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Can Agricultural Industry Integration Reduce the Rural–Urban Income Gap? Evidence from County-Level Data in China

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Abstract: The improvement in urban production efficiency has led to income distribution being skewed towards urban labor, thereby widening the urban–rural income gap. However, integration of the agricultural industry at the county level can accelerate the flow of production factors between industries. Therefore, this study evaluates the degree of agricultural industry integration at the county level using the entropy weight method and explores its impact on the urban–rural income gap, based on sample data from 1122 counties in China spanning from 2014 to 2021. The research findings reveal the following: (1) The fixed model demonstrates that enhancing agricultural industry integration can significantly narrow the urban–rural income gap; (2) The mediating model indicates that this narrowing effect can be achieved by improving the green total factor productivity of agriculture; (3) Regional heterogeneity analysis indicates that the impact of agricultural industry integration is more pronounced in the central region and main crop production areas; (4) The results of the spatial Durbin model demonstrate that agricultural industry integration also exhibits a significant positive spatial spillover effect on neighboring areas. The outcomes of this study contribute to enriching the research on agricultural industry integration for green and low-carbon agricultural development, further promoting the development of county-level agricultural industry integration, and providing valuable insights for other similar countries.

Keywords: agricultural green total factor productivity; biennial Malmquist–Luenberger; fixed effect; spatial spillover effects

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1. Introduction

The rapid urban economic development in urban areas has drawn rural labor to cities, transferring production factors from low-productivity to high-productivity sectors [1]. While this shift boosts economic growth, it simultaneously widens the urban–rural income gap [2–4], mainly because urban labor markets tend to favor workers with higher qualifications, leaving less-educated rural laborers to engage in low-wage jobs [5]. This transition not only escalates competition within the urban labor market but also concentrates resources in cities, thereby attracting rural labor to non-agricultural employment opportunities. Consequently, although labor migration seems to reduce the urban–rural income gap initially, it ultimately exacerbates the disparity of income gap over time as rural laborers face tougher job markets in cities. Moreover, the focus on urban development detracts from agricultural advancement, causing the neglected agriculture sector to lag technologically behind urban industries [6].

Pinandhito et al. [7] analyzed upstream, farming business, downstream, marketing, and support services of the agricultural product subsystem. They found that development disparities in any segment can negatively impact agricultural production. Nevertheless, agricultural industry integration presents a novel approach to mitigating the urban–rural income gap by extending the agricultural value chain to rectify the problem of insufficient connections among the primary, secondary, and tertiary sectors [8]. Predominantly based

on the primary sector, agricultural industrial integration employs new technologies within the agricultural domain by merging elements of the secondary and tertiary sectors. This revitalizes agricultural production factors and expands the industrial chain, thus driving the high-quality advancement of agriculture and rural regions [9]. Serving as a source for high-quality agricultural development, agricultural industry integration represents a crucial strategy in a transition from traditional to modern agriculture. The Japanese six industries have significantly advanced the modernization of the agro-processing industry. Additionally, the French model of rural tourism facilitates the incorporation of local agriculture into the tertiary sector [10]. Consequently, agricultural industrial integration effectively exerts the multiplier effect of integrating the three sectors through the coordinated development of inter-industry elements [11], aiming to achieve high-quality agricultural progress. Nevertheless, the literature on authoritative indicator systems for measuring agricultural industrial integration remains relatively undeveloped. Upon reviewing the recent literature [8,12,13], agricultural industry integration comprises three main components: internal integration within agriculture, the extension of the agricultural industry chain, and multifunctional expansion. Through these three dimensions, agricultural production, processing, and circulation are seamlessly integrated by extending the industry chain [9].

In China, the Central Document No. 1, issued by the Central Committee of the Communist Party of China to direct agricultural production and rural livelihoods [14], initially proposed the enhancement of agricultural industry integration and the augmentation of farmers' incomes in 2015. In subsequent years, the Central Document No. 1 continued to emphasize the development of agricultural industry integration. Particularly after the introduction of the 'Rural Revitalization Strategy' at the 19th National Congress in 2017, there has been heightened attention to collaborative efforts to build a modern rural industrial system, achieving deep integration of rural industries and enhancing farmers' incomes. Hence, research on agricultural industry integration is increasingly gaining prominence in China. Utilizing Chinese household-level data, Guo & Zhang [15] discovered that agricultural industry integration has the potential to reduce the intra-rural income gap. Analyzing provincial-level panel data in China, Cao et al. [16] determined that agricultural industry integration enhances farmers' incomes. Regarding specific pathways, Cao & Nie [17], utilizing data from China's Hainan Province, concluded that agricultural industry integration could elevate farmers' incomes by upgrading the agricultural industry structure. Employing cross-sectional county data, Wang et al. [18] ascertained that agricultural industry integration has the capacity to narrow the urban–rural income gap through the upgrading of the industrial structure. Consequently, while the majority of studies focus on the provincial and micro-individual levels, only a few address related issues at the county level. This oversight masks the issue of industrial development imbalance between urban and rural areas and fails to fundamentally address the employment challenges faced by rural residents in urban areas.

