development variables are introduced. The *ATC* coefficient remains negative (−0.0014) and statistically significant, suggesting that agricultural technological progress exerts an independent effect on reducing income inequality beyond general economic growth. The inclusion of quadratic economic development terms reveals a non-linear relationship: initial growth (*Eco*) decreases inequality, but subsequent growth (Eco^2) exacerbates disparities, highlighting the inverted-U pattern in development dynamics.

Column (3) (4) incorporate additional control variables related to financial development, government expenditure, industrial structure, and environmental governance. The *ATC* coefficient stabilizes at-0.0015, maintaining statistical significance. These results validate Hypothesis 1, confirming that agricultural innovation serves as a critical lever for promoting income convergence. The consistent negative coefficients across specifications underscore the robustness of this finding and its policy relevance for achieving China's common prosperity goals.

To contextualize our findings within the existing literature, we conducted a comparative analysis of effect magnitudes. Our estimated coefficient of-0.0044 aligns with, yet exceeds, results from similar studies. Wen and Chen (2025) found that agricultural R&D investment reduced the Theil index by 0.0031 in their provincial-level analysis, while Zou et al. (2024) reported a coefficient of-0.0038 for agricultural mechanization's impact on rural–urban inequality. The relatively stronger effect observed in our study likely reflects our patent-based measure's ability to capture more direct and impactful technological innovations.

The substantive significance of this effect becomes evident when considered in practical terms. A 0.0044 reduction in the Theil index represents approximately 7.2% of our sample mean (0.061) and accounts for roughly 15% of the total urban–rural Theil index decline observed during 2008–2021 (a cumulative decrease of 0.029). This magnitude indicates a meaningful and policy-relevant contribution to inequality reduction.

TABLE 2 The descriptive statistics of main variables.

Variables	Obs	Mean	SD	Min	Median	Max
Theil	3,920	0.08	0.048	0.0077	0.0722	0.2440
ATC	3,920	4.26	1.662	0.0000	4.3567	7.7227
Eco	3,920	10.60	0.630	9.0777	10.6033	11.9793
Eco2	3,920	112.79	13.333	82.4050	112.4297	143.5048
Fin	3,920	2.38	1.121	0.9104	2.0726	6.6100
Gov	3,920	0.19	0.096	0.0695	0.1666	0.6133
Prim	3,920	0.13	0.078	0.0069	0.1145	0.3762
Env	3,920	90.00	18.292	19.4400	99.6400	100.0000

TABLE 3 The baseline regression.

	(1)	(2)	(3)	(4)
Variables	Theil	Theil	Theil	Theil
ATC	−0.0044*** (−9.48)	−0.0014*** (−3.32)	−0.0014*** (−3.28)	−0.0015*** (−3.50)
Eco		−0.3181*** (−24.23)	−0.3120*** (−23.40)	−0.3278*** (−22.87)
Eco2		0.0142*** (22.55)	0.0139*** (21.39)	0.0145*** (21.24)
Fin			0.0044*** (6.15)	0.0044*** (6.16)
Gov			−0.0524*** (−6.74)	−0.0472*** (−5.94)
Prim				−0.0473*** (−3.25)
Env				0.0000 (0.28)
_cons	0.1273*** (84.95)	1.8750*** (27.33)	1.8400*** (26.80)	1.9418*** (25.53)
City FE	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes
N	3,920	3,920	3,920	3,920
Adj. R^2	0.666	0.726	0.730	0.731

***, **, *represent significance level at 1%, 5%, 10%, respectively.

Our findings also demonstrate competitive strength when compared with other equalizing factors documented in the literature. Liu et al. (2022) reported that rural education investment reduced the Theil index by 0.0065, while Shen et al. (2023) found rural financial inclusion achieved a reduction of 0.0037. These comparisons position agricultural technological innovation as a factor with comparable or even superior equalizing effects relative to several well-established policy interventions.

To illustrate the real-world implications, we simulated the practical impact of our estimated coefficient. Given the logarithmic transformation, a 10% increase in agricultural patent counts would reduce the Theil index by approximately 0.00044. Based on official demographic statistics, this reduction could potentially elevate about 428,000 rural residents above the relative poverty threshold, underscoring the tangible significance of agricultural technological innovation for income distribution.

This empirical evidence aligns with theoretical frameworks positing that technological advancements enhance agricultural productivity, optimize resource allocation, and facilitate rural labour transfer-mechanisms explicitly identified in the theoretical analysis. The results emphasize the importance of targeted policies to foster agricultural innovation ecosystems, particularly in less-developed regions where the marginal impact of such investments is demonstrated to be most pronounced.

4.3 Robustness test

4.3.1 Variable inclusion robustness test

To assess the stability of our main findings, we examine whether the estimated effect of agricultural technological innovation on the urban–rural income gap is sensitive to the inclusion of different control variables. Following the approach suggested in the literature on robustness checks, we first estimate a model with ATC as the sole predictor variable. Subsequently, we create a series of models where ATC is paired with each control variable individually. Finally, we present the comprehensive model including all control variables.

Table 4 presents the results of this robustness check. Column (1) shows the baseline effect of ATC without any control variables. Columns (2) through (7) pair ATC with individual control variables, while Column (8) includes all control variables simultaneously. The results demonstrate that the coefficient of ATC remains consistently negative and statistically significant across all specifications, with coefficients ranging from-0.0044 to-0.0015. This stability is particularly noteworthy given the substantial differences in model specifications and the theoretical importance of each control variable.

It is worth noting that the magnitude of the ATC coefficient decreases when economic development variables (Eco and Eco2) are included, suggesting that part of the relationship between agricultural technological innovation and the urban–rural income gap is related to overall economic development. However, the persistent significance of ATC across all specifications confirms that agricultural technological innovation has an independent effect on reducing income inequality beyond general economic factors.

The consistency of these results across different model specifications provides strong evidence for the robustness of our main finding that agricultural technological innovation plays a significant role in narrowing the urban–rural income gap in China.

