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How does rural industrial integration affect farmers' income?—An empirical study based on Jiangxi Province

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Introduction: Amid global economic shifts and rural decline, promoting rural industrial integration has become a core strategy for China's Rural Revitalization and sustainable farmers' income growth. However, existing studies mostly focus on macro-policy interpretation or case descriptions, lacking mechanism testing and heterogeneity analysis based on large-sample county-level data. Jiangxi Province, a typical agricultural province with distinctive terrain and urgent rural industrial revitalization needs, provides an ideal empirical context. This study aims to systematically explore the impact, transmission mechanisms, and heterogeneous characteristics of rural industrial integration on farmers' income.

Methods: Using panel data from 95 counties in Jiangxi Province during 2014–2023, we constructed a Rural Industrial Integration Index (RIII) covering four dimensions: chain extension, multi-functionality expansion, multiformat integration, and technology penetration. A combination of two-way fixed effects models, mediating effect models, and full quantile regression methods was employed to conduct empirical analysis.

Results: The RIII exerts a significantly positive effect on farmers' income: every 1% increase in the RIII leads to a 3.1–3.3% growth in rural residents' *Per Capita* Disposable Income (PCDI). Non-agricultural employment serves as a key transmission mechanism, with its mediating effect contributing 23.74% of the total effect. The income-increasing effect exhibits notable heterogeneity, being more pronounced in middle-low income counties, hilly terrain areas, and central Jiangxi regions.

Discussion: This study enriches agricultural economics theories by verifying the causal relationship between rural industrial integration and farmers' income. The findings provide empirical evidence for formulating regionally differentiated rural industrial integration policies, offering critical decision-making insights for boosting farmers' income growth and advancing rural revitalization strategies in Jiangxi and similar agricultural regions.

KEYWORDS
farmers' income, Jiangxi Province, mediating effect, non-agricultural employment, Rural Industrial Integration Index

1 Introduction

Amid significant global economic shifts and persistent rural decline, identifying effective strategies for comprehensive rural revitalization and sustainable farmer income growth has become a central concern for many developing nations (Liu and Li, 2017). China's rural society mirrors this global trend, facing a multifaceted downturn driven by population outflow, population aging, and limited economic opportunities. To counteract these severe rural challenges, China introduced its national Rural Revitalization Strategy (Liu et al., 2020), one of whose core objectives is achieving "prosperous living," with sustained growth in farmers' income being a central indicator of this goal (Zhang and Fan, 2024). Given China's resource endowment constraints characterized by a large population, limited arable land, and water scarcity (Zhou et al., 2020), coupled with the uncertainties climate change imposes on agricultural production (Piao et al., 2010), relying solely on traditional agricultural models makes it difficult to overcome income growth bottlenecks. Consequently, advancing the high-quality integration of rural industries—through measures that lengthen the industrial chain, increase value addition, and streamline the supply chain—is broadly acknowledged as a crucial strategy for activating internal growth drivers in rural areas and boosting farmer incomes (Chamberlain et al., 2020; Jiang, 2016; Xie et al., 2025).

Since the Central Rural Work Conference of China in December 2014 first proposed introducing industrial chains, value chains, etc. from modern industrial organization methods into rural industries, industrial integration has become a core strategy to address challenges such as low added–value in traditional agriculture and stagnant growth of farmers' income. It injects new momentum into the rural economy by deeply integrating agriculture with processing, service, cultural tourism, and other industries through industrial chain extension, format innovation and factor recombination (Wang et al., 2025; Zhao et al., 2023; Zheng et al., 2022).

Although existing studies have explored the motivations, development models, and income effects of rural industrial integration, three critical research gaps remain to be filled. First, most existing studies are limited to macro-policy interpretation at the provincial level or qualitative analysis of typical cases, with few studies carrying out quantitative mechanism testing and heterogeneity analysis based on long-term large-sample panel data at the county level, which makes it difficult to reveal the net effect and internal logic of industrial integration on farmers' income at the grassroots administrative level. Second, the existing literature on the transmission mechanism of industrial integration affecting farmers' income mostly focuses on the micro household level, lacking quantitative identification of the mediating mechanism at the county level, and fails to accurately measure the contribution degree of key transmission paths. Third, most studies on the heterogeneous effects of industrial integration only focus on regional or income-level differences, while rarely clarifying the role of topographic factors in the income-increasing effect of industrial integration, especially for agricultural provinces with complex terrain such as Jiangxi, there is a lack of targeted empirical evidence. As a typical major agricultural province in central China with a terrain pattern of "70% mountains, 10% water, and 20% farmland," Jiangxi Province has prominent regional differences in industrial integration development and urgent practical needs for rural revitalization, which not only provides an ideal natural experimental scenario for this study, but also makes the research conclusions have strong practical pertinence and replicability for similar agricultural regions.

Against the above practical and theoretical background, this study takes Jiangxi Province as a case example. Utilizing 2014–2023 panel data from 95 counties, we construct a RIII evaluation system based on four dimensions: industrial chain extension, multi-functional agricultural development, intra-agricultural multi-formal integration, and technology penetration. Employing integrated methods including Two Way Fixed Effects Model (TWFE Model), Mediating Effect Model (ME Model), and Full Quantile Regression methods (FQR), this study systematically identifies the impact mechanisms, transmission pathways, and heterogeneous characteristics of the RIII on farmers' income. This research not only contributes to enriching theories in agricultural economics, but also provides references for formulating differentiated rural industrial policies in Jiangxi and other similar regions.

2 Theoretical analysis and research hypotheses

Rural industrial integration provides diversified paths for the growth of farmers' income by systematically restructuring agricultural production factors and expanding industrial boundaries and functions. Its core mechanisms are manifested as follows: Through the vertical extension of the industrial chain, horizontal expansion, and technological penetration, it enhances the added value of agriculture and creates new sources of income. This section, based on core theoretical frameworks such as the industrial value chain theory, labor transfer theory, factor allocation theory and geographical location and regional development theory, systematically expounds on the theoretical mechanisms by which rural industrial integration affects farmers' income, and accordingly puts forward research hypotheses.

2.1 Direct effects of industrial integration on farmers' income growth

The industrial chain theory posits that vertical extension and horizontal integration can optimize resource allocation and reduce transaction costs, thereby enhancing the added value of the industry (Sturgeon, 2002). Rural industrial integration extends agriculture to links such as processing, circulation, and services, promoting the integrated development of "production–processing–sales" and effectively enhancing farmers' bargaining power in the value chain. For instance, deep processing and branding of agricultural products can reduce the loss rate in intermediate links and significantly increase the premium space for primary products (Reardon et al., 2007). Through vertical integration and horizontal expansion, industrial integration significantly reduces transaction costs such as information asymmetry and contract execution costs, optimizing the allocation efficiency of production factors. At the same time, the integration process can revitalize idle rural resources, forming a sustainable competitive advantage (Gereffi et al., 2005). The penetration of digital technology further shortens the supply chain, achieving precise connection between production and sales and directly increasing farmers' operating income (Ge et al., 2022; Yin et al., 2022). Theoretical analysis indicates that an increase in the level of industrial integration is expected to directly promote the growth of farmers' income through the above–mentioned mechanisms. Based on this, we propose:

> *H1*: Rural industrial integration has a significant positive impact on farmers' income.

2.2 The mechanisms of industrial integration in promoting the increase of farmers' income

According to the labor transfer theories, industrial integration promotes the transfer of agricultural labor to sectors with higher productivity by creating non-agricultural employment opportunities, thus increasing wage income (Lewis, 1954; Todaro, 1969). The service demands for processing, logistics, tourism, etc. generated by rural industrial integration can directly absorb rural labor force, forming a transmission path of "integration → non–agricultural employment → income growth" (Zhang and Fan, 2024). Industrial integration not only increases wage income through non-agricultural employment but also broadens the sources of operating income through business format innovation, and enhances farmers' human capital through skill training, strengthening the resilience of income increase (Barrett et al., 2001). Existing theories suggest that rural non-agricultural employment may play a key mediating role between industrial integration and farmers' income. Based on this, we propose:

> *H2*: Rural non-agricultural employment plays a partial mediating role in the impact of industrial integration on farmers' income.

2.3 Heterogeneity of income growth effects from industrial integration across counties with different income levels

The factor allocation theory indicates that differences in resource endowments can lead to varying returns on integration investments (Holmes and Mitchell, 2010). In low-income counties, the scarcity of capital and technology implies that the marginal returns from initial integration are relatively high, as the upgrade of basic infrastructure can rapidly boost productivity (Fan and Zhang, 2004). Conversely, high–income counties face diminishing returns due to the saturation effect. In addition, differences in the initial distribution of economic resources lead to spatial divergence in development effects. Low-income counties and districts, with a high degree of dependence on traditional agriculture, experience greater marginal returns from industrial integration. In high–income counties and districts, where the non–agricultural economy is already relatively developed, the room for income growth through integration is relatively limited (Wang et al., 2023). Based on this, this study proposes:

> *H3*: The income–increasing effect of the Rural Industrial Integration Index (RIII) is more significant in low–and middle–income counties.

2.4 The moderating role of topography

Economic geography emphasizes that topographic features, as an exogenous and time-invariant geographical condition, play a moderating role in regional economic development by influencing infrastructure construction costs, industrial layout suitability, and resource development marginal costs (Krugman, 1991). It should be clearly clarified that terrain is not a proxy indicator of different rural industrial integration models: although different terrain conditions will derive differentiated industrial integration development models, terrain itself does not directly characterize the type or level of industrial integration, but acts as a moderating condition to affect the income-increasing effect of rural industrial integration, by adjusting the implementation cost, resource allocation efficiency and value conversion efficiency of industrial integration practices. Specifically, hilly areas have moderate resource diversity and relatively low terrain barriers, which can reduce the implementation cost of compound integration models such as "agriculture + cultural tourism + deep processing," and amplify the marginal income-increasing effect of industrial integration; plain areas are dominated by large-scale, intensive grain production, facing serious homogenization of agricultural products and limited value-added space of industrial chain extension, which weakens the income-increasing effect of industrial integration (Liu et al., 2025); mountainous areas are constrained by high transportation and infrastructure construction costs caused by terrain, which increases the threshold of industrial chain extension and multi-functional expansion, thus limiting the full release of the income-increasing effect of industrial integration (Wang et al., 2025).

Considering the overall topographic distribution characteristics of Jiangxi Province, the central region is predominantly hilly, which facilitates industrial chain synergy. The northern region is mainly plain, focused primarily on single-crop rice cultivation. The southern region is mountainous, where the integration effect may not be fully realized due to infrastructure and industrial hierarchy limitations. Accordingly, we propose:

> *H4*: Topographic features moderate the income-enhancing effect of industrial integration, with the strongest effect in hilly areas, followed by plains, and the weakest in mountainous areas.
>
> *H5*: The income effect of industrial integration exhibits regional variation, being strongest in central Jiangxi, followed by northern Jiangxi, and weakest in southern Jiangxi.

Taken together, the above theoretical analysis and five research hypotheses systematically construct an integrated analytical framework for the impact of rural industrial integration on farmers' income, which clarifies the core causal relationship, key transmission mechanism, and heterogeneous effects with boundary conditions of this study in a progressive logical order. Specifically, this framework not only identifies the direct income-enhancing effect of the Rural Industrial Integration Index (RIII), but also decomposes the internal transmission path centered on non-agricultural employment, and further clarifies the differential income-increasing effects of RIII under the constraints of different income levels, topographic features, and geographic regions. To visually and concisely present the complete theoretical logic, action paths and heterogeneous characteristics of how RIII drives farmers' income growth, we draw the following schematic diagram of the income-enhancement mechanism (Figure 1).