Constructing integrated agricultural industries at the county level and promoting the flow of production factors between urban and rural areas can do more than just extend the agricultural value chain and expand its multi-functionality. It can also enhance the efficient allocation of resources and the rational distribution of labor, thereby promoting the growth of the agricultural sector. Alongside the advancement of county-level agricultural industry integration, does this progress aid in narrowing the income gap between urban and rural areas? Considering that primary, secondary, and tertiary industries have historically driven a unilateral transfer of production factors to urban areas, we must explore whether the development of integrated agricultural industries can lessen the urban–rural income gap by boosting agricultural productivity. At the regional level, considering China's geographical diversity, does the impact of such integration differ across areas? Additionally, does the advancement of agricultural industry integration in one region influence the growth of agriculture in surrounding areas, consequently narrowing the urban–rural income gap in those neighboring regions?

To address the aforementioned questions, this study utilizes county-level data from China. Firstly, employing the entropy weight method, the study constructs indicators to measure county-level agricultural industry integration, which serves to investigate its impact on the urban–rural income gap. Secondly, agricultural green total factor productivity is selected as the mediating variable, measured by the biennial Malmquist–Luenberger productivity index (BMLPI), to determine whether county-level agricultural industry integration influences the urban–rural income gap through its effect on green total factor productivity. Finally, the study investigates the spatial spillover effects of county-level agricultural industry integration on neighboring counties.

The main contributions of this study are as follows. Firstly, the prior literature has primarily focused on agricultural industry integration and the urban–rural income gap at the provincial level. However, the phenomenon of urban bias has led to simultaneous overdevelopment in major cities and underdevelopment in rural industries. Agricultural industry integration at the provincial level is insufficient to address the issue of imbalanced regional development. Given that the county constitutes the grassroots unit of China's administrative divisions, this study selects counties as the unit of analysis and examines the impact of agricultural industry integration at the county level on the urban–rural income gap, thereby offering insights for China's coordinated regional development. Secondly, previous research has mainly focused on the structure of the agricultural industry, analyzing how agricultural industrial integration contributes to increasing farm household income and reducing the urban–rural income gap. However, these studies have neglected to consider the importance of green and low-carbon agricultural development. With a focus on green sustainable development, this study adopts the agricultural green total factor productivity indicator as a mediator to delve further into the mechanisms through which agricultural industry integration can narrow the urban–rural income gap. Finally, the findings reveal that agricultural industry integration significantly narrows the local urban–rural income gap by enhancing the agricultural green total factor productivity. Concurrently, the integration of agricultural industries at the county level can exert a demonstrative effect, leading to a reduction in the urban–rural income gap in neighboring regions.

The rest of this study is organized as follows: Firstly, we present the theoretical framework outlining the direct, mediating, and spatial spillover effects of agricultural industry integration on the urban–rural income gap (Section 2). Secondly, we analyze the data and develop the empirical model (Section 3). Thirdly, we describe and discusses the empirical results of agricultural industry integration's effects on the urban–rural income gap, considering direct, mediating, and spatial spillover effects, and use a series of methods to test the robustness of the results (Section 4). Finally, we summarize the findings and provide policy recommendations (Section 5).

2. Theoretical Analysis

2.1. Agricultural Industry Integration and the Rural–Urban Income Gap

Given that non-agricultural productivity significantly surpasses agricultural productivity [19], farmers' incomes are lower than those of urban residents, thus widening the urban–rural income gap. According to the economic growth accounting framework, agricultural economic growth mainly depends on agricultural production factors' input and the total factor productivity's growth [20]. However, agriculture is susceptible to natural and market risks, leading to a growth rate of agricultural production that lags behind that of the industrial and service sectors.