4.3.2 Replacing the explained variable

This investigation employs the Theil index as the primary metric for measuring urban–rural income disparity in the benchmark regression analysis. To strengthen the robustness, an alternative dependent variable—the urban–rural income ratio (*RUIR*)—is also incorporated. *RUIR* is determined by dividing urban per capita disposable income by rural per capita net income. Recognizing that nominal income comparisons may be influenced by regional variations in living costs, we have enhanced our robustness analysis by incorporating the Consumer Price Index (CPI) as an additional control variable to account for cost-of-living differentials across regions. The regression outcomes, presented in Column (1) of Table 5, demonstrate that even after controlling for regional price variations, the coefficient for *ATC* remains significantly negative at-0.0269, confirming that our findings are robust to cost-of-living adjustments and align with the initial regression results. This specification ensures

TABLE 4 Variable inclusion robustness test results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	Theil	Theil	Theil	Theil	Theil	Theil	Theil	Theil
ATC	−0.0044*** (−9.48)	−0.0032*** (−7.11)	−0.0035*** (−7.74)	−0.0043*** (−9.35)	−0.0044*** (−9.48)	−0.0036*** (−7.80)	−0.0042*** (−9.14)	−0.0015*** (−3.50)
Eco		−0.0239*** (−15.44)						−0.3278*** (−22.87)
Eco2			−0.0010*** (−12.89)					0.0145*** (21.24)
Fin				0.0045*** (7.26)				0.0044*** (6.16)
Gov					−0.0128* (−1.82)			−0.0472*** (−5.94)
Prim						0.1168*** (9.38)		−0.0473*** (−3.25)
HDG							−0.0001*** (−5.30)	0.0000 (0.28)
_cons	0.1273*** (84.95)	0.3620*** (23.71)	0.2209*** (29.82)	0.1192*** (63.92)	0.1291*** (71.64)	0.1079*** (42.36)	0.1338*** (69.14)	1.9418*** (25.53)
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3,920	3,920	3,920	3,920	3,920	3,920	3,920	3,920
Adj. R^2	0.666	0.687	0.681	0.671	0.667	0.674	0.669	0.731

***, **, *represent significance level at 1%, 5%, 10%, respectively.

TABLE 5 The robustness test of model setting.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	RUIC	Theil	Theil	Theil	Theil	Theil
ATC	−0.0269*** (−4.99)				−0.0014*** (−3.10)	−0.0017*** (−5.24)
Eff		−0.0032** (−2.01)				
Inv			−0.0015*** (−4.19)			
Uti				−0.0008* (−1.88)		
_cons	21.1572*** (18.96)	0.1161*** (106.06)	1.9606*** (26.01)	1.9620*** (25.83)	0.3103*** (12.74)	0.3373*** (13.76)
Controls	Yes	Yes	Yes	Yes	Yes	
City FE	Yes	Yes	Yes	Yes	Yes	
Year Fe	Yes	Yes	Yes	Yes	Yes	
Prov-year FE	No	No	No	No	Yes	No
Area-year FE	No	No	No	No	No	Yes
N	3,779	3,845	3,920	3,920	3,836	3,920
Adj. R^2	0.670	0.656	0.731	0.730	0.952	0.920

***, **, *represent significance level at 1%, 5%, 10%, respectively.

that our measured effects capture genuine improvements in relative purchasing power rather than nominal income changes, thereby providing a more accurate assessment of agricultural technological innovation's impact on real income disparities.

4.3.3 Replacing the core explanatory variables

In the main regression, patent output is employed as the metric for assessing agricultural technological innovation. In this context, research and development efficiency (*Eff*) is used as the key explanatory variable. *Eff* is calculated as the ratio of granted agricultural patents to patent applications. The regression outcomes in Table 5, Column (2), show that improvements in *R&D* efficiency have a positive impact on reducing the urban–rural income gap, with a marginally stronger effect compared to patent output.

Additionally, patents are categorized into invention patents, utility model patents, and design patents, each reflecting different levels of technological complexity. This section further examines the influence of invention patents (*Inv*) and utility model patents (*Uti*) on the urban–rural income disparity. The regression results for Inv and *Uti*, shown in Columns (3) and (4) of Table 5, reveal that the coefficients for *Eff*, *Inv*, and *Uti* are all negative and statistically significant.

Comparing the results with those of the baseline regression reveals that the coefficient for *Eff* is slightly larger than that for *ATC*, while the coefficient for *Uti* is notably smaller, with a corresponding reduction in statistical significance. This indicates that agricultural technological innovation efficiency has a greater impact on narrowing the urban–rural income gap, whereas the effect of patent application is primarily embodied in invention patents.

4.3.4 High-dimensional fixed effects

In the primary regression analysis, this study incorporates fixed effects for both city and year to account for unobserved factors influencing the urban–rural income disparity at these levels. Additionally, recognizing that geographic location, economic capacity, and industrial composition vary across provinces and may impact income disparities within cities, the analysis extends to include fixed effects for province and region. To address the influence of time-varying factors, particularly shifts in provincial and regional strategies over different years, the extended Equation 3 introduces cross-fixed effects for "*province* × *year*" and "*area* × *year*" (Goodman-Bacon, 2021). Where ρ_{pt} denotes the "*province* × *year*" cross fixed effect capturing policy or economic fluctuations over time in each province, ω_{rt} denotes the "*region* × *year*" cross fixed effect controlling for time-varying factors (e.g., adjustments in regional development strategies) at the regional level, and the remaining variables have the same meaning as in model (1). The findings in Columns (5)–(6) of Table 5 confirm that the study's conclusions remain consistent and reliable.

$$Theil_{it} = \beta_0 + \beta_1 ATC_{it} + \lambda Control_{it} + \delta_i + \eta_t + \gamma_p + \rho_{pt} + \omega_{rt} + \varepsilon_{it} \quad (3)$$

4.3.5 Endogenous problem

The benchmark regression model in this paper may face endogeneity concerns arising from potential bidirectional relationships. While advancements in agricultural technology can reduce the urban–rural income disparity, the converse is also possible: a decrease in this disparity might draw skilled labor to rural areas, thereby fostering agricultural technological progress and creating endogeneity issues.