3 Characteristics of the study area and data sources

3.1 Basic information of Jiangxi Province

Jiangxi Province, located in the central region of China, is an important part of the Yangtze River Economic Belt. It is also a National Ecological Civilization Pilot Zone and a major traditional agricultural

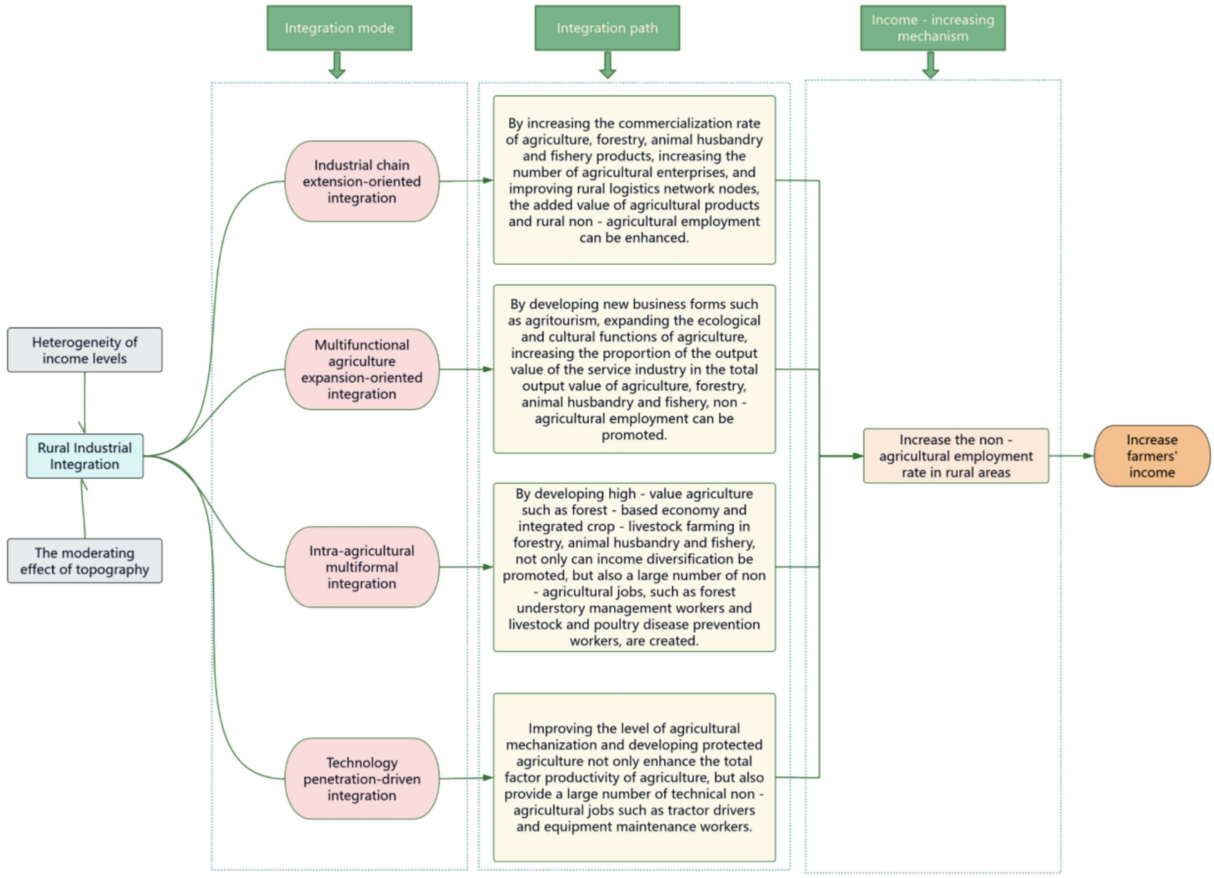

FIGURE 1
Schematic diagram of the income-enhancement mechanism of RIII.

province, with typical geomorphic characteristics where the ratio of mountainous areas, water areas and cultivated land is approximately 7:1:2. The province covers an area of approximately 166,900 square kilometers, governing 11 cities and 100 counties. In 2023, the permanent population of Jiangxi Province was approximately 45.15 million, among which the rural population accounted for more than 40%. Agriculture continued to serve as a fundamental pillar of the regional economy. This study utilizes panel data from 95 counties/districts in Jiangxi Province covering the period 2014–2023 (Figure 2). The analysis excludes four purely urban districts of Nanchang City (Donghu, Xihu, Qingyunpu, and Qingshanhu) due to the absence of a rural population, along with Wanli District, whose administrative division was dissolved in 2020. To ensure data consistency amid several administrative realignments during this period—for instance, Longnan County becoming Longnan City in 2020 and Shangrao County being redesignated as Guangxin District in 2019—all historical data were standardized according to the latest administrative divisions.

There are significant regional development disparities within Jiangxi Province. Northern Jiangxi features gentle terrain and a more developed economy, with a high degree of integration between agriculture and urban economies. Central Jiangxi is dominated by hilly topography, offering considerable potential for multifunctional agricultural expansion. Southern Jiangxi has a high proportion of mountainous areas, with a relatively weak agricultural foundation but abundant distinctive resources. Such spatial heterogeneity provides an ideal natural experimental setting for this study, facilitating the exploration of the differential mechanisms through which industrial integration affects farmers' incomes under varying geographic, economic, and resource conditions. Therefore, selecting Jiangxi Province as the study area holds substantial practical and policy relevance, as well as significant academic value, with the research outcomes expected to provide a replicable and scalable model for agricultural provinces in central and western China.

3.2 Data sources

The data used in this study are mainly derived from publicly published statistical materials and official public data, specifically including "Jiangxi Provincial Statistical Yearbook," the urban statistical yearbooks of various cities in Jiangxi Province, and the statistical bulletins on national economic and social development of each county in Jiangxi Province. The data on the number of enterprises engaged in agriculture, forestry, animal husbandry, and fishery is sourced from the annual enterprise industrial and commercial registration information publicly released by the former Jiangxi Provincial Market Supervision Administration. Enterprises that have been deregistered have been excluded. To address the county–level administrative division adjustments that occurred during the research period (2014–2023), such as the conversion of Longnan County into Longnan City in 2020 and the renaming of Shangrao County to Guangxin District in 2019, this study took the following standardization measures to ensure the comparability and continuity of the 10 year panel data. For counties or districts that were merged or split, the data of all administrative units involved before and after the adjustment were combined and aggregated, which was regarded as a continuous observation sample. For partially missing

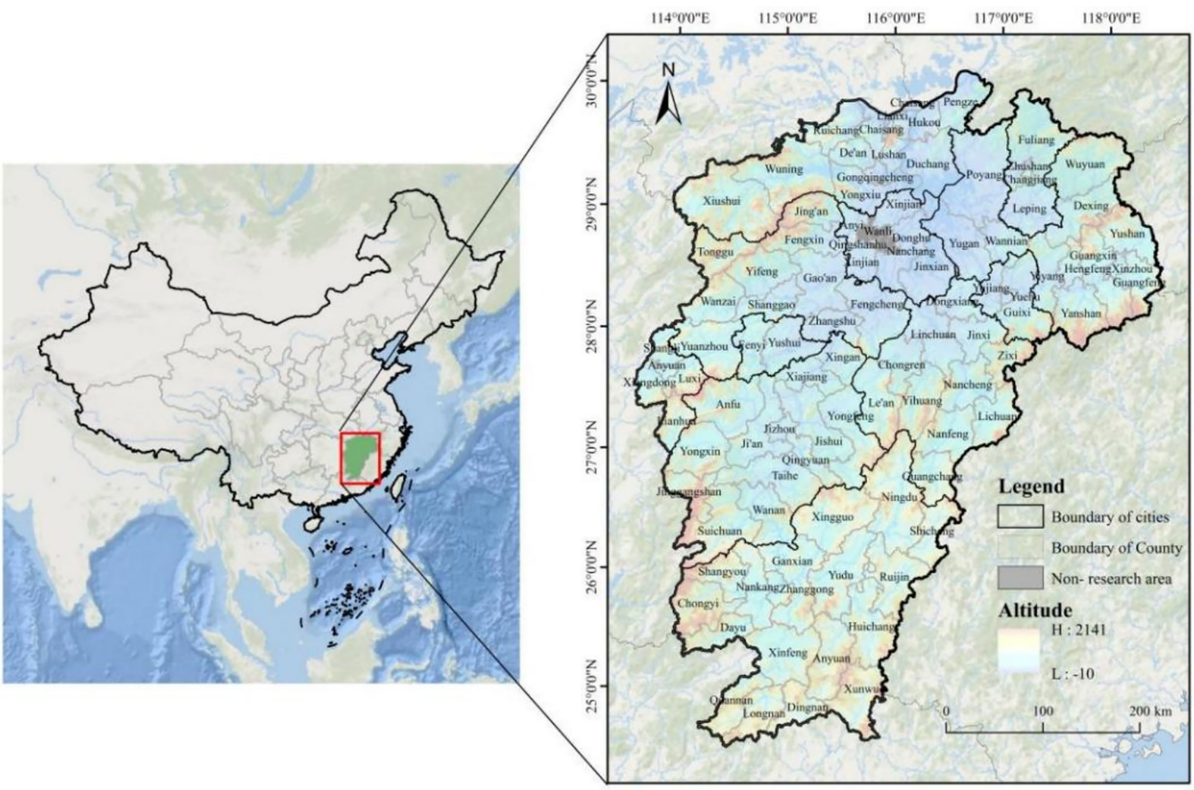

FIGURE 2
Map of districts and counties in the study area.

data, supplements were made by consulting publicly available documents such as government work reports and agricultural and rural development reports from relevant counties (cities, districts), with cross-verification against statistical yearbook data to ensure consistency. The raw data was subjected to strict cleaning and validation processes, such as the removal of outliers and the interpolation of individual missing data values, to guarantee the high credibility and reliability of the dataset. All data were sourced from yearbooks and bulletins issued by official statistical institutions, exhibiting logical coherence, temporal continuity, and comprehensive regional representation, thus facilitating a robust empirical analysis in this research. Furthermore, descriptive statistics and correlation analysis of key variables revealed no significant measurement errors or systematic biases, confirming that the data quality meets the requirements for econometric model estimation. In summary, this study lays a robust data foundation for subsequent empirical analyses by leveraging a provincially representative sample of Jiangxi counties and a meticulously curated panel dataset.

4 Variable selection and model specification

4.1 Variable selection

4.1.1 Explained variable

While China's industrial upgrading since 1978 has driven remarkable economic growth, it has also exacerbated the urban–rural income gap (Chen and Ma, 2022). Consequently, this study employs the *Per Capita* Disposable Income (PCDI) of rural residents as the key dependent variable to measure farmers' income. This metric is selected for its comprehensive nature, encompassing four primary sources—operational, wage, property, and transfer income—which allows for a holistic assessment of the impacts of the RIII. In contrast to per capita net income, disposable income excludes mandatory expenditures such as personal income tax and social security contributions. This provides a more accurate representation of a rural household's actual purchasing power and minimizes the measurement bias associated with single-source income indicators. In the econometric analysis, this variable is logarithmically transformed (ln_inc). This procedure is appropriate for the data's continuous positive distribution and aligns with the assumptions of the TWFE panel model. Furthermore, the transformation allows the regression coefficients to be interpreted as elasticities, facilitating a direct understanding of the percentage change in income resulting from a 1% increase in the RIII (Hausman, 1978).