As a bridge between urban and rural areas, counties facilitate the seamless flow of production factors across various industries, thereby diminishing regional income differences [21]. Additionally, through the integration of new production technologies, human resources, and capital, county-level agricultural industry integration may facilitate large-scale and mechanized farming [22]. This strategy shifts agriculture from labor-intensive practices towards industrialization [23], fostering large-scale agricultural production and management, enhancing efficiency, mitigating natural risks, and reducing production costs. Consequently, it raises farmers' incomes and helps narrow the urban–rural income gap.

In the realm of income distribution, farmers were previously unable to benefit from economic growth dividends, exacerbating the income gap between urban and rural regions. Agricultural industry integration transforms traditional paradigms where farmers were confined to basic agricultural roles or industrial labor by harnessing their land and labor resources. This shift allows farmers to enjoy the rewards of agricultural production, including dividends and other forms of profit sharing [24]. Simultaneously, this integrated approach increases the added value of agricultural products, extends the value chain [25], and generates additional employment and entrepreneurial opportunities for local farmers. As a result, it boosts their income and contributes to narrowing the urban–rural income divide.

2.2. Agricultural Industry Integration, Agricultural Green Total Factor Productivity, and the Rural–Urban Income Gap

In the agricultural sector, recycling and utilizing agricultural resources significantly diminishes environmental hazards from agricultural waste and reduces the reliance on chemical fertilizers [26]. Extending the agricultural industry chain via cross-industry integration and innovation fosters the advancement of green technologies, enhances resource utilization, boosts eco-friendly production, and results in superior agricultural outputs [27]. Furthermore, precision and smart agriculture, employing AI, sensors, and digital technologies, enhance fertilizer utilization and reduce the excessive use of pesticides and fertilizers [28]. This elevation of agricultural quality and efficiency boosts farmers' income and lessens the urban–rural income disparity.

During non-peak farming periods, idle natural resources in rural areas are revitalized through the development of leisure agriculture. The rural environment is optimized, and agro-ecological development is promoted through the establishment of agricultural industrial parks and rural museums, thereby attracting more tourists [29]. This approach provides local farmers with new jobs and self-employment opportunities, enhances their earnings, thereby narrowing the income disparity between urban and rural areas. Additionally, rural e-commerce platforms mitigate environmental pollution caused by agricultural product decay and reduce the hidden costs associated with selling agricultural goods. Moreover, these platforms eliminate intermediaries in the sale of agricultural products and reduce market transaction costs, thereby enhancing local farmers' green income, which refers to environmentally friendly earnings, and concurrently narrowing the urban–rural income gap.

2.3. Spatial Spillover Effects of Agricultural Industry Integration and the Rural–Urban Income Gap

The first law of geography posits that everything is spatially interrelated, with proximity correlating to increased spatial interdependence [30]. When agricultural industry integration at the county level effectively narrows the local urban–rural income gap, it can stimulate neighboring counties to emulate and learn from this successful experience via a demonstration effect. This, in turn, leads to agricultural development in neighboring areas, thereby reducing the urban–rural income gap in those neighboring regions as well [31]. Conversely, the siphon effect suggests that integration may draw neighboring factor resources during its development [20], channeling them from areas of low to high return rates, potentially stunting agricultural industry growth and exacerbating the urban–rural income disparity in adjacent regions. In summary, when viewed through the lens of the demonstration effect, county-level agricultural industry integration may exhibit a positive spillover effect. However, from the perspective of the siphon effect, county-level industrial integration may have a negative spillover effect, which requires to be empirically tested.

Hence, county-level agricultural industry integration significantly narrows the urban–rural income gap in the region. Additionally, it has the potential to reduce the income gap in neighboring regions through spatial spillover effects, though there is a risk of inadvertently exacerbating the urban–rural income gap in those neighboring regions.

3. Data and Methodology

3.1. Variables and Data

3.1.1. Variables

The explained variable is the urban–rural income gap, which is measured by the ratio of urban–rural per capita disposable income as referenced in [12]. The higher the ratio of urban–rural disposable income, the wider the urban–rural income gap.