Considering that the impact of current agricultural technological innovation on the urban–rural income gap in Chinese cities may exhibit a time lag, future reductions in this gap are unlikely to influence present agricultural innovation. To address this potential issue, agricultural technological innovation lagged by one or two periods can be utilized as instrumental variables for the current values, effectively mitigating concerns of reverse causality.

In Table 6, columns (1) and (2), showcase the regression outcomes using a one-period lag, both with and without control variables factored in. The findings clearly indicate that *L1. ATC* positively influences the urban–rural income gap. Similarly, Columns (3) and (4) in Table 6 display the regression results with a two-period lag. The coefficient for *L2. ATC* remains negative and statistically significant at the 1% level.

TABLE 6 Lagged regression of endogenous variables.

	(1)	(2)	(3)	(4)
Variables	Theil	Theil	Theil	Theil
L1. ATC	−0.0049*** (−10.71)	−0.0032*** (−7.18)		
L2. ATC			−0.0043*** (−10.17)	−0.0016*** (−4.02)
_cons	0.1289*** (87.81)	0.5658*** (14.16)	0.1191*** (88.62)	2.1395*** (25.60)
Controls	No	Yes	No	Yes
City FE	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes
N	3,640	3,640	3,360	3,360
Adj. R^2	0.656	0.685	0.645	0.715

***, **, *represent significance level at 1%, 5%, 10%, respectively.

4.4 Heterogeneity test

Agricultural technological innovation's impact on urban–rural income disparity varies considerably across different regional and institutional contexts. Building on technology diffusion theory and innovation systems theory, we develop a multi-dimensional heterogeneity framework that examines how agricultural technological innovation affects income distribution through three key dimensions: (1) regional characteristics encompassing geographical location and administrative hierarchy, (2) innovation ecosystems comprising regional innovation capacity and intellectual property rights protection, and (3) information infrastructure covering technology accessibility and information diffusion channels. Additionally, to ensure the validity of regression results and avoid data imbalance caused by grouping, this section reports the statistical characteristics of different subsamples. Tables 7–9 provide detailed information on the means and standard deviations of main variables for each subsample. Comparing the statistical characteristics between the full sample and individual subsamples reveals that while subsample sizes differ somewhat, each group contains sufficient observations to ensure statistical power, and the distribution characteristics of selected variables remain largely consistent with the full sample.

This framework addresses two fundamental considerations. First, it captures China's uneven regional development patterns as an empirical reality. Second, it incorporates the core determinants that shape technological innovation diffusion and adoption processes. Through this approach, we can better understand the contextual mechanisms whereby agricultural technological innovation produces differential effects on income distribution across diverse socioeconomic and institutional environments.

4.4.1 Affiliated region

Significant disparities exist across regions in terms of economic development, natural resource endowments, and agricultural structures. To investigate whether the effect of agricultural

TABLE 7 Descriptive statistics for subgroups—affiliated region.

	Affiliated region							
	(1) East		(2) Mid		(3) West		(4) Norwest	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Theil	0.06	0.03	0.09	0.04	0.11	0.06	0.05	0.03
ATC	5.04	1.54	4.07	1.55	3.79	1.74	3.86	1.28
Eco	10.91	0.59	10.50	0.56	10.40	0.66	10.54	0.50
Eco2	119.40	12.86	110.51	11.80	108.69	13.70	111.43	10.58
Fin	2.53	1.16	2.09	0.90	2.44	1.18	2.56	1.22
Gov	0.14	0.06	0.18	0.06	0.24	0.12	0.22	0.11
Prim	0.09	0.06	0.12	0.07	0.15	0.08	0.17	0.11
Env	94.05	14.22	88.96	19.59	88.39	19.04	86.23	20.54

TABLE 8 Descriptive statistics for subgroups—administrative level and Innovative vitality.

	Administrative level				Innovative vitality			
	(1) High		(2) Low		(3) High		(4) Low	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Theil	0.05	0.03	0.09	0.05	0.05	0.03	0.09	0.05
ATC	6.14	1.19	4.01	1.55	6.06	1.17	3.86	1.48
Eco	11.18	0.45	10.52	0.61	11.23	0.44	10.46	0.58
Eco2	125.11	10.05	111.14	12.85	126.40	9.83	109.76	12.06
Fin	4.33	1.23	2.12	0.81	3.36	1.30	2.17	0.95
Gov	0.14	0.04	0.20	0.10	0.13	0.04	0.21	0.1
Prim	0.04	0.03	0.14	0.08	0.04	0.03	0.14	0.07
Env	95.00	10.65	89.34	18.98	96.01	9.09	88.67	19.52

TABLE 9 Descriptive statistics for subgroups—intellectual property protection and Information accessibility.

	Intellectual property protection				Information accessibility			
	(1) High		(2) Low		(3) High		(4) Low	
Variables	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Theil	0.06	0.04	0.09	0.05	0.05	0.03	0.1	0.05
ATC	5.26	1.57	3.82	1.5	5.35	1.39	3.55	1.42
Eco	10.91	0.63	10.46	0.58	11.08	0.45	10.29	0.53
Eco2	119.42	13.61	109.85	12.1	122.9	10.02	106.19	10.86
Fin	2.89	1.25	2.16	0.98	3.04	1.26	1.96	0.76
Gov	0.16	0.07	0.21	0.1	0.18	0.09	0.2	0.1
Prim	0.09	0.08	0.14	0.07	0.09	0.07	0.15	0.07
Env	93.16	15.47	88.6	19.25	97.98	6.9	84.8	21.29

technological innovation on the urban–rural income gap differs by region, this study classifies the data according to the four major economic regions defined by the National Bureau of Statistics of China. The regression results for each region are presented in Table 10. Columns (1) to (4) correspond to the eastern, central, western, and northeastern regions, respectively. The regression outcomes reveal that the signs and statistical significance of the *ATC* coefficients vary across the different regional samples. Specifically, agricultural technological innovation in the eastern and western regions significantly reduces the urban–rural income gap. In contrast, in the central region, agricultural technological innovation is correlated with the local Theil index. Additionally, the coefficient for *ATC* in the northeastern region does not exhibit statistical significance.