4.1.2 Core explanatory variable

Drawing upon existing research in rural industrial integration (Bai and Yang, 2023), this study develops a composite Rural Industrial Integration Index (RIII). The index is constructed from an indicator system spanning four dimensions: industrial chain extension, agricultural multi-functional expansion, multi-format integration within agriculture, and technology penetration. To ensure objectivity, the entropy weight method is employed to determine the contribution of each indicator. This method quantifies the information provided by each indicator, assigning weights in inverse proportion to the indicator's entropy value; an indicator with lower entropy (i.e., greater variation) contains more information and is therefore assigned a higher weight (Zou et al., 2006). In contrast to subjective approaches such as the expert scoring method, the entropy weight method relies entirely on the inherent characteristics of the data, thereby eliminating researcher bias from the weighting process. The complete RIII indicator system for Jiangxi Province, developed based on theoretical relevance and data availability, is detailed in Table 1.

4.1.2.1 Industrial chain extension dimension

The integration of smallholder farmers into the agricultural value chain is regarded as an important approach to increasing farmers' income (Kissoly et al., 2017). This study selects the commercial rate of agricultural products, the number of agricultural enterprises, and the number of rural logistics outlets as indicators to evaluate the industrial chain extension dimension of the RIII.

Commodity rate of agricultural products: This indicator reflects the proportion of agricultural products entering the market for circulation and serves as a core indicator to measure the connection between agricultural production and the market. A higher commodity rate of agricultural products indicates that agricultural production can more accurately meet market demand (Reardon et al., 2003) and enhance the added value of the industrial chain by reducing losses in circulation links. Existing studies have confirmed that this indicator has a significantly positive correlation with the depth of industrial chain extension.

Number of agricultural enterprises: As important entities for industrial chain extension, the number of such enterprises directly affects the length and complexity of the industrial chain. By driving links such as the deep processing of agricultural products and branded sales, these enterprises can significantly extend the industrial chain and create value-added space (German et al., 2020).

Number of Rural Logistics Outlets: Rural logistics outlets are key infrastructure nodes that ensure the circulation of agricultural products and the smooth operation of the industrial chain (Su and Gai, 2025), and cold chain logistics is crucial for transporting fresh agricultural products from farms to Chinese consumers (Fan et al., 2024). Sufficient logistics outlets can effectively reduce the transportation costs and losses of agricultural products, improve the operational efficiency of the industrial chain, and are of great importance to industrial chain extension (Liu et al., 2019).

4.1.2.2 Multi-business format dimension within agriculture

The development of multi-business formats within agriculture is a core approach to realizing internal agricultural circulation, reducing external input, and enhancing system resilience (Costa et al., 2018; Lobell et al., 2009; Martin et al., 2016). To evaluate the integration of multiple business formats within the agricultural sector, this study utilizes several key metrics. These include the agricultural output value generated per laborer, the share of diversified operations' output value relative to the total agricultural output value, and the respective proportions of forestry and fishery output values within the total agricultural output value.

This metric is defined as the ratio of the output value from diversified operations to the total agricultural output value. Engaging in diversified operations is a critical strategy for mitigating risks inherent in agricultural production, thereby improving the stability and overall profitability of farming enterprises. High-value agricultural products, in particular, are instrumental in elevating farmers' income levels (Shi and Huang, 2023). Consequently, this ratio serves as a primary

TABLE 1 Evaluation index system for the RIII in Jiangxi Province.

Evaluation object	Evaluation dimension	Evaluation indicator	Unit	Causality
RIII	Industrial chain extension	Commodity rate of agricultural products	%	+
		Number of agricultural enterprises	One	+
		Number of rural logistics network points	Site	+
	Multi-format within Agriculture	The proportion of forestry output value in the total agricultural output value	%	+
		Agricultural output value created per agricultural laborer	Yuan	+
		The proportion of the output value of animal husbandry in the total output value of agriculture	%	+
		The proportion of fishery output value in the total agricultural output value	%	+
	Agricultural multi-functional expansion	The proportion of the output value of the agricultural service industry in the total agricultural output value	%	+
		Ratio of the output value of diversified operations to the total output value of agriculture	%	+
	Agricultural technology penetration	Electricity Consumption per Hectare of Cultivated Land Area	kWh/ha	+
		Proportion of mechanized harvest area in sown area	%	+
		Total power of agricultural machinery *Per Capita*	kW/person	+
		Proportion of facility agricultural area in regularly used cultivated land area	%	+

indicator of the coordinated development among various business formats and is essential for assessing the degree of multi-format integration within the agricultural sector.

The proportion of the output values of forestry, animal husbandry and fishery in the total agricultural output value: These ratios reflect the rationality of the structure of various industries within agriculture and the degree of diversification. The diversification of forestry, animal husbandry and fishery plays a supporting role in the rural economy (Gregersen et al., 2017), and a reasonable industrial structure is conducive to the optimization of resource allocation and the integrated development of multi-business formats within agriculture.

The agricultural output value created per labor force: This indicator characterizes the production efficiency of agricultural labor. In the development of multi-business formats within agriculture, high-efficiency labor can promote resource integration and collaborative production among different business formats (Evenson and Gollin, 2003), and it is an important indicator to measure the benefits of multi-business format integration.

4.1.3 Agricultural multi-function extension dimension

Agricultural systems are inherently multi-functional; they not only produce grain, fiber, or oil but also exert profound impacts on many elements of economic and ecological systems (Hodbod et al., 2016; Pretty et al., 2010). This study selects the proportion of the output value of the agricultural service industry in the total agricultural output value to represent the agricultural multi-function expansion dimension. With the extension of agricultural multi-functionality, the proportion of the service industry in agriculture shows an upward trend. This ratio reflects the degree of agriculture's transformation from traditional production to multi-functional orientations (such as service-oriented and experience-oriented) and serves as an important indicator to measure the level of agricultural multi-function extension.

4.1.3.1 Agricultural technology penetration dimension

Agricultural technology facilitates the growth of farmers' income through enhancing production efficiency, expanding sales channels, and promoting the upgrading of the agricultural structure (Wang et al., 2019; Xie and Huang, 2021). This study selects the following indicators to assess the integration of agricultural technology penetration: Electricity consumption per hectare of arable land, Ratio of machine–harvested area to sown area, Total agricultural machinery power per capita, and Ratio of facility agriculture area to regularly–used cultivated area.

Electricity consumption per hectare of arable land: Electricity consumption per unit of arable land can characterize the application level of technologies such as mechanization and automation in agricultural production. Higher electricity consumption usually indicates the input of more advanced technological equipment, reflecting the level of agricultural technology penetration (Luo et al., 2025).

Ratio of mechanically-harvested area to sown area: This ratio serves as a crucial indicator for assessing the level of agricultural mechanization. As an important manifestation of technology penetration (Liu, 2024), agricultural mechanization increases agricultural output and reduces production costs. A higher ratio of machine-harvested area indicates the widespread application of technology in the production process.

Total agricultural machinery power per capita: This indicator reflects the overall capacity of mechanical equipment in agricultural production, serving as a comprehensive manifestation of the level of agricultural technical equipment (Belton et al., 2021; Qian et al., 2022), and is of great value for evaluating the degree of technology penetration.

Ratio of facility agriculture area to cultivated area in regular use: Facility agriculture is a concentrated manifestation of the application of advanced agricultural technologies. The land area devoted to these facilities reflects the adoption scope of associated technologies in agricultural production (Dou et al., 2025), thus serving as a vital indicator for assessing the level of agricultural technology penetration.

4.1.3.2 Calculation method of the RIII index

First, the raw data are standardized to eliminate any influence stemming from differing units of measurement. All the indicators in this study are positive indicators, and their standardization formula is:

$$y_{ijt} = \frac{x_{ijt} - \min_j}{\max_j - \min_j} \tag{1}$$

In the Equation 1, where y_{ijt} and x_{ijt} are the normalized value and the original value of indicator j respectively; $\max_j$ and $\min_j$ represent the maximum and minimum values of indicator j among all counties in all years of the entire panel data, respectively.

Secondly, the entropy-weight method is employed to determine the weight of each indicator. As an objective weighting technique, this method assigns weights based on information entropy within a multi-indicator comprehensive evaluation system. This method quantifies the information content of each indicator by calculating its information entropy value: there is a negative correlation between the entropy value and the information content. Specifically, the smaller the entropy value of an indicator, the greater the amount of information it provides, and the higher the assigned weight; conversely, the larger the entropy value, the smaller the amount of information, and the lower the corresponding weight. In contrast to subjective approaches like the expert scoring method, the entropy-weight method determines weights entirely based on the informational characteristics inherent in the data. By avoiding the interference of human factors, it significantly improves the objectivity of the weight–allocation process (Sahin, 2021). The specific calculation process is as follows: First, calculate the proportion of each indicator $j$in all samples. The formula is as follows:

$$p_{ijt}^{j} = \frac{y_{ijt}}{\sum_{i=1}^{N}\sum_{t=2014}^{2023} y_{ijt}} \tag{2}$$

In the Equation 2, the denominator j is the sum of the indicator across all years and all counties. Here $\sum_{i=1}^{N}\sum_{t=2014}^{2023} p_{ijt}^{j} = 1$, meaning that the sum of the proportions of all indicators is 1.

Then calculate the information entropy, which is used to measure the degree of dispersion of indicator *j*. The formula is as follows:

$$e_j = -\frac{1}{\ln(K)} \sum_{i=1}^{N} \sum_{t=2014}^{2023} p_{ijt}^{j} \ln\left(p_{ijt}^{j}\right) \tag{3}$$

In the Equation 3, $K = N \times T$ represents the total number of samples, $\ln(\cdot)$ is the natural logarithm, and the constant $\frac{1}{\ln(K)}$ ensures that $e_j \in [0,1]$.

Next, calculate the degree of difference d_j. The information entropy is inversely proportional to the importance of the indicator. That is, the larger the entropy, the more uniform the data is, and the less information it contains. The calculation formula is:

$$d_j = 1 - e_j \tag{4}$$

In the Equation 4, the larger the value of d_j, the higher the degree of dispersion of the indicator *j*. This indicates that this indicator makes a more substantial contribution to the evaluation of RIII.

Finally, calculate the weight, which is the normalized value of the degree of difference:

$$w_j = \frac{d_j}{\sum_{k=1}^{M} d_k} \tag{5}$$

In the Equation 5, w_j represents the final weight of indicator *j*, satisfying $\sum_{j=1}^{M} w_j = 1$.

The calculation formula for the comprehensive index of the RIII is:

$$RIII_{ij} = \sum_{j=1}^{M} w_j \times y_{ijt} \tag{6}$$

In the Equation 6, y_{ijt} is the normalized value, w_j is the final weight of the indicator. The range of the $RIII_{ij}$ index is [0, 1]. The larger the value, the higher the RIII.

4.1.4 Control variables

In this study, population density (popden), per capita GDP (gdp), per capita cultivated land area (land_pc), per capita local government general budget expenditure (exp_pc), per capita year–end savings deposit balance (sav_pc), per capita year–end balance of various loans of financial institutions (loan_pc), and per capita fixed–asset investment (inv_pc) are selected as control variables.