The explanatory variable is agricultural industry integration, which signifies the progress of integrating agricultural industries across Chinese counties. Indicators are measured across three dimensions: internal integration within the agricultural industry, extension of the agricultural industry chain, and the multi-functional expansion of agriculture [8]. Additionally, five sub-indicators are selected based on the specific mode of agricultural industrial integration (Table 1). According to the table, Taobao villages, defined as those with over 10% of households engaged in online commerce and an annual transaction volume exceeding CNY 10 million, carry the highest weight, symbolizing agricultural e-commerce's pinnacle [32]. Unlike traditional agriculture, where farmers produce without benefiting from other industries' profits, rural e-commerce, especially through Taobao villages, enables direct linking of production with sales, lowers costs, and boosts transactions [33]. Agricultural e-commerce represents a practical model for merging primary and tertiary sectors [34]. By the end of 2021, Only 602 counties had Taobao villages, with some hosting up to 222, while many counties still lack them. This underscores the significance of Taobao villages in evaluating agricultural industry integration, emphasizing the increasing importance of the digital economy in unifying rural industries [35–37].

Table 1. Indicators of agricultural industry integration.

Indicator	Variable	Measurement Method	Significance of Variable	Unit
Intra-agricultural integration	Agricultural cultivation	Area of agricultural crops (0.076)	Responding to agricultural cultivation	1000 Hm^2
	Agricultural output	Gross output value of agriculture, forestry, livestock, and fisheries (0.070)	Responding to the level of agricultural productivity	10,000 Yuan
Agricultural chain extension	Agricultural machinery	Gross power of agricultural machinery (0.072)	Responding to the level of mechanization of agricultural cultivation	Kw
Multi-functional expansion of agriculture	Facility agriculture	Area covered by agricultural facilities (0.074)	Responding to the construction of new technologies in agricultural production	1000 Hm^2
	Agricultural e-commerce	Number of Taobao villages in each county (0.708)	Responding to the use of agricultural technology in agricultural marketing	Pcs

Indicator weights for the entropy weighting method are in parentheses.

To ensure the objectivity and credibility of the assigned indicator weights, this study employs the entropy value method (EVM) [25] to determine the optimal weights of each sub-indicator [38,39].

To mitigate the impact of the diverse nature of the indicators on post-processing and analysis, the data collected in this study are scaleless:

$$\text{Positive indicator } v_{tij} = \frac{x_{tij} - \min x_{tij}}{\max x_{tij} - \min x_{tij}} \tag{1}$$

$$\text{Negative indicator } v_{tij} = \frac{\max x_{tij} - x_{tij}}{\max x_{tij} - \min x_{tij}} \tag{2}$$

where x_{tij} is the value of indicator j of county i in year t. v_{tij} is the normalized value.

Based on standardized indicators, the weights of the j indicator for region i are as follows:

$$P_{ij} = v_{ij} / \sum_{i=1}^{m} v_{ij} \tag{3}$$

The entropy value of the j indicator is as follows:

$$N_j = -(\frac{1}{\ln m}) \sum_{i=1}^{m} P_{ij} \cdot \ln P_{ij} \tag{4}$$

The coefficient of variation for indicator j is as follows:

$$H_j = 1 - N_{ij} \tag{5}$$

The weights of j indicator are as follows:

$$W_j = H_j / \sum_{j=1}^{n} F_j \tag{6}$$

Based on the weights of each indicator measured previously, the overall score of agricultural industry integration for region i in any given year can be calculated as follows:

$$Score_i = \sum_{i=1}^{m} W_j v_{ij} \tag{7}$$

The mediator is the agricultural green total factor productivity (AGTFP). While the Global Malmquist–Luenberger (GML) method is commonly used to measure AGTFP and address the challenge of measuring green productivity with undesired outputs [40], its results are prone to instability and necessitate the reconstruction of the entire frontier when new data are incorporated. Hence, following [41], this study opts for the BMLPI to measure AGTFP. The BMLPI model, which calculates efficiency and variables at two-period intervals, effectively mitigates result fluctuations caused by the addition of new data. Taking the two-period technology as a reference, the directional vector of green total factor productivity in agriculture is $(y_i^t, -b_i^t)$, which means that the total factor productivity in agriculture in each region increases or decreases in equal proportions in the expected output and non-expected output dimensions. Assume that each province uses L inputs, where $x = (x_1, x_2, x_3, \ldots, x_l)$, to produce M expected outputs, where $y = (y_1, y_2, y_3, \ldots, y_m)$, and N non-expected outputs, where $b = (b_1, b_2, b_3, \ldots, b_m)$. The formula for the AGTFP is as follows:

$$\begin{aligned} BML_t^{t+1} = \frac{1 + \overrightarrow{D}_0^B(x^t, y^t, b^t; y^t, -b^t)}{1 + \overrightarrow{D}_0^B(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})} = \frac{1 + \overrightarrow{D}_0^t(x^t, y^t, b^t; y^t, -b^t)}{1 + \overrightarrow{D}_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})} \\ \times \frac{1 + \overrightarrow{D}_0^B(x^t, y^t, b^t; y^t, -b^t)}{1 + \overrightarrow{D}_0^t(x^t, y^t, b^t; y^t, -b^t)} \times \frac{1 + \overrightarrow{D}_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})}{1 + \overrightarrow{D}_0^B(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})} \end{aligned} \tag{8}$$

where $\overrightarrow{D}_0^t(x^t, y^t, c^t; y^t, -b^t)$ denotes the directional distance function of the production unit in period t. $\overrightarrow{D}_0^B(x^t, y^t, b^t; y^t, -b^t)$ is the directional distance function constructed from the

productivity index in period t under the level of technology for the construction of two observations in periods t and $t+1$. $\overrightarrow{D}_0^B(x^{t+1}, y^{t+1}, c^{t+1}; y^{t+1}, -b^{t+1})$ denotes the directional distance function of the production unit in period $t+1$. x is the input indicators. Specific indicator screening involves the input indicators, which encompass land inputs, machinery inputs, agricultural irrigation, and fertilizer inputs [42,43] (Table 2). y is the expected output indicator, measured by the total agricultural output value. b is the unexpected output indicator, measured by the agricultural carbon emissions. Given that carbon emissions are the primary contributor to global warming and a major pollutant in agricultural production, it is justifiable to consider carbon emissions as the unintended output in this study [44,45].

Table 2. Agricultural green total factor productivity indicators.

Indicator	Measurement Method	Unit
Output Indicators		
Expected output	Gross agricultural output	10,000 Yuan
Unexpected output	Carbon emissions from agriculture	Ton
Input Indicators		
Land	Area of agricultural crops	1000 Hm^2
Machine	Gross power of agricultural machinery	kw
Water	Effective irrigated area	1000 Hm^2
Fertilizer	Agricultural fertilizer application rate by the pure method	Ton

Based on the agricultural production process, agricultural carbon emissions primarily stem from the production and utilization of agricultural inputs, including fertilizers, electricity consumption during agricultural irrigation, and the use of fossil fuels, such as diesel by agricultural machinery. Consequently, this study opts to measure agricultural carbon emissions through the factors of machinery, fertilizer, and agricultural irrigation [46,47], shown as follows:

$$c = \sum c_r = \sum s_r \cdot \delta_r \tag{9}$$

where c_r is carbon emissions from source r. s_r is the total amount of carbon emissions from source r, and δ_r is the carbon emissions coefficient of the corresponding carbon source r. Specifically, the carbon emissions from fertilizer application, after discounting (in 10,000 tons), are measured using a corresponding factor of 0.8965 kg/kg (Oak Ridge National Laboratory, ORNL). The gross power of agricultural machinery is quantified using a corresponding coefficient of 0.18 kg/kw [48], while agricultural irrigation is assessed using the effective irrigated area, with a corresponding coefficient of 20.476 kg/hm^2 [49].

To select control variables (Table 3), this study incorporates significant regional characteristic variables that are anticipated to influence the urban–rural income gap [12]. Notably, education [50], industrial development [51], welfare level [52], government expenditure [53], financial development [54], and economic development [55] have been chosen as the control variables.

Table 3. Definition of variables.

Variable	Description	Definition	Unit
Explained Variable			
Gap	Urban–rural income gap	Ratio of per capita disposable income for urban and rural residents	Non-dimensional
Explanatory Variable			
Int	Rural industry integration index	Rural industrial integration index	Non-dimensional

Table 3. *Cont.*

Variable	Description	Definition	Unit
Control Variables			
Lnedu	Education	General secondary and elementary school enrolment	People
Lnind	Industrial development	Above-scale industrial enterprises	Pcs
Lnwel	Welfare level	Number of beds in various social welfare adoption units	Pcs
Lngov	Government expenditure	Public financial expenditures	10,000 Yuan
Lnfin	Financial development	Financial institutions' year-end financial loan account balances	10,000 Yuan
Lngdp	Economic development	The value of GDP	10,000 Yuan
Mediator			
AGTFP	Agricultural green total factor productivity	Green total factor productivity index	Non-dimensional

3.1.2. Data Sources

The data for this study were collected from the National Bureau of Statistics (NBS), the prefecture and city statistical bureaus, and the China County Statistical Yearbook. To ensure comprehensive and available data, this study opted to use panel data from 1122 counties across 28 provinces during 2014–2020 in China (excluding Hong Kong, Macao and Taiwan, as well as the three municipalities of Beijing, Tianjin, and Shanghai). In cases where data are missing, linear interpolation has been utilized for imputation. Table 4 provides descriptive statistics for the variables of interest to us, such as the urban–rural income gap, agricultural green total factor productivity, and agricultural industry integration. It shows that, on average, the urban–rural income gap is still significant as the mean of Gap is 2.246. And increase in the agricultural green total factor productivity is indicated, as the mean of $AGTFP$ is 1.003, which is greater than the baseline value of 1.