The empirical results demonstrate stark regional asymmetries in agricultural innovation's inequality effects. Coastal eastern provinces leverage robust economic ecosystems to accelerate agricultural tech

TABLE 10 Heterogeneity test—affiliated region and administrative level.

	Affiliated region				Administrative level	
Variables	(1) East	(2) Mid	(3) West	(4) Norwest	(5) High	(6) Low
ATC	−0.0038*** (−4.99)	0.0026*** (3.64)	−0.0020*** (−2.86)	−0.0010 (−0.54)	−0.0079*** (−3.78)	−0.0012 (−1.54)
_cons	1.6115*** (11.27)	1.6625*** (9.44)	2.3712*** (17.12)	−0.8180** (−2.33)	3.3520*** (9.05)	1.8998*** (9.12)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes	Yes	Yes
N	1,386	1,106	1,148	476	252	3,668
adj. R^2	0.693	0.796	0.808	0.479	0.759	0.735

***, **, *represent significance level at 1%, 5%, 10%, respectively.

absorption, where rural productivity gains directly counteract urban wage premiums (Jin et al., 2010). Western regions reveal policy-driven growth corridors-targeted subsidies and infrastructure investments enable leapfrog technological adoption (Hsu et al., 2023), though sustainability concerns persist as noted by Han et al. (2024).

Central China's fragmented infrastructure and underdeveloped markets constrain tech penetration, creating winner-takes-all dynamics that exacerbate rural stratification (Han et al., 2023). This corroborates Huang et al.'s (2013) findings on uneven agricultural modernization in central provinces. Northeastern rustbelt areas present industrial monocultures and demographic hollowing that blunt innovation's redistributive potential—here, aging farming populations and entrenched state-owned enterprises create structural inertia that even advanced technologies struggle to disrupt (Rozelle and Swinnen, 2004). These geographical fault lines underscore how institutional path dependencies mediate technological impacts on inequality.

4.4.2 Administrative level

The fiscal system and administrative hierarchy of China imply differing priorities among cities of various administrative levels in terms of fiscal transfer payments, land policies, and infrastructure development, which affect their capacity to promote technological innovation. To investigate whether urban administrative levels influence the effectiveness of agricultural technological innovation in narrowing the urban–rural income gap, this paper divides the entire sample into high and low administrative levels subsamples for grouped regression analysis. Columns (5) and (6) of Table 10 present the results of heterogeneity tests based on urban administrative levels.

Administrative levels influence local governments' fiscal resources, policy implementation capacity, and support for innovation (Rodríguez-Pose, 2013). This hierarchical structure has been extensively documented by Xu (2011) who analyzed how China's administrative ranking system affects resource allocation and economic outcomes. Cities directly governed by the central government, along with provincial capitals and sub-provincial urban centers, generally enjoy stronger financial backing and greater decision-making freedom. These findings align with Zhang (2006) who demonstrated that higher administrative rank correlates with increased fiscal transfers and policy autonomy in Chinese cities. This positions them to drive technological advancements and build out essential infrastructure more efficiently than other regions, which may contribute to narrowing the urban–rural income gap. In contrast, ordinary prefecture-level cities may suffer from inadequate resources, making it challenging to effectively drive agricultural technological innovation, and thus having a weaker impact on income disparity. This resource constraint pattern is consistent with Jin and Zou (2005) who found significant fiscal disparities between different administrative tiers in China's intergovernmental system.

4.4.3 Innovative vitality

Innovation vitality is a significant indicator of urban development quality. According to the theory of innovation diffusion, the rate at which technological innovation effects spread varies across different regions (Chen et al., 2024) This theoretical foundation builds upon Rogers (2003) seminal work on diffusion of innovations, which established how innovation adoption rates differ across geographic and institutional contexts. Areas with strong innovation vitality can adopt new technologies more rapidly, thereby narrowing the productivity and income gaps between urban and rural areas. To examine whether the impact of agricultural technological innovation on the urban–rural income gap varies across cities with different levels of innovation vitality, this paper employs the Urban Innovation Index to characterize urban innovation vitality. Cities are classified into high and low groups based on their annual mean values. The results, presented in columns (1) and (2) of Table 11, indicate that the estimated coefficient of *ATC* is significantly negative, suggesting that improvements in agricultural technological innovation have a positive effect on narrowing the urban–rural income gap in cities with varying innovation vitality. However, this effect is stronger and more significant in cities with high innovation vitality.

The reasons are as follows: cities with strong innovation vitality typically possess more comprehensive research and development systems, technology transfer mechanisms, and market structures, enabling them to more rapidly apply agricultural technological innovations to actual production. These findings are consistent with Cooke et al. (1997) who demonstrated that regional innovation systems with stronger institutional capacity exhibit superior technology absorption and diffusion capabilities. This facilitates a more effective enhancement of agricultural productivity, thereby improving farmers' incomes and narrowing the urban–rural income gap. Conversely, in cities with weaker innovation vitality, the diffusion and application of agricultural technologies progress relatively slowly, and the effect of technological innovation on improving income distribution patterns is relatively limited.

TABLE 11 Heterogeneity test: innovative vitality, intellectual property protection and information accessibility.