From the perspective of theoretical and literature support, the selected variables are all mainstream control variables in the field of agricultural economics when studying the relationship between RIII and farmers' income: Population density is used to separate the synergy effect of population agglomeration from the effect of industrial integration itself, which is in line with the extremely unbalanced population distribution characteristics in Jiangxi Province caused by its terrain of "seven mountains, one water, and two parts of fields". To isolate the specific impact of the RIII from general economic trends, this study includes per capita GDP as a control variable. This accounts for the influence of industrialization-led growth, a crucial consideration in the context of Jiangxi's industry-focused county economies and the existing urban–rural disparity (Yao et al., 2004). The per capita cultivated land area is intended to isolate the influence of the traditional cultivated land scale effect. Fiscal incentives exert a significant influence in narrowing the income gap (Tang and Sun, 2022). Per capita fiscal expenditure, per capita loan balance, and per capita fixed–asset investment are used to control the interference of fiscal support bias, misallocation of financial resources, and non–agriculturalization of capital investment respectively, while per capita savings is used to control the impact of precautionary wealth accumulation.

In terms of overall adaptability, the above seven types of control variables comprehensively cover seven dimensions: population spatial distribution, total economic scale, agricultural resource endowment, fiscal support intensity, financial resource allocation, residents' wealth accumulation, and capital input intensity. This design not only effectively avoids omitted variable bias but also closely aligns with the core realistic characteristics of fragmented cultivated land, the non–agricultural tendency of fiscal and financial resources, and uneven population distribution in counties of Jiangxi Province. This design ensures that the estimated impact of the RIII represents a net effect, isolated from these potential confounding variables. Such a framework provides a robust foundation for the subsequent regression analysis and enhances the validity of the study's conclusions.

4.1.5 Mediating variables

In this study, the rural non–agricultural employment rate is taken as the mediating variable.

Theoretically, the four dimensions of the RIII–industrial chain extension, multi–format integration within agriculture, expansion of agricultural multi-functionality, and integration through technological penetration–can all affect the non–agricultural employment rate through direct or indirect paths: Industrial chain extension directly creates non–agricultural jobs in processing, circulation, sales, etc.; The expansion of agricultural multi-functionality and technological penetration, respectively, stimulate the demand for non–agricultural services, release the traditional agricultural labor force and promote its transfer to non–agricultural sectors. Eventually, relying on the growth of wage income, the rural PCDI is increased, forming a transmission mechanism of "industrial integration → non–agricultural employment → income growth." As a vital livelihood strategy for rural residents, non-agricultural employment is a primary driver of rural economic development, income growth, and the sustainable transformation of rural areas (Liu and Hu, 2010; Zheng, 2023). In terms of regional adaptability, the terrain characteristics of "seven mountains, one water, and two parts of fields" in Jiangxi Province restrict the employment absorption capacity of traditional agriculture. This makes non-agricultural employment the core path to break through the terrain constraints and match the characteristics of the regional income structure. Meanwhile, this is also in line with the guiding requirement of "boosting non–agricultural employment and income through integration" in the policy of promoting the RIII in Jiangxi Province. In terms of econometric evidence, the data on the total rural employed population and the number of employees in agriculture required for calculating this indicator are all from official sources such as the "Jiangxi Statistical Yearbook," with consistent statistical caliber, temporal continuity (panel data of 95 counties from 2014 to 2023) and good integrity. The robust data accessibility and high adaptability to the actual circumstances in Jiangxi Province can effectively guarantee the validity of the mediating effect test and precisely uncover the internal mechanism by which augmenting the RIII can facilitate the increase in farmers' income in Jiangxi Province.

In conclusion, the symbols and descriptive statistical outcomes of each variable are presented in Table 2.

4.2 Model specification

4.2.1 Two–way fixed–effects panel model

The two–way fixed–effects model specification, as an effective approach to identify the net effect of the core explanatory variable, is widely employed in empirical research (Autor et al., 2013). In this study, by controlling for the individual effects of counties and the year effects, the following model is constructed:

$$\ln\_inc_{it} = \alpha + \beta_1 \ln\_RIII_{it} + \gamma Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{7}$$

In the Equation 7, i represents the county, t represents time, and $\ln\_inc_{it}$ is the explained variable, which is the logarithm of the rural PCDI in county i in year t. $\ln\_RIII_{it}$ is the core explanatory variable, that is, the RIII in county i in year t. $Controls_{it}$ is a series of control variables, including the area, population, economic scale, infrastructure, agricultural production resources and educational resources of the county. α is the constant term, β is the coefficient of the core explanatory variable, and γ is the coefficient variable of the control variable. μ_i is the individual fixed effect of the county, which is used to control the characteristics of the county that do not change over time. λ_t is the time–fixed effect, which is used to control the macro–economic fluctuations in different years. ε_{it} is the random error term.

4.2.2 Mediating effect model

In this study, the non-agricultural employment rate is selected as the mediating variable for the impact of the RIII on farmers' income. The three-step method of Baron and Kenny (1986) is adopted, and the improvements made by later scholars to this method are drawn on (Hayes, 2009; Zhao et al., 2010):

Step 1: Test the total effect of the RIII on farmers' income.

$$\ln\_inc_{it} = \alpha_1 + \beta_1 \ln\_RIII_{it} + \gamma_1 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{1it} \tag{8}$$

Step 2: Examine the impact of the RIII on the mediating variable, the non–agricultural employment rate.

$$nonfarm_{it} = \alpha_2 + \beta_2 \ln\_RIII_{it} + \gamma_2 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{2it} \tag{9}$$

Step 3: Incorporate the mediating variable to test the direct effect.

$$\begin{aligned}\ln\_inc_{it} &= \alpha_3 + \beta_3 \ln\_RIII_{it} + \delta nonfarm_{it} \\ &+ \gamma_3 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{3it}\end{aligned} \tag{10}$$

In the Equation 8–10, $Controls_{it}$ represents a series of control variables, $nonfarm_{it}$ is the mediating variable, the non–agricultural employment rate, δ is the coefficient of the mediating variable, and the meanings of other symbols are the same as those in the two–way fixed–effects model. Among them, the calculation method of the rural non–farm employment rate is $nonfarm = \frac{TRLF - ALF}{TRLF} \times 100\%$, TRLF represents the Total Rural Labor Force, and ALF represents the Agricultural Labor Force (Fang et al., 2019).

4.2.3 Full quantile regression model

To deeply explore the heterogeneous impacts of the RIII on counties at different income levels, this study further adopts the full quantile regression method. There are technical complexities in directly introducing fixed effects within the full quantile regression framework. This study uses the Method of Moments Quantile Regression (MMQR) proposed by Machado and Silva for estimation (Machado and Santos Silva, 2019), This method can effectively handle the fixed–effect problems of panel data and provide consistent and reliable estimation results. This method can estimate the marginal effects of the explanatory variables at different quantile points of the conditional distribution of the explained variable, thus revealing the dependence relationships between variables more comprehensively.

$$Q_\tau\left(\ln\_inc_{it} | X_{it}\right) = \alpha_\tau + \beta_\tau \ln\_RIII_{it} + \gamma_\tau Controls_{it} + \mu_i + \lambda_t \tag{11}$$

In the Equation 11, $Q_\tau\left(\ln\_inc_{it} | X_{it}\right)$ represents the conditional quantile of the explained variable $\ln\_inc$ at the τ quantile, given the core explanatory variable and the set of control variables X_{it}, where $\tau \in (0,1)$, In this study, quantile points of 10, 20%, …, 90% are selected for estimation to comprehensively capture the changing trajectory of the industrial integration effect from the low–income to the high–income range. β_τ is the core estimated coefficient of this model. It represents the percentage change in income when the RIII increases by 1% at the τ quantile of farmers' income, while keeping other variables constant. Compared with the mean coefficient β_1 in Equation 7, β_τ is allowed to vary at different quantile points, which is the key to revealing distributional heterogeneity γ_τ is the coefficient vector of the control variables at the τ quantile. μ_i and λ_t represent the individual fixed effect of counties and the time–fixed effect respectively, which are used to control the characteristics of counties that do not change over time and the common trends that change over time.

5 Empirical results and analysis

5.1 Spatiotemporal characteristics of the RIII in Jiangxi Province

In order to intuitively analyze the changes in 95 counties in Jiangxi Province from 2014 to 2023, this study divides the RIII into 5 stages, as shown in Table 3.

According to the classification method in Table 3, this study has drawn the spatiotemporal evolution map (Figure 2) of the RIII in 95 counties of Jiangxi Province from 2014 to 2023. From 2014 to 2023, the RIII in Jiangxi Province showed a trend of "three-stage evolution, significant fluctuations in growth rate and differentiation" in the temporal dimension. The period from 2014 to 2017 was a transition stage from the germination period to the primary period. The

TABLE 2 Variable names and variable symbols.

Variable type	Variable name	Variable symbol	Unit	Mean	Variance
Explained variable	rural PCDI	inc	Ten thousand yuan	1.532	0.501
Core explanatory variable	Rural Industrial Integration Index	RIII	——	0.310	0.122
Control variable	Population density	popden	Person per km^2	274.814	133.858
	Per capita GDP	gdp	Ten thousand yuan	6.367	5.313
	Per capita cultivated land area	land_pc	Mu	0.837	0.425
	Per capita general budget expenditure of local finance	exp_pc	Ten thousand yuan	0.910	0.483
	Per capita year–end balance of savings deposits	sav_pc	Ten thousand yuan	3.244	1.506
	Per capita year–end balance of various loans of financial institutions	loan_pc	Ten thousand yuan	3.726	2.574
	Per capita fixed–asset investment	inv_pc	Ten thousand yuan	5.821	8.528
Mediating variable	Non-farm employment rate in rural areas	nonfarm	——	0.463	0.049

province-wide average RIII rose from 0.15 to 0.28, marking an average annual growth rate of 22%. Areas such as Anyuan County and Dingnan County in Ganzhou City, which are close to Guangdong Province, initially explored the "agriculture + culture and tourism" model relying on characteristic resources; Traditional agricultural counties with extremely low bases such as Yongxin County and Wan'an County in Ji'an City, although having a fast growth rate, still mainly took the path of selling primary agricultural products for integration. The period from 2018 to 2021 entered the stage of differentiation from the primary period to the intermediate period, with the average growth rate slowing down. High–value areas such as Shangyou County and Quannan County in Ganzhou entered the middle–high stage through "characteristic industries + full–chain industrial integration"; low–value areas such as Yongfeng County in Ji'an and Duchang County in Jiujiang had a slow growth rate due to the lack of leading–enterprise drive, and the gap between counties continued to widen. The period from 2022 to 2023 was a breakthrough stage from the intermediate stage to the advanced stage. The integration level of 10 counties in Ganzhou City entered the advanced stage, forming a high–value cluster; low–value areas such as Wan'an County in Ji'an and Xiushui County in Jiujiang slowly improved their quality driven by policy support, and the overall integration level advanced towards high quality.

In terms of the spatial dimension, the RIII in Jiangxi Province has always shown a spatial pattern of "strong in the south and weak in the north, high in the east and low in the west," which has continued to solidify, with prominent agglomeration characteristics in high–value areas. In 2023, Dingnan County, whose integration level entered the maturity stage, and the nine counties whose integration levels entered the advanced stage were all concentrated in Ganzhou City, forming the "Gannan characteristic industrial integration belt." Relying on mountainous ecological resources, characteristic agricultural products such as Gannan navel oranges and tea, and the rural revitalization financial reform policy, a "production–processing–sales–service" full–chain industrial integration model was constructed. Districts and counties with the RIII reaching the middle–high stage are scattered in eastern, central and northern Jiangxi. They develop, respectively, relying on the advantages around cities (such as "suburban agriculture + recreational picking" in Nanchang County), the advantages of transportation trunk lines (such as "culture and tourism + e–commerce" in Wuyuan County), and the advantages of traditional agricultural bases (such as "large–scale planting + primary processing" in Gao'an City), without obvious agglomeration. Districts and counties with a low RIII are concentrated in Ji'an City in central Jiangxi and Jiujiang City in northern Jiangxi. Due to the homogenization of traditional grain–planting resources and the lack of leading enterprises, they are trapped in a path dependence of "difficult to start and slow to upgrade".

From the perspective of spatiotemporal interaction characteristics, the RIII in Jiangxi Province presents an evolution pattern of "partial diffusion of high–value areas and high–degree solidification of low–value areas." Overall, the spatiotemporal changes in the RIII in Jiangxi Province are characterized by "fluctuating upward growth rate over time, solidified spatial gradient differences, and prominent core–periphery in spatiotemporal interaction." The driving force for integration growth gradually shifted from quantity expansion in the initial stage to quality improvement in the later stage. The differences in resource endowments in space and the insufficient policy adaptability jointly led to the long–term imbalance in the integration level among regions (Figure 3).

5.2 Benchmark regression results

Firstly, based on the panel data of 95 counties in Jiangxi Province from 2014 to 2023 (sample size $N = 950$), this study uses a TWFE

TABLE 3 Classification of the RIII in Jiangxi Province.

RIII	Development stage
0 < RIII≦0.2	Germination stage
0.2 < RIII≦0.4	Primary stage
0.4 < RIII≦0.6	Intermediate stage
0.6 < RIII≦0.8	Advanced stage
0.8 < RIII≦1.0	Maturity stage

model of time and counties to explore the impact of the RIII on the rural PCDI. In Table 4, Model 1 is the regression result of the TWFE model of time and counties for the logarithm–transformed rural PCDI and the RIII without adding control variables. Models 2–8 are the regression results of the TWFE model of time and counties after successively adding seven logarithm–transformed control variables: population density, per capita regional GDP, per capita cultivated land area, per capita local fiscal public expenditure, per capita year–end savings amount, per capita loan amount, and per capita fixed–asset investment.

The findings presented in Table 4 indicate that the coefficient of the core explanatory variable, namely the logarithmically transformed RIII (ln_RIII), consistently assumes a positive value ranging from 0.031 to 0.033, and it is statistically significant at the 1% significance level. Its economic implication is that for every 1% increase in the RIII, the rural PCDI increases significantly by 3.1 to 3.3%. In the context of Jiangxi Province, this elasticity coefficient holds significant practical relevance. Taking the projected per capita disposable income of rural residents of 23,956 yuan in 2025 as a baseline, a 1% increase in the Rural Industry Integration Index (RIII) corresponds to an income growth of approximately 743–790 yuan. Given that Jiangxi is a traditional agricultural province with farmers' income heavily reliant on the agricultural sector, this increment underscores the crucial role of industrial integration in overcoming the limitations of traditional agriculture for income enhancement and fulfilling the requirement of a "prosperous life" under the rural revitalization strategy. After gradually incorporating seven control variables such as population density and per capita GDP, the coefficient fluctuates minimally, confirming that the positive promoting effect of the RIII on farmers' income is highly robust, and there is no estimation bias caused by omitted variables. Therefore, Hypothesis 1 is verified.

Regarding the control variables, only the coefficient of the logarithm-transformed population density (ln_popden) (0.083–0.085) shows a significant positive impact at the 1% level, reflecting the synergistic effect between population agglomeration and industrial integration. The coefficients of per capita GDP and per capita year–end savings balance are negative, yet they are statistically non–significant. This implies that the overall level of economic development fails to exert a statistically significant influence on farmers' income. The GDP growth and savings accumulation in most counties of Jiangxi Province rely more on the industrial and urban sectors, resulting in the asynchronous characteristic between "overall economic growth" and "farmers' income growth." Improving the RIII is an effective and crucial way to bridge this asynchrony. The coefficient for per capita cultivated land area is negative yet lacks statistical significance. This finding likely reflects Jiangxi Province's topographical characteristics, where a prevalence of mountainous and hilly landscapes results in significant land fragmentation. Such fragmentation impedes the development of economies of scale in agricultural production. Although the coefficients of per capita fixed–asset investment, per capita local fiscal expenditure, and per capita loan balance are marginally positive, they do not reach the 10% statistical significance level, reflecting that traditional economic and resource factors have limited driving effects on the income of farmers in Jiangxi Province, further highlighting the crucial role of industrial integration. The overall goodness–of–fit of the model is high (R^2 is greater than 0.9), and robust standard errors are used to control heteroscedasticity, making the estimation results reliable. Empirical research findings indicate that an increase in the RIII is a key factor driving the growth of the PCDI of rural residents in Jiangxi Province. This underscores its function as a critical pathway for augmenting farmers' earnings within the context of the rural revitalization strategy.

5.3 Endogeneity treatment

To address the potential two-way causal endogeneity problem between the RIII and farmers' income, this study is based on the panel data of 95 counties in Jiangxi Province from 2014 to 2023. It uses the variables of the RIII lagged by 1–5 periods as the core explanatory variables, and conducts regression in combination with all control variables as well as the TWFE of time and counties (Models 9–13).

The findings presented in Table 5 indicate that the coefficients of ln_RIII corresponding to each lag period exhibit significant positive values. Specifically, the coefficients of the first to fourth lag periods are statistically significant at the 1% significance level, while the coefficient of the fifth lag period is statistically significant at the 5% significance level. This result presents a dynamic feature of "significant short–term effect and gradual attenuation of long–term effect," confirming that the positive impact of the RIII on farmers' income is causal and persistent. The sample size decreases reasonably as the lag order increases. This indicates that the model estimation results are robust and reliable, further verifying Hypothesis 1.

A comparison with the benchmark regression outcomes reveals that the incorporation of lagged terms efficiently alleviates potential endogeneity stemming from bidirectional causality. Although the estimated coefficient values are marginally lower than those of the benchmark regression, the core conclusion that "an increase in the RIII facilitates the growth of farmers' income" remains intact. In summary, after solving the endogeneity problem by introducing lag terms, the empirical results further confirm that within the scope of Jiangxi Province, an increase in the RIII has a significant positive causal effect on the rural PCDI, and this effect is persistent and robust. Specifically, the short–term income–increasing effect is the most significant, while the long–term effect shows a gradually attenuating trend. This research result not only provides more rigorous causal evidence for promoting farmers' income increase by improving the RIII, but also provides a quantitative basis for formulating long–term sustainable industrial policies under the background of the rural revitalization strategy.

5.4 Robustness checks

5.4.1 Removing extreme samples

To address the potential estimation bias caused by extreme observations of the RIII in the benchmark regression, this study conducts

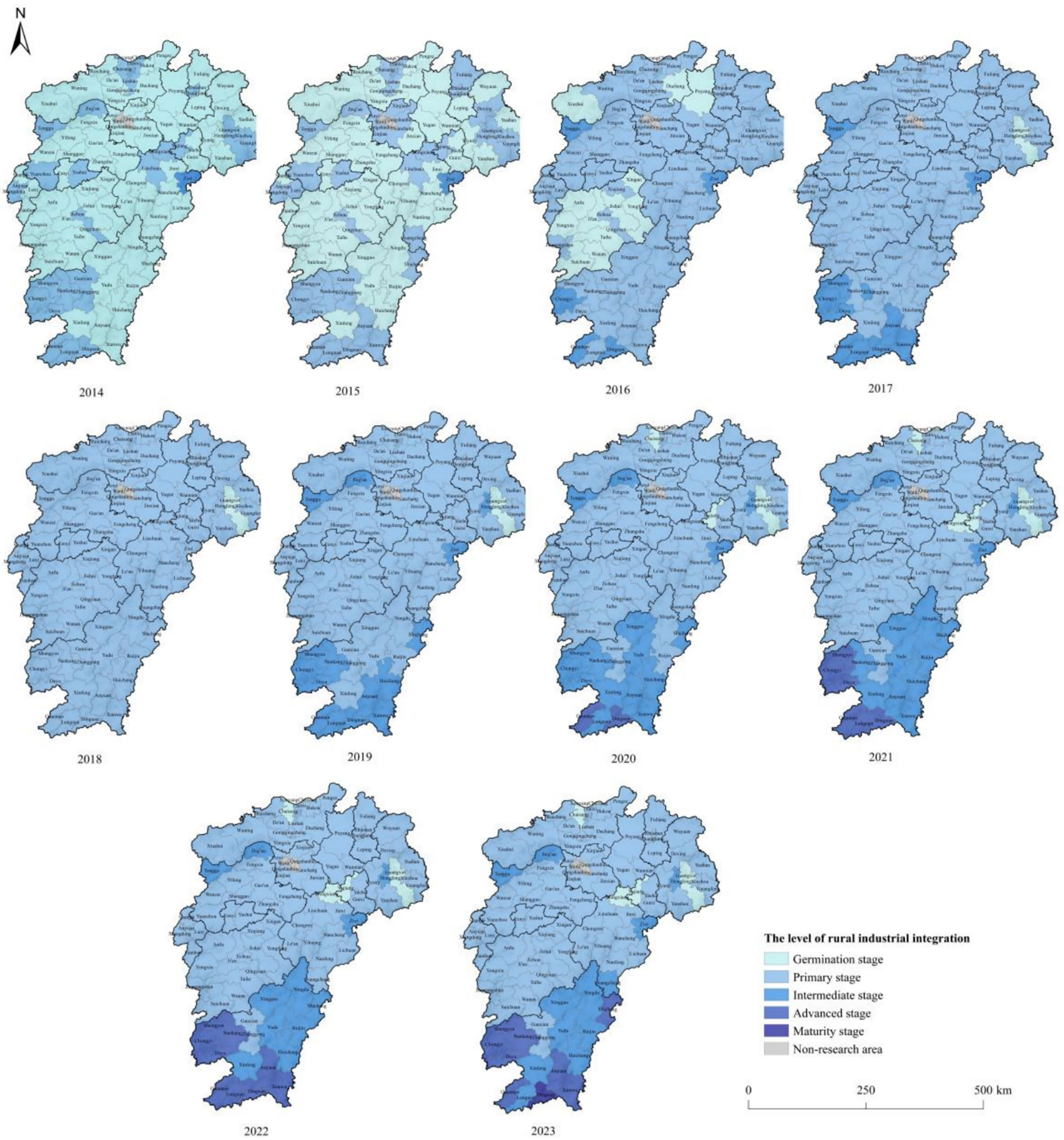

FIGURE 3
The spatio-temporal evolution diagram of the RIII in Jiangxi Province.

robustness checks using a strategy of gradually removing extreme values at both the high and low ends: Model 14 removes Quannan County with the highest average integration level and Zixi County with the lowest average integration level; Model 15 further removes Jishui County with the second–highest observation value and Yongxin County with the second–lowest observation value; Model 16 continues to remove Dingnan County with the third–highest observation value and Guangxin District with the third–lowest observation value. All models retain all control variables as well as the TWFE of time and counties.