	Innovative vitality		Intellectual property protection		Information accessibility	
Variables	(1) High	(2) Low	(3) High	(4) Low	(5) High	(6) Low
ATC	−0.0052*** (−3.08)	−0.0023** (−2.36)	−0.0036*** (−4.81)	−0.0008 (−1.59)	−0.0027*** (−2.89)	−0.0007 (−0.72)
_cons	2.4440*** (4.96)	0.5240 (1.59)	1.8087*** (15.52)	1.9191*** (17.55)	1.8839*** (5.10)	1.9243*** (6.40)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes	Yes	Yes
N	714	3,206	1,204	2,716	1,316	2,604
Adj. R^2	0.795	0.688	0.758	0.680	0.738	0.742

***, **, *represent significance level at 1%, 5%, 10%, respectively.

4.4.4 Intellectual property protection

The strength of IP safeguards directly impacts the motivation for tech advancements (Furukawa, 2010). To examine the effect of urban intellectual property protection on the impact of agricultural technological innovation on the urban–rural income gap, this paper classifies the entire sample of cities into high and low protection level groups based on the average level of intellectual property protection. Subsequently, regression analyses are performed for each group. The results are presented in Columns (3) and (4) of Table 11.

The analysis reveals intellectual property (IP) regimes' pivotal role in mediating agricultural innovation's distributional outcomes. Regions with robust IP frameworks demonstrate technology's equalizing potential: enforceable patent protections stimulate sustained R&D investment while ensuring scalable tech transfer to smallholders. Here, innovation commercialization correlates strongly with productivity surges (15–22% yield improvements) and rural income growth (Chu et al., 2014; Yang et al., 2014), effectively narrowing urban–rural wage differentials through dual channels—direct farm revenue boosts and secondary employment in agritech sectors.

Conversely, weak IP enforcement regions exhibit innovation stagnation. Underdeveloped legal infrastructures create "technology deserts" where limited adoption (<30% penetration rates) disproportionately benefits commercial farms, leaving subsistence farmers trapped in low-productivity cycles. This bifurcation aligns with endogenous growth theory's predictions (Bielig, 2015): strong IP regimes function as economic equalizers by boosting innovation returns and diffusion breadth, whereas fragmented protections exacerbate rural stratification through uneven technological dividends.

4.4.5 Information accessibility

Scholtz posits that economic effects cannot be generated without technology diffusion, and that the flow of information is a key factor driving both technology diffusion and the application of innovations (Scholtz, 2018). This perspective aligns with Aker (2011) who demonstrated how information and communication technologies significantly reduce transaction costs and improve market efficiency in agricultural settings. Whether the flow of information factors promotes a stronger economic effect of agricultural technology innovation, thereby influencing income disparity, is investigated in this paper. Using the average number of Internet broadband users per 100 individuals as a standard, this paper explores the impact of varying levels of information accessibility on the income-regulating effects of agricultural technology innovation. The results are presented in columns (5) and (6) of Table 11.

The results indicate that in regions with high information accessibility, agricultural technological innovation significantly reduce the urban–rural income gap. Efficient information transmission channels provide farmers with more convenient access to agricultural technology and market information. Consequently, the latest agricultural production techniques and market demands can be promptly understood and swiftly applied by farmers in their production processes, facilitating the optimization of agricultural production workflows and enabling timely adjustments in production strategies to align with market demands. These findings corroborate Jensen's (2007) seminal study on fishermen in Kerala, India, which showed that mobile phone adoption led to significant improvements in market efficiency and welfare gains.

In contrast, in regions with low information accessibility, the flow of information is hindered, which obstructs the advancement and implementation of agricultural tech innovation. Farmers face difficulties in timely acquiring relevant knowledge and resources, resulting in a significant decline in the diffusion rate of technology. Additionally, the lack of effective market information exposes farmers to considerable un-certainty in their production and sales decisions, hindering the conversion of the eco-nomic benefits derived from technological innovation into actual income growth. This pattern is consistent with Foster and Rosenzweig's (2022) research on learning and technology adoption in agriculture, which highlighted how information constraints can significantly impede the adoption of profitable agricultural technologies. Therefore, the level of information accessibility emerges as a crucial variable determining whether agricultural technological innovation can effectively narrow the urban–rural income gap. The efficiency of information flow directly influences the equitable distribution of technological benefits across urban and rural regions.

5 Further analysis

5.1 Mechanism test

To delve deeper into how advancements in agricultural technology help bridge the income disparity between urban and rural areas, and building on the earlier theoretical framework, this study aims to develop a model to examine the mechanisms through which employment structure, resource allocation, and productivity play a role. The model is constructed as outlined below.

$$M_{i,t} = \beta_0 + \beta_1 ATC_{it} + \lambda Control_{it} + \delta_i + \eta_t + \varepsilon_{it} \quad (4)$$

$$Theil_{it} = \beta_0 + \beta_1 ATC_{it} + \alpha M_{i,t} + \lambda Control_{it} + \delta_i + \eta_t + \varepsilon_{it} \quad (5)$$

In these equations, M serves as the mediating factor, covering employment structure, resources allocation and productivity. Equation 4 tests the influence of agricultural technological innovation change on each intermediary variable. Equation 5 tests the influence of various mediating variables on the urban–rural income gap.

5.1.1 Employment structure

This paper employs the proportion of the employees engaged in the primary industry as an indicator for measuring local employment structure (*Emp_stru*). Column (1) of Table 12 reports the impact of agricultural technological innovation on local employment structure. The estimated coefficient is significantly negative at the 1% statistical level, indicating that agricultural technological innovation may lead to a greater outflow of labor from the agricultural to non-agricultural industries. The results in column (2) suggest that agricultural technological innovation can reduce income disparity, while a higher proportion of labor remaining in the agricultural sector exacerbates the urban–rural income gap. Overall, agricultural technological innovation releases surplus labor in rural areas and narrows the income disparity by improving the employment structure.

The economic significance of this finding is that technological advancements in agriculture reduce the demand for labor in traditional farming activities, freeing up workers to seek employment in more productive sectors such as manufacturing and services. This reallocation of labor from low-income agricultural jobs to higher-income non-agricultural jobs contributes to narrowing the income gap between urban and rural areas.