The results of Model 14–Model 16 in Table 6 above show that the coefficient of the core explanatory variable ln_RIII is significantly positive at the 1% level in all three models. The sample size decreases to 890 as extreme values are removed, and the R^2 of the models remains at a relatively high level, indicating that the overall fitting effect of the models is good. Consistent with the benchmark regression, the analysis confirms the core finding that an increase in the RIII has a positive impact on farmers' income. Notably, the regression coefficient becomes larger after excluding extreme values, suggesting the initial model may have slightly underestimated the true effect. This indicates that the benchmark regression slightly underestimates the true effect due to including extreme–value samples with a weak correlation between the RIII and the rural PCDI. The above results further confirm that this core conclusion has strong robustness and universality at the level of each district and county in Jiangxi Province.

TABLE 4 Regression results of the TWFE Model.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln_RIII	0.031***	0.033***	0.032***	0.032***	0.032***	0.031***	0.031***	0.031***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
ln_popden		0.085***	0.084***	0.084***	0.084***	0.082***	0.083***	0.083***
		(0.021)	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)	(0.022)
ln_gdp			−0.007	−0.008	−0.008	−0.009	−0.008	−0.009
			(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
ln_land_pc				−0.013	−0.017	0.001	−0.026	−0.028
				(0.120)	(0.121)	(0.119)	(0.121)	(0.123)
ln_exp_pc					0.014	0.016	0.014	0.014
					(0.010)	(0.010)	(0.011)	(0.011)
ln_sav_pc						−0.034	−0.045	−0.046
						(0.029)	(0.030)	(0.029)
ln_loan_pc							0.033	0.033
							(0.023)	(0.023)
ln_inv_pc								0.004
								(0.014)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.013***	−0.450***	−0.440***	−0.441***	−0.434***	−0.400***	−0.420***	−0.425***
	(0.017)	(0.117)	(0.120)	(0.121)	(0.122)	(0.126)	(0.126)	(0.128)
N	950	950	950	950	950	950	950	950
R^2	0.987	0.988	0.988	0.988	0.988	0.988	0.988	0.988

The values in parentheses are robust standard errors, *** Indicates $p < 0.01$.

5.4.2 Slice regression method

Considering the substantial disparities in economic base, industrial structure, and resource endowment among the 11 cities in Jiangxi Province, specific samples from a single city may disrupt the overall conclusion. To test whether the conclusion that improving the RIII can increase farmers' income depends on specific city samples, this study conducts robustness checks by using the "slicing method" of sequentially removing samples from a single city. Models 17 to 27 correspond to the estimations performed after removing the samples for Nanchang, Jingdezhen, Pingxiang, Jiujiang, Xinyu, Yingtan, Ganzhou, Ji'an, Yichun, Fuzhou, and Shangrao, respectively. Each of these models maintained the full set of control variables and included both time and county-level individual fixed effects.

The empirical results in Table 7 show that the coefficient of the core explanatory variable ln_RIII exhibits a significant positive effect in all 11 models, is statistically significant at the 1% level, and the coefficient values range from 0.025 to 0.033. The goodness–of–fit of the model, R^2, remains at a relatively high level. This finding comprehensively validates that the promotional effect of enhancing the RIII on augmenting farmers' income remains invariant across specific cities. Consequently, this offers robust empirical evidence for the coordinated execution of policies aimed at enhancing the RIII at the provincial level.

5.4.3 Regression in different time periods

To assess the potential structural influence of the COVID–19 pandemic that emerged at the end of 2019 on rural economic activities and verify the robustness of the core conclusion that enhancing the RIII can facilitate farmers' income growth under diverse external environments, this study partitions the data into two sub–samples: the pre–pandemic period (2014–2019, Model 28) and the post–pandemic period (2020–2023, Model 29). An econometric model is constructed while retaining all control variables and the TWFE of time and districts/counties. The focus is on analyzing the differences and consistencies of the effect that improving the RIII can increase farmers' income within the two time periods, thus answering the academic

TABLE 5 The lagged impact of the RIII on farmers' income.

Variables	(9)	(10)	(11)	(12)	(13)
ln_RIII_lag1	0.022***				
	(0.007)				
ln_RIII_lag2		0.017***			
		(0.006)			
ln_RIII_lag3			0.014***		
			(0.005)		
ln_RIII_lag4				0.013***	
				(0.005)	
ln_RIII_lag5					0.010**
					(0.004)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Constant	−0.368***	0.569	0.701	0.866	1.103
	(0.107)	(0.773)	(0.758)	(0.821)	(0.679)
N	855	760	665	570	475
R^2	0.987	0.988	0.987	0.984	0.982

The values in parentheses are robust standard errors. ** Indicates $p < 0.05$, and *** indicates $p < 0.01$.

question of whether external shocks shake the core research conclusion.

The results of Model 28 and Model 29 in Table 8 show that the coefficient of the core explanatory variable ln_RIII exhibits a significant positive impact both before and after the pandemic. Before the pandemic, the coefficient was 0.018, significant at the 1% level, indicating that for every 1% increase in the RIII, farmers' income increased correspondingly by 1.8%. After the pandemic, the coefficient increased to 0.075, significant at the 5% level, and the income–increasing elasticity increased to 7.5%. The reason is that before the outbreak of the epidemic, the increase of the RIII in Jiangxi Province mainly relied on the "off–line processing + traditional sales" model, resulting in limited added value. The pandemic has led to the rapid penetration of rural e-commerce and live-streaming sales, enabling the direct conversion of agricultural product premiums into farmers' income, combined with the synergistic effects of a sharp increase in local demand and policy resource allocation. This validates that the conclusion suggesting that an increase in the RIII promotes the growth of farmers' income remains unaltered by the pandemic. It also indicates that industrial integration demonstrates significant income–augmenting resilience when confronted with external risks, offering empirical evidence for the establishment of rural economic resilience.

TABLE 6 Regression results after excluding extreme values.

Variables	(14)	(15)	(16)
ln_RIII	0.050***	0.052***	0.053***
	(0.007)	(0.007)	(0.006)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Constant	−1.058***	−1.059***	−1.008***
	(0.123)	(0.122)	(0.139)
N	930	910	890
R^2	0.974	0.974	0.976

The values in parentheses are robust standard errors. *** Indicates $p < 0.01$.

5.5 Mediating effect analysis

5.5.1 The mediating effect of non–agricultural employment

To reveal the internal transmission mechanism by which increasing the RIII promotes farmers' income growth, this study uses the non–agricultural employment rate (nonfarm) as a mediating variable and constructs a three–stage mediating effect test procedure to examine the total effect, mediating effect, and direct effect in sequence. Based on the panel data of 95 counties in Jiangxi Province from 2014 to 2023, combined with the TWFE model, this study empirically tests the transmission path of "rural industrial integration → increase in non–agricultural employment → increase in farmers' income". Specifically:

(1) The total-effect model employs Model 8 in Table 2 to investigate the overall influence of the rise in the RIII on the growth of farmers' income. Specifically, a regression equation of ln_inc on ln_RIII is constructed. If the coefficient of ln_RIII is significantly positive, it indicates that the total effect holds.
(2) The mediation analysis (Model 30) examines the relationship between the independent variable and the mediator. This involves regressing the non-agricultural employment rate (nonfarm) on the ln_RIII. A statistically significant, positive

TABLE 7 Regression results of excluding samples of cities one by one.

Variables	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
ln_RIII	0.031***	0.031***	0.028***	0.029***	0.031***	0.032***	0.025***	0.031***	0.032***	0.032***	0.033***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.462***	−0.436***	−0.444***	−0.210	−0.413***	−0.415***	−0.440***	−0.440***	−0.436***	−0.429***	−0.433***
	(0.123)	(0.130)	(0.128)	(0.217)	(0.128)	(0.131)	(0.090)	(0.118)	(0.131)	(0.127)	(0.138)
N	910	910	900	820	930	920	770	820	850	840	830
R^2	0.988	0.988	0.988	0.988	0.988	0.988	0.988	0.991	0.987	0.988	0.988

The values in parentheses are robust standard errors, *** Indicates $p < 0.01$.

TABLE 8 Results of robustness tests in different time periods.

Variables	(28)	(29)
ln_RIII	0.018***	0.075**
	(0.006)	(0.030)
Controls	Yes	Yes
Year FE	Yes	Yes
County FE	Yes	Yes
Constant	−0.457***	0.499
	(0.120)	(0.830)
N	570	380
R^2	0.988	0.980

Values in parentheses are robust standard errors. ** and *** represent $p < 0.05$ and $p < 0.01$, respectively.

coefficient for ln_RIII in this model is required to establish that a potential mediation pathway exists.

(3) In the direct-effect model (Model 31) assesses the direct and indirect effects by including both the independent variable (ln_RIII) and the mediator in the primary regression predicting farmers' income (ln_inc). The existence and nature of the mediation are then determined as follows: if the coefficient on the mediator is significant and the coefficient on ln_RIII remains statistically significant but is smaller in magnitude than in the total-effect model, a partial mediation is confirmed. If the coefficient on ln_RIII becomes statistically insignificant upon the inclusion of the mediator, this indicates a complete mediating effect.

The total-effect model (Model 8, Table 4) indicates that the logarithmic coefficient for the core explanatory variable, ln_RIII, is 0.031 and is statistically significant at the 1% level. This implies that improving the RIII has a significant positive overall effect on increasing farmers' income. The regression results of the mediating–effect model (Model 30) in Table 9 show that the coefficient of ln_RIII is 0.032, and it is significant at the 1% level. This indicates that an increase in the RIII can significantly raise the non-agricultural employment rate. The regression results of the direct–effect model (Model 31) show that the coefficient of the mediating variable, the non–agricultural employment rate (nonfarm), is 0.230 ($p < 0.01$). At the same time, the coefficient of ln_RIII significantly decreases from 0.031 in the total–effect model to 0.024 (p < 0.01), supporting the existence of a partial mediating effect. Quantitative analysis shows that the mediating effect value is 0.032 × 0.230 = 0.0074, accounting for 23.74% of the total effect. This means that approximately 23.74% of the promoting effect of the RIII on farmers' income is achieved through the path of "promoting non–agricultural employment," indicating that the non–agricultural employment rate is an important transmission mechanism for the RIII to increase the income of farmers in Jiangxi. Hypothesis 2 is verified.

5.5.2 Bootstrap sampling test

To enhance the robustness of the conclusions of the mediating–effect test, based on the three–step method proposed by Baron and Kenny (1986), this study further uses the Bootstrap sampling method to verify the mediating path of "rural industrial integration → non–agricultural employment → farmers' income." The Bootstrap method uses repeated sampling with replacement to construct the empirical distribution of the mediating effect. Thus, it does not need to make strict normality assumptions about the sampling distribution shape. It is especially suitable for mediating–effect tests in the case of small and medium–sized samples and can provide more reliable confidence intervals. The results of the Bootstrap sampling test are shown in the following table:

As shown in Table 10, the indirect–effect coefficient is 0.007, which is significant at the 1% significance level. Its 95% confidence interval is [0.004, 0.011], not including 0. This result indicates that the indirect effect is significant. Specifically, industrial integration promotes the transfer of farmers to non-agricultural employment, thus promoting an increase in farmers' income, and the mediating effect is significant. The direct–effect coefficient is 0.024, significant at the 1% significance level, and the 95% confidence interval also does not include 0. This means that industrial integration increases farmers' income through non-agricultural employment channels such as optimizing the agricultural structure and developing emerging industries, and the direct effect is significant. The total effect, which is the sum of the direct and indirect effects, is pronounced and statistically significant, with a coefficient of 0.031 ($p < 0.01$) and a 95% confidence interval that excludes zero.

In summary, the RIII in Jiangxi Province increases farmers' income through both direct and indirect paths. Non-agricultural employment, as a partial mediating variable, empirically verifies the mechanism of "rural industrial integration → increase in

TABLE 9 Regression results of the mediating effect.

Variables	(30)	(31)
ln_RIII	0.032***	0.024***
	(0.005)	(0.008)
nonfarm		0.230***
		(0.065)
Controls	Yes	Yes
Year FE	Yes	Yes
County FE	Yes	Yes
Constant	0.600***	−0.563***
	(0.057)	(0.142)
N	950	950
R^2	0.175	0.988

The values in parentheses are robust standard errors. *** Indicates $p < 0.01$.

TABLE 10 Results of bootstrap test for mediating effect (500 replications).

Effect Type	Coefficient	95% Confidence interval
Indirect	0.007***	[0.004, 0.011]
	0.002	
Direct	0.024***	[0.013, 0.034]
	0.005	
Total	0.031***	[0.021, 0.041]
	0.005	

The values in parentheses are standard errors. *** Indicates $p < 0.01$.

non-agricultural employment → increase in farmers' income." The Bootstrap sampling test with 500 repeated replications further confirms that the indirect effect of non-agricultural employment is significant at the 1% level, and the 95% confidence interval does not contain 0, which means the mediating effect of "non-agricultural employment" is significant and robust, eliminating the interference of sample bias and non-normal distribution of data on the research conclusions.

Meanwhile, it should be noted that this study only focuses on the core mediating path of non-agricultural employment, and does not carry out an in-depth test on other potential transmission paths. Subsequent robustness tests and mechanism expansion can be carried out by introducing multiple mediating variables, so as to more comprehensively reveal the internal logic of rural industrial integration affecting farmers' income.

5.6 Heterogeneity analysis

5.6.1 Differences in the income−increasing effects ofthe RIII in districts and counties with different income levels

To conduct an in-depth exploration of the heterogeneous impacts of the RIII on the rural PCDI in counties with different income levels, this study is based on the panel data of 95 counties in Jiangxi Province from 2014 to 2023 and conducts empirical analysis using the full quantile regression method combined with the TWFE model. Models 32 to 40, respectively, present the regression results of the RIII on the rural PCDI at the 10 to 90% quantiles.

Based on the results presented in Table 11, the coefficient for the ln_RIII variable is statistically significant and positive at the 1% level across all full quantile regression models. However, the magnitude of this effect follows an inverted U-shaped pattern. Specifically, for counties within the 10 to 40% income quantiles (representing low to lower-middle income levels), the coefficient escalates from 0.021 to 0.030. Conversely, for counties in the 40 to 90% income quantiles (encompassing lower-middle to high income levels), the coefficient progressively declines from 0.030 to 0.011. These empirical findings suggest that while enhancing the RIII significantly boosts farmer income across all county income strata, the income-generating effect is most pronounced in lower-middle-income counties. Hypothesis 3 is verified. This finding provides empirical evidence for Jiangxi Province to formulate differentiated industrial policies, that is, strengthening basic capacity building in low−income counties, focusing on increasing the input of integration elements in lower−middle−income counties, and striving to promote the upgrade of the industrial integration level in high−income counties.

5.6.2 Differences in the income−increasing effects of the RIII in different terrains

Jiangxi Province has a terrain pattern characterized by "seven mountains, one water, and two parts of farmland," mainly consisting of mountains and hills, supplemented by plains and water areas. To assess the heterogeneous effects of RIII development on farmers' income across diverse topographical settings, this study segmented the sample into three distinct groups. The classification was based on the predominant terrain—mountains (Model 41), hills (Model 42), and plains (Model 43)—within each district and county of Jiangxi Province. This was determined by identifying the terrain type with the largest proportional area, with basin terrains being categorized as plains for this analysis. The TWFE model is used for empirical analysis to examine the significant differences in the promoting effect of the RIII on farmers' income increase among different terrain regions.

The results in Table 12 show that the ln_RIII elastic coefficients of the three types of terrain counties all exhibit a significant positive relationship, which means that promoting rural industrial integration has a universal positive income-increasing effect on farmers in counties with different terrain types, but there are significant differences in the intensity of the effect, which verifies the moderating role of terrain as a geographical condition. Specifically, the coefficient value of hilly counties (Model 42) is the highest (0.034), significant at the 1% confidence level, indicating that the moderating effect of hilly terrain is the most positive, which can significantly amplify the income-increasing marginal effect of RIII; the coefficient value of mountainous counties (Model 41) is 0.029, significant at the 5% confidence level, where the positive moderating effect of terrain is relatively weakened due to infrastructure constraints; the coefficient value of plain counties (Model 43) is the lowest (0.021), significant at the 1% confidence level, where the income-increasing effect of RIII is weakened due to the high homogenization of agricultural products and limited value-added space caused by terrain-dominated large-scale single planting structure.

The above heterogeneous effects are not caused by terrain being a proxy for different integration models, but by the moderating effect of terrain as an exogenous condition: terrain does not directly determine the type or level of industrial integration, but affects the marginal return of industrial integration investment by adjusting the

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TABLE 11 Results of full quantile regression.

Variables	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)
ln_RIII	0.021***	0.022***	0.024***	0.030***	0.027***	0.024***	0.022***	0.017***	0.011***
	(0.002)	(0.002)	(0.006)	(0.007)	(0.007)	(0.006)	(0.005)	(0.002)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.449***	−0.452***	−0.651***	−0.731**	−0.774***	−0.717**	−0.643***	−0.614***	−0.613***
	(0.071)	(0.075)	(0.249)	(0.289)	(0.126)	(0.327)	(0.239)	(0.059)	(0.076)
N	950	950	950	950	950	950	950	950	950
Pseudo R^2	0.955	0.946	0.939	0.934	0.930	0.929	0.931	0.935	0.941

The values in parentheses are robust standard errors. ** Indicates $p < 0.05$, and *** indicates $p < 0.01$.

construction cost of supporting infrastructure, the matching degree of resource endowments and integration models, and the difficulty of industrial chain extension. The hilly terrain has the best moderating effect, because its moderate resource diversity and low terrain barrier reduce the implementation cost of industrial integration and improve the efficiency of value conversion; while the mountainous and plain terrains have different degrees of constraints on the release of industrial integration benefits due to high infrastructure costs and limited value-added space, respectively. This empirical result is completely consistent with the theoretical expectation, and Hypothesis 4 is verified.

TABLE 12 Terrain differences in the income–increasing effect of the RIII.

Variables	(41)	(42)	(43)
ln_RIII	0.029**	0.034***	0.021***
	(0.012)	(0.009)	(0.006)
Controls	Yes	Yes	Yes
County FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Constant	0.009	1.386***	0.006
	(0.201)	(0.494)	(0.084)
N	420	210	320
R^2	0.991	0.996	0.997

The values within parentheses are robust standard errors. *** Indicates $p < 0.01$.

5.6.3 Differences in the income–increasing effects of the RIII in different regions

Considering geographical, historical, cultural and economic factors, the prefecture–level administrative regions of Jiangxi Province can be divided into three regional categories: northern Jiangxi, central Jiangxi and southern Jiangxi. The northern Jiangxi region mainly includes 53 counties under the jurisdiction of Nanchang, Jiujiang, Jingdezhen, Pingxiang, Yingtan, Yichun and Shangrao cities. The landforms are mainly Poyang Lake Plain and Jiangnan Hills. It has a relatively high level of economic development, with relatively concentrated manufacturing, business activities, and scientific and educational resources. The central Jiangxi region mainly includes 24 counties under the jurisdiction of Ji'an and Fuzhou cities. The terrain has the characteristics of both plains and hills. It is an important agricultural and industrial base in Jiangxi Province, and the dialect is mainly Gan language. The southern region of Jiangxi Province, centered around the 18 counties under the jurisdiction of Ganzhou City, is strategically situated in the southern part of Jiangxi. As the largest city in Jiangxi in terms of both area and population, it boasts a profound legacy of Hakka culture and is endowed with abundant agricultural and mineral resources.

To investigate the regional heterogeneity of the RIII's effect on farmers' income within Jiangxi Province, this study categorizes the 95 district-county units into the aforementioned regions. A TWFE model is then utilized to empirically assess the differential income-enhancing impacts of the RIII across these areas. The analysis accounts for the distinct characteristics of the three regions, which feature a decreasing economic gradient and an increasing topographical-constraint gradient from north to south. Specifically, northern Jiangxi is the most economically advanced region, whereas southern Jiangxi is comparatively less developed. Moreover, mountainous terrain accounts for over 70% of southern Jiangxi, in contrast to the higher proportion of plains in the northern region. The regression results derived from the TWFE models for the northern, central, and southern regions of Jiangxi are detailed in Models (44), (45), and (46), respectively.

The regression results in Table 13 show that there are significant differences among regions: the ln_RIII coefficient in central Jiangxi is the highest, at 0.026, and it is significant at the 1% level ($p < 0.01$); the ln_RIII coefficient in northern Jiangxi is 0.017, significant at the 5% level ($p < 0.05$); the ln_RIII coefficient in southern Jiangxi is 0.013, and it does not reach the 10% statistical significance level. This discrepancy stems from the heterogeneity in regional foundational conditions and industrial compatibility: the central Jiangxi region (represented by some counties in Ji'an) exhibits the strongest effect, owing to its locational advantage as the "central part of Jiangxi." Its terrain, dominated by rolling hills, is suitable for diversified operations. Moreover, positioned at a mid-level economic development gradient, it holds the potential to absorb technological diffusion from the north while leveraging its hinterland advantages to develop distinctive resources in the south, resulting in a significant marginal effect of policy interventions. In contrast, the southern Jiangxi region shows an insignificant effect, primarily constrained by two factors: first, its mountainous terrain limits large-scale, standardized industrial layouts; second, despite possessing distinctive resources (such as navel oranges and oil-tea camellia), its industrial chains are relatively short, with processing stages often outsourced. This leads to substantial outflow of value-added benefits, resulting in relatively limited gains for local farmers, thereby validating Hypothesis 5. This highlights the need for future policies to prioritize addressing infrastructure and industrial chain gaps in the southern region. Gradient-basedThe research conclusion confirms that the RIII has a significant positive promoting effect on the income of farmers in central and northern Jiangxi, providing empirical evidence for Jiangxi Province to formulate a gradient–based integration policy of "strengthening industrial clusters in central Jiangxi, increasing the degree of integration differentiation in northern Jiangxi, and making up for basic short–comings in southern Jiangxi."

6 Conclusions and discussion

6.1 Main conclusions

This study empirically examines the impact of rural industrial integration on farmers' income using panel data from 95 counties in Jiangxi Province (2014–2023). The core findings are summarized as follows:

(1) Robust income-enhancing effect of RIII

The Rural Industrial Integration Index (RIII) significantly boosts farmers' income. A 1% increase in RIII raises rural per capita disposable income (PCDI) by 3.1–3.3% ($p < 0.01$), equivalent to an approximate gain of 660–700 yuan based on 2023 income levels. This effect remains robust after controlling for socioeconomic factors, addressing endogeneity via lagged variables, and addressing extreme samples and regional heterogeneity.