5.1.2 Resources allocation

Persistent urban–rural resource misallocation critically impedes dual-economy transformation (Wang and Bai, 2013). Rural capital-technology deficits and labor trapping in low-yield agriculture generate dual inefficiencies—allocative distortions and factor productivity mismatches (Restuccia and Rogerson, 2008). To test whether agricultural innovation mediates income convergence through improved allocation efficiency, this study operationalizes the *Res_allo* index as a structural mediator. The mediation analysis specifically examines how technological advances reconfigure rural production factors (land consolidation, labor upskilling, capital redeployment) to counteract urban-biased resource lock-in effects.

In column (3) of Table 12, the coefficient of ATC is-0.0061, which is statistically significant at the level of 5%, indicating that agricultural technological innovation significantly reduces the degree of resource misallocation. This finding suggests that with advancements in agricultural technology, resources can be allocated more efficiently among different industries. In column (4), the coefficient of *ATC* is significantly negative at the level of 1%, while the coefficient of *Res_allo* is significantly positive at the same level, indicating that a higher degree of resource misallocation corresponds to a wider income gap. In other words, the distortion in resource allocation exacerbates income inequality, while agricultural technological innovation can optimize resource allocation and further narrow the income gap.

5.1.3 Productivity

Solow (1957) pointed out that technological progress is the primary driver of productivity enhancement. In the context of China's economic transformation and high-quality development, technological innovation has emerged as a crucial power for improving productivity. According to dual economy development theory of Lewis, productivity improvement in the agricultural sector is a key driving force behind income growth in rural area. The rural labor productivity is used as the indicator of agricultural production efficiency (*Prod_eff*), examining the third pathway through which agricultural technological innovation affects the urban–rural income gap.

Columns (5) and (6) of Table 12 present the corresponding results. The findings reveal that the coefficient of ATC is significantly positive at the level of 1%, indicating that advancements in agricultural technology leads to improvements in rural labor productivity, thereby enhancing agricultural productivity. Furthermore, the coefficient of *Prod_eff* on Theil is significantly negative, suggesting that increasing

TABLE 12 Mechanism test.

	Employment structure		Resources allocation		Productivity	
Variables	(1) Emp_stry	(2) Theil	(3) Res_allo	(4) Theil	(5) Prod_eff	(6) Theil
ATC	−0.1730*** (−4.54)	−0.0042*** (−9.11)	−0.0061** (−2.25)	−0.0035*** (−7.20)	0.0056*** (2.88)	−0.0035*** (−7.60)
Emp_stry		0.0008*** (4.01)				
Res_allo				0.0180*** (6.02)		
Prod_eff						−0.0122*** (−3.04)
_cons	3.8468*** (18.28)	0.1261*** (63.75)	0.3924*** (26.88)	0.1034*** (36.04)	6.9866*** (451.34)	0.1879*** (6.66)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes	Yes	Yes
N	3,907	3,907	3,920	3,920	3,906	3,906
Adj. R^2	0.238	0.670	0.542	0.662	0.827	0.675

***, **, *represent significance level at 1%, 5%, 10%, respectively.

productivity in rural areas can effectively narrow the income disparity between urban and rural regions.

The underlying reason for this effect is that technological advancements in agriculture, such as improved farming techniques, better seeds, and more efficient machinery, directly enhance the productivity of rural labor. As rural workers become more productive, their incomes rise, which helps to close the income gap with urban areas. Additionally, higher agricultural productivity can stimulate rural economic growth, further contributing to income convergence.

5.2 Threshold effect test

The threshold effect analysis is based on the theory of nonlinear economic relationships, which posits that the impact of a given variable on an outcome may change depending on the level of another variable. This nonlinearity arises because certain conditions or thresholds must be met for the effect to emerge or vary in intensity. In the context of agricultural technological innovation, the diffusion and adoption of new technologies depend on factors such as the level of urbanization, educational investment, and information accessibility. These factors establish thresholds that determine the extent to which technological innovation can effectively reduce income disparities between urban and rural areas.

In regions with low urbanization or limited access to information, the benefits of agricultural innovation may be constrained by barriers such as inadequate infrastructure and insufficient technical knowledge. However, once these factors exceed specific thresholds, the impact of innovation on income inequality becomes more significant. This nonlinear relationship aligns with the theory of technology diffusion, which highlights that the adoption and effectiveness of new technologies are shaped by the socio-economic and institutional environment.

In order to accurately examine the threshold for the impact of agricultural technological innovation on the urban–rural income gap in China, and to avoid estimation biases caused by artificially setting threshold values, this paper introduces a threshold panel model to do the further analysis. First, the single-panel threshold model setting is as follows:

$$\begin{aligned} Theil_{it} &= \beta_0 + \beta_{11} ATC_{it} \times I\left(Thres_{it} \le \tau\right) \\ &+ \beta_{12} ATC_{it} \times I\left(Thres_{it} > \tau\right) + \lambda Control_{it} + \delta_i + \eta_t + \varepsilon_{it} \end{aligned} \tag{6}$$

In Equation 6, $Theil_{i,t}$ is the Theil index of urban–rural income gap, $ATC_{i,t}$ is the level of agricultural technological innovation, $Thres_{i,t}$ stands for the threshold variables. In this paper, urbanization level (*Urban*), educational attention (*Edu*), and information accessibility (*Int*) are selected as threshold variables, measured, respectively, by the proportion of the resident population in urban areas, the ratio of educational expenditure in total fiscal general public budget expenditures, and the number of broadband Internet users per hundred individuals. τ is the specific threshold value, and $I(\cdot)$ is the indicator function. β_{11} and β_{12} are the influence coefficients of agricultural technological innovation on urban–rural income gap when threshold variables happen when $Thres_{i,t} \le \tau$ and $Thres_{i,t} > \tau$, and ε_{it} is the random disturbance term. After testing, the selected variables exhibit significant threshold characteristics. Among them, Edu has only one threshold value, while Urban and Int have two threshold values. Therefore, Equation 6 is extended to a double-panel threshold model (Equation 7):

$$\begin{aligned} Theil_{it} &= \beta_0 + \beta_{11} ATC_{it} \times I\left(Thres_{it} \le \tau_1\right) + \beta_{12} ATC_{it} \\ &\times I\left(\tau_1 < Thres_{it} \le \tau_2\right) + \beta_{13} ATC_{it} \times I\left(Thres_{it} > \tau_2\right) \\ &+ \lambda Control_{it} + \delta_i + \eta_t + \varepsilon_{it} \end{aligned} \tag{7}$$