(2) Key mediating role of non-agricultural employment

Non-agricultural employment acts as a critical transmission channel, accounting for 23.74% of RIII's total income-enhancing effect. Specifically, a 1% rise in RIII increases non-agricultural employment by 0.032 units ($p < 0.01$), which in turn elevates PCDI by 0.230% ($p < 0.01$). This confirms the pathway of "industrial integration → non-agricultural employment → income growth".

TABLE 13 Differences in the income–increasing effects of the RIII in different regions.

Variables	(44)	(45)	(46)
ln_RIII	0.017**	0.026***	0.013
	(0.008)	(0.006)	(0.010)
Controls	Yes	Yes	Yes
County FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Constant	−0.037	4.302***	0.105
	(0.061)	(0.795)	(0.126)
N	530	240	180
R^2	0.995	0.996	0.997

The values in parentheses are robust standard errors. ** Indicates $p < 0.05$ and *** indicates $p < 0.01$.

(3) Heterogeneous effects across contexts

The heterogeneous effects of rural industrial integration on farmers' income vary significantly under different scenarios: In terms of income levels, the effect presents an inverted U–shaped distribution, being most significant in lower–middle–income counties (40th percentile, coefficient = 0.030), and gradually weakening in high–income counties (90th percentile, coefficient = 0.011). Regarding topography, the effect is strongest in hilly areas (coefficient = 0.034, $p < 0.01$), followed by mountainous areas (coefficient = 0.029, $p < 0.05$), and weakest in plains (coefficient = 0.021, $p < 0.01$), mainly due to differences in terrain adaptability and resource diversity. At the regional level, central Jiangxi benefits the most (coefficient = 0.026, $p < 0.01$), followed by northern Jiangxi (coefficient = 0.017, $p < 0.05$), while the effect in southern Jiangxi is not significant due to infrastructure constraints. These findings highlight the need to consider regional specificity in policy–making to maximize the income–increasing potential of industrial integration.

6.2 Discussion

This study systematically evaluated the impact of rural industrial integration on farmers' income, confirming its direct promoting effect, the mediating role of non-agricultural employment, and significant heterogeneous characteristics. These findings not only provide empirical evidence for rural revitalization practices in Jiangxi Province but also have the following contributions and limitations.

6.2.1 Research contributions

Existing studies on rural industrial integration have either focused on macro-policy interpretation at the provincial level or concentrated on qualitative analysis of typical case descriptions(Jia and Zhu, 2024; Lu et al., 2025), while generally lacking quantitative mechanism testing and causal identification based on long-term large-sample panel data at the county level, which makes it difficult to accurately reveal the net effect and internal logic of rural industrial integration on farmers' income growth at the grassroots administrative level.

On the basis of filling this research gap, the core academic contributions of this study beyond the existing literature are mainly reflected in the following three progressive dimensions. First, this study constructs a comprehensive and objective Rural Industrial Integration Index (RIII) evaluation system covering four core dimensions: industrial chain extension, agricultural multi-functional expansion, intra-agricultural multi-format integration, and technology penetration. Different from the one-sided evaluation indicators in existing studies that only focus on a single dimension of industrial chain extension, we adopt the entropy weight method to assign objective weights to each indicator based on the inherent characteristics of the data, which effectively avoids subjective bias and provides a more scientific and comprehensive measurement tool for the quantitative research of rural industrial integration in county-level agricultural regions.

Second, based on 10-year panel data of 95 counties in Jiangxi Province, a typical major agricultural province in central China, we use a two-way fixed effects model and a series of robustness tests to rigorously verify the causal relationship between rural industrial integration and farmers' income growth at the county level, which enriches the empirical research system of industrial integration theory with large-sample quantitative evidence from the county level, and also provides replicable empirical reference for other central and western agricultural provinces with similar resource endowments in China.

Third, this study quantitatively validates the key transmission path of "rural industrial integration → increased non-agricultural employment → growth in farmers' income" at the county level. This finding closely integrates the classical labor transfer theory (Lewis, 1954; Todaro, 1969), with the practical development of rural industries in China, expands the application scenario of this classical theory to the research of county-level rural industrial integration, and provides county-level micro evidence for the deep integration of labor transfer theory and industrial integration theory.

Specifically, this study accurately calculates that the mediating effect of non-agricultural employment accounts for 23.74% of the total income-increasing effect of rural industrial integration, which means that nearly a quarter of farmers' income growth brought by industrial integration is achieved through the core path of "creating non-agricultural jobs → promoting rural labor transfer → increasing farmers' wage income." This quantitative finding not only echoes the classical view that non-agricultural income diversification is the core livelihood strategy for farmers to increase income (Barrett et al., 2001), and is consistent with the research conclusion that agricultural economic transformation affects farmers' income through the employment transmission channel (Zhang and Fan, 2024), but also makes an important incremental contribution to the existing research on this mechanism. Different from the existing studies that mostly verify the mediating effect of non-agricultural employment at the micro farmer household level, this study for the first time accurately measures the contribution degree of this key transmission path at the county level in China's central agricultural provinces, and verifies the robustness of this mediating effect through the Bootstrap sampling test. This finding reveals the "black box" of the income-increasing mechanism of rural industrial integration at the county level, deepens the academic understanding of the internal operational logic of rural industrial integration, and also provides a direct quantitative basis for the policy design of "promoting employment through integration and increasing income through employment" in the context of China's rural revitalization strategy.

6.2.2 Research limitations

Although this study strives for rigor, there are still some limitations that need to be clarified and addressed in future research:

First, in terms of indicator construction, although the RIII index aims to be comprehensive, given the availability of county-level data, it is difficult to fully capture the characterization of RIII through existing statistical indicators. Future research could attempt to combine methods such as questionnaire surveys and online big data to more accurately measure the "qualitative" aspects of industrial integration.

Second, in terms of the mediating mechanism setting, this study selects rural non-agricultural employment as the core mediating variable, and verifies its significant transmission effect. However, it should be clearly acknowledged that rural industrial integration is a systematic project covering industrial chain extension, multi-functional expansion, multi-format integration and technology penetration, with a broader conceptual connotation and more diversified income-increasing transmission paths. The single mediating variable of non-agricultural employment cannot fully cover all the action mechanisms of rural industrial integration on farmers' income, and there is a limitation of insufficient matching with the conceptual breadth of the core explanatory variable. Future research can further explore multiple parallel and chain mediating mechanisms such as agricultural total factor productivity improvement and human capital accumulation to form a more systematic analytical framework for the transmission mechanism.

Third, in terms of research methodology, although we employed a two-way fixed-effects model and conducted a series of robustness tests, which to some extent controlled for unobserved confounding factors, the model may still suffer from endogeneity issues due to omitted variables. Although lagged-term regression provided supporting evidence for causal inference, future research could more strongly establish the causal relationship between industrial integration and farmers' income if more effective instrumental variables or natural experiments can be utilized.

7 Policy recommendations

In conclusion, the augmentation of the RIII exerts a significant driving influence on the income growth of farmers in Jiangxi Province. Furthermore, there exist heterogeneous characteristics in terms of regions, topographical features, and income levels. To fully leverage the core driving function of industrial integration in rural revitalization and farmers' income enhancement, the following policy recommendations are proposed:

7.1 Implement an adaptable strategy for promoting industrial integration

Empirical analysis shows that the promoting effect of the RIII on farmers' income is particularly significant in central Jiangxi, hilly–terrain counties, and lower–middle–income counties. Therefore, policymaking must abandon the "one-size-fits-all" model and adopt regionally differentiated integration strategies:

(1) *Hilly regions of central Jiangxi*: Focus on supporting the development of clustered, full-chain integration of "agriculture + processing + cultural tourism." It is recommended to establish a special fund for hilly-region industries, giving priority to supporting the construction of deep-processing parks for advantageous agricultural products such as navel oranges and tea, along with supporting rural tourism infrastructure (e.g., sightseeing trails, homestay clusters). Provide land transfer subsidies and tax reductions for enterprises that settle in these areas, promoting the formation of a scaled integration model of "one county, one industrial chain".

(2) *Mountainous areas in southern Jiangxi*: Focus on bridging the short–board of infrastructure. Provincial finances should be tilted to support projects such as cold–chain logistics and 5G network coverage. In view of the advantages of forestry economy, special subsidies for under–forest economy should be set up to encourage the development of labor–intensive business forms such as bamboo product processing and Chinese herbal medicine planting. Also, explore the "enclave economy" model, guiding enterprises to set up processing workshops in municipal–level industrial parks to break through the transportation bottleneck.

(3) *Plain areas in northern Jiangxi*: Promote the upgrade of industrial integration towards technology–intensive. Relying on the scientific and educational resources around Nanchang, build

smart agriculture demonstration parks, and provide equipment purchase subsidies for new business entities that adopt UAV–based plant protection and big–data–enabled production–marketing connection. Simultaneously, popularize the "contract farming + futures insurance" model to reduce the risk of market price fluctuations.

7.2 Strengthening non-agricultural employment to expand farmers' income sources

The findings of the mediating–effect test indicate that non–agricultural employment serves as a crucial mediating pathway through which the augmentation of the RIII facilitates the income growth of farmers (the proportion of the mediating effect amounts to 23.74%). At the policy level, policies should strongly support the development of industries such as county-level agricultural product processing, rural logistics (especially cold-chain logistics), and rural e-commerce. These labor–intensive industries can rapidly expand the capacity to absorb non–agricultural employment. At the same time, it is necessary to carry out systematic employment skills training for farmers that meets the needs of rural industrial integration, so as to enhance their employment competitiveness when participating in industrial integration. In addition, it is urgent to improve the construction of the rural labor market information platform to promote the efficient flow and optimal allocation of labor among various links of the industrial chain.

7.3 Implement a hierarchical and classified support system for industrial integration

For low-income counties, establish special development funds for industrial integration, focusing on supporting integration projects with low thresholds and quick results. Provide credit interest–subsidy support for new agricultural business entities to reduce their financing costs. Prioritize the allocation of agricultural technology extension personnel for on–site guidance to enhance their basic industrial integration capabilities. For upper–middle–income counties, guide the upgrade of the industrial integration model towards high–quality and high–value–added directions, focusing on supporting technology research and development and business–form innovation. Encourage integrated enterprises to establish an integrated "production–education–research–application" collaborative mechanism with universities and research institutions, and enhance the efficiency of industrial integration through technological penetration. For high–income counties, promote the combination of industrial integration and the two–way flow of urban–rural elements, attract urban capital, technology, talent and other elements to participate in integration projects, explore the model of "co-development of industrial integration and collective economy," and through the share–cooperation mechanism, promote farmers to share the value–added benefits brought by the increase of the RIII.

Data availability statement

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

Author contributions

FL: Writing – original draft, Writing – review & editing, Data curation, Formal analysis, Methodology, Software. JG: Funding acquisition, Writing – original draft, Writing – review & editing, Resources, Supervision, Validation, Visualization. LW: Conceptualization, Funding acquisition, Investigation, Supervision, Writing – original draft, Writing – review & editing, Validation, Visualization. YF: Data curation, Methodology, Project administration, Writing – original draft, Writing – review & editing. XX: Software, Writing – original draft, Writing – review & editing.

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Conflict of interest

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

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