5.2.1 Urbanization level

Based on the regression results of the single-panel threshold model (Equation 6) presented in Table 13, when Urban $\le$ 0.3317, the relationship between agricultural technological innovation and the urban–rural income gap is negatively correlated, but lacks statistical significance. When 0.3317 < Urban $\le$ 0.4410, there is a significant effect on improving the urban–rural income gap, with a coefficient of −0.0027. When Urban < 0.4410, the impact of agricultural technological innovation on income disparity is further strengthened, with the absolute value of the coefficient increasing to 0.0043. In the early stages of urbanization, rural infrastructure is relatively underdeveloped, and the mobility of production factors such as labor and capital are restricted, making it difficult for technological innovation to be fully translated into productivity improvements. During this stage, the diffusion and application of agricultural technological innovation are constrained, resulting in a negligible effect on reducing the urban–rural income gap. However, as urbanization accelerates, the flow of resources between cities and countryside intensifies, gradually boosting agricultural technology's impact. Upgraded rural infrastructure—think better roads and internet access—helps spread new farming methods that boost crop yields. These technological leaps do not just improve harvests; they put more money directly in farmers' pockets through efficient operations. Meanwhile, the urban job market pulls rural workers cityward, creating a double effect—fewer hand on farms drive tech adoption, while urban wages pull up rural earnings through remittances.

This dynamic aligns perfectly with China's development playbook that intentionally ties urban growth to countryside revitalization. Beijing's push to connect cities with villages through infrastructure upgrades has essentially built the plumbing systems needed for agricultural tech to flow where it's most effective—in areas already experiencing significant urban expansion.

5.2.2 Educational attention

The results of double-panel threshold model (Equation 7) indicate that the impact intensity of agricultural technological innovation on the urban–rural income gap becomes more pronounced as the level of educational attention increases. When *Edu* $\le$ 0.1053, the coefficient is −0.0007 and lacks statistical significance. However, when *Edu* > 0.1053, the coefficient increases to −0.0038, which meets the significance threshold at 1%.

This suggests that once educational attention surpasses the threshold of 0.1053, the income regulating effect of agricultural technological innovation becomes significantly evident. When educational attention is relatively low, the promotion of agricultural technological innovation is constrained by factors such as infrastructure, funding, and technical training, resulting in an inability to significantly reduce the urban–rural income gap. Nevertheless, when educational attention exceeds this

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TABLE 13 Threshold effect test.

Variables	Threshold model (1)			Threshold model (2)		Threshold model (3)		
	Urban ≤ 0.3317	0.3317 < Urban ≤ 0.4410	Urban > 0.4410	Edu ≤ 0.1053	Edu > 0.1053	Int ≤ 8.5061	8.5061 < Int ≤ 23.2499	Int > 23.2499
ATC	−0.0004 (−0.45)	−0.0027*** (−3.31)	−0.0043*** (−6.31)	−0.0007 (−1.20)	−0.0038*** (−9.45)	−0.0020*** (−4.38)	−0.0038*** (−9.40)	−0.0048*** (−11.67)
_cons	1.6287*** (8.20)	1.6287*** (8.20)	1.6287*** (8.20)	1.7154*** (22.48)	1.7154*** (22.48)	−9.068*** (0.430)	−9.068*** (0.430)	-9.068*** (0.430)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	3,920	3,920	3,920	3,920	3,920	3,920	3,920	3,920
Adj. R^2	0.707	0.707	0.707	0.703	0.703	0.707	0.707	0.707

***, **, *represent significance level at 1%, 5%, 10%, respectively.

threshold, the barriers to technology promotion are lowered through policy guidance, financial support, infrastructure development, and optimization of market mechanisms. Consequently, scale effects and resource allocation efficiency are enhanced, allowing innovative outcomes to benefit rural communities more broadly.

This finding aligns with China's national strategy of prioritizing education and rural development. The government's increased investment in education and rural infrastructure has played a crucial role in enhancing the capacity of rural areas to adopt and benefit from agricultural technologies.

5.2.3 Information accessibility

According to the results of threshold model (3), when $Int \leq 8.5061$, the coefficient of *ATC* is 0.0020. When $0.0020 < Int \leq 23.2499$, the effect of agricultural technological innovation on reducing the urban–rural income gap improves, with the coefficient increasing to 0.0038. When $Int > 23.2499$, the impact coefficient changes to-0.0048. The economic significance of these threshold values is that regions with low information accessibility (below 8.5061 broadband users per 100 individuals) face significant barriers to the dissemination of agricultural technologies. In such regions, farmers have limited access to information about new technologies and market conditions, which hinders the adoption and application of innovations. However, as information accessibility surpasses the first threshold (8.5061), the flow of information between urban and rural areas improves, facilitating the diffusion of agricultural technologies and enhancing rural productivity. When information accessibility exceeds the second threshold (23.2499), the impact of agricultural innovation on income inequality be-comes even more pronounced, as improved information flow enables farmers to optimize production decisions and achieve higher market returns.

Improved information accessibility accelerates the dissemination of agricultural technology between urban and rural areas, facilitating the acquisition and application of cutting-edge technologies, and enhances productivity and income. It also alleviates market information asymmetry, enabling farmers to optimize production decisions and achieve higher market returns. Consequently, as information accessibility rises, the role of agricultural technological innovation in narrowing the urban–rural income gap steadily intensifies, demonstrating a gradually progressive stepped strengthening effect. These findings are closely linked to China's efforts to promote digital rural development and bridge the digital divide between urban and rural areas. The government's initiatives to expand broadband infrastructure and improve information accessibility in rural regions have created an enabling environment for the diffusion of agricultural technologies, particularly in regions with higher levels of information accessibility.

6 Conclusion and policy suggestion

6.1 Conclusion

This study systematically examines the impact of agricultural technological innovation on the urban–rural income gap based on panel data from 280 cities in China spanning the period 2008–2021. The findings can be summarized into four interrelated core insights:

First, agricultural technological innovation significantly narrows the urban–rural income gap, validating the core hypothesis of this

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study. Empirical results indicate that a 10% increase in agricultural technological innovation leads to an average reduction of approximately 0.81% in the urban–rural income gap (as measured by the Theil index). This finding remains robust across various tests, including sample adjustments, variable substitutions, endogeneity treatments, and high-dimensional fixed effects, suggesting that agricultural technological innovation is a crucial driver of integrated urban–rural development. Notably, invention patents exhibit the most pronounced effect in reducing the income gap, highlighting the pivotal role of original technological breakthroughs.

Second, the effects of agricultural technological innovation exhibit significant regional and institutional heterogeneity. At the regional level, the moderating effects are more pronounced in the eastern and western regions, while the central region shows an opposite trend. In terms of institutional environments, cities with higher administrative levels, greater innovative capacity, stronger intellectual property protection, and better information accessibility demonstrate stronger moderating effects. These findings corroborate the predictions of technology diffusion theory regarding the in-fluence of institutional environments and absorptive capacity on technological out-comes.

Third, the mechanism analysis reveals three key pathways through which agricultural technological innovation affects the urban–rural income gap: employment structure optimization, factor allocation improvement, and production efficiency enhancement. These pathways form an integrated framework that collectively promotes agricultural modernization and urban–rural income convergence, supporting the theoretical mechanism proposed in this study.

Fourth, threshold effect analysis indicates that the impact of agricultural techno-logical innovation exhibits nonlinear characteristics. As urbanization levels increase, education expenditure rises, and information accessibility improves, the moderating effect of agricultural technological innovation on the urban–rural income gap shows a stepwise enhancement. Specifically, the moderating effect reaches its optimum when the urbanization rate exceeds 44.10%, the share of education expenditure surpasses 10.53%, or the number of broadband users per 100 people exceeds 23.25. These findings provide an empirical basis for formulating differentiated regional policies.

In summary, this study not only validates the significant role of agricultural technological innovation in narrowing the urban–rural income gap but also elucidates its mechanisms and heterogeneous effects, offering theoretical and policy insights for advancing agricultural modernization and integrated urban–rural development.

6.2 Policy suggestion

Drawing from the aforementioned findings, this study proposes the following policy suggestions.

1. Strengthen support for agricultural technological innovation

The government should increase investment in agricultural research and development, particularly in key areas such as smart agriculture and green agriculture. Establishing special funds to support innovative projects in universities, research institutions, and agricultural enterprises can enhance agricultural productivity and increase farmers' income. Additionally, strengthening intellectual property protection will incentivize innovation and facilitate the rapid dissemination of agricultural technologies in rural areas.

2. Optimize rural labor structure and enhance productivity

Promoting skills training and vocational education for rural laborers is essential for the effective implementation of agricultural technologies. The government should focus on providing training in modern agricultural techniques, such as smart agriculture and digital management, to improve farmers' technical proficiency and employment competitiveness. Furthermore, encouraging the development of high-value-added agriculture, such as organic farming and green product processing, can create more employment opportunities and boost rural incomes.

3. Promote urbanization and information infrastructure development

Accelerating new urbanization and improving rural information infrastructure are crucial for enhancing the diffusion of agricultural technologies. A scientific urbanization layout can improve connectivity in transportation, logistics, and information networks, facilitating the dissemination of technology in rural areas. Prioritizing the construction of rural information infrastructure, such as internet access, will enable the adoption of advanced agricultural technologies like precision agriculture, further improving productivity and reducing the urban–rural income gap.

4. Strengthen policy coordination and government support

The government should increase support for agricultural research and technology dissemination through fiscal subsidies and tax incentives. Ensuring that innovations reach grassroots farmers is essential for narrowing the income gap between urban and rural areas.

7 Limitations

This paper examines the impact of agricultural technological innovation on the urban–rural income gap; however, it has the following limitations. First, our macro-level analysis may overlook micro-level dynamics; future research should examine individual income and production decisions through farmer and enterprise surveys. Second, patent data may not fully capture innovation's multidimensional nature; comprehensive indicator systems including R&D investment, technological talent, and technology dissemination should be developed. Third, nominal income comparisons may be affected by regional cost-of-living variations. While we control for regional CPI, ideal measurements would use comprehensive urban–rural price indices, though such detailed data are unavailable at the prefecture-city level at the moment. Fourth, our conventional econometric techniques could be enhanced through advanced statistical or machine learning methods for improved precision and uncertainty interpretation.

Future research should integrate macro and micro-level data with multidimensional evaluation systems and advanced analytical techniques for more accurate assessment of agricultural technological innovation's impact on urban–rural income gaps.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: https://data.cnki.net/yearBook/single?id=N2025020156&pinyinCode=YZGCA.

Author contributions

RL: Project administration, Writing – original draft, Methodology, Resources, Supervision, Conceptualization, Funding acquisition, Software. YW: Investigation, Software, Validation, Writing – review & editing, Data curation. YB: Resources, Investigation, Formal analysis, Writing – review & editing, Methodology, Project administration, Supervision. JL: Supervision, Investigation, Writing – review & editing, Resources, Visualization, Project administration.

Funding

The author(s) declare that no financial support was received for the research and/or publication of this article.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declare that no Gen AI was used in the creation of this manuscript.

Publisher's note

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