Table 4. Descriptive statistics.

Variable	Obs	Mean	SD	Min	Max
Gap	8976	2.246	0.558	1.340	4.074
Int	8976	0.052	0.023	0.010	0.187
Lnedu	8976	10.713	0.871	7.590	12.830
Lnind	8976	4.322	1.696	0.693	11.029
Lnwel	8976	6.964	1.223	3.584	9.114
Lngov	8976	12.761	0.665	11.444	15.185
Lnfin	8976	13.829	1.077	11.083	16.797
Lngdp	8976	14.140	1.022	11.497	16.554
AGTFP	8976	1.003	0.018	0.802	1.238

3.2. Empirical Models

3.2.1. Benchmark Model

A basic econometric model is employed to examine the influence of agricultural industry integration on the urban–rural income gap by establishing a panel regression model:

$$Gap_{it} = b_0 + b_1 Int_{it} + \sum_{k=2}^{7} b_k controls_{it} + \omega_{it} + \varepsilon_{it} \quad (10)$$

where Gap_{it} is the urban–rural income gap of county i in year t. Int_{it} is agricultural industrial integration. $controls_{it}$ are the control variables, including $Lnedu_{it}$, $Lnind_{it}$, $Lnwel_{it}$, $Lngov_{it}$, $Lnfin_{it}$, $Lngdp_{it}$. ω_{it} is the unobservable individual effect. ε_{it} is the error term. b_0 is the constant term. And b_k $(k = 2, 3, 4, \ldots, 7)$ are coefficients.

3.2.2. Transmission Mechanism Model

Agricultural industrial integration might reduce the urban–rural income gap by promoting agricultural green total factor productivity. To investigate this mechanism, a three-step mediation model is shown in Equations (10)–(12):

$$AGTFP_{it} = c_0 + c_1 Int_{it} + \sum_{k=2}^{7} c_k controls_{it} + \omega_i + \varepsilon_{it} \quad (11)$$

$$Gap_{it} = d_0 + d_1 Int_{it} + d_2 AGTFP_{it} + \sum_{k=3}^{8} d_k controls_{it} + \omega_i + \varepsilon_{it} \quad (12)$$

where $AGTFP_{it}$ is the mediator of agricultural industrial integration in narrowing the urban–rural income gap. c_0 and d_0 are constant terms. c_k $(k = 2, 3, 4, \ldots, 7)$ and d_k $(k = 3, 4, 5, \ldots, 8)$ are coefficients.

3.2.3. Spatial Econometric Model

When examining regional issues for the county demonstration effect, it is crucial to consider the spatial interdependence that exists between regions. Neglecting this spatial dependence may potentially distort the empirical findings. Therefore, a spatial econometrics model, which is employed to assess the spatial impact of agricultural industry integration at the county level on the urban–rural income gap, is shown as follows:

$$\begin{aligned} Gap_{it} = {} & \varphi_0 + \rho \sum_{j=1}^{n} w_{it} Gap_{it} + \varphi_1 Int_{it} + \theta_1 \sum_{j=1}^{n} w_{it} Gap_{it} \\ & + \sum_{k=2}^{7} \varphi_k controls_{it} + \theta_2 \sum_{k=2}^{7} w_{ij} controls_{it} + \omega_i + \varepsilon_{it} \end{aligned} \quad (13)$$

where w_{ij} is the spatial weight matrix. ρ refers to the spillover effect. φ_0 is a constant term, and φ_k $(k = 2, 3, 4, \ldots, 7)$ are coefficients.

Considering the limited influence range of the two cities, Lee & Wang [56] utilized distances of 100, 150, 200, 250, 300, 350, 400, 450, and 500 km as matrix boundaries to explore the varying effects of influence under different distance thresholds. They discovered a significant shift in the spatial spillover effect at the 400 km boundary—the coefficient was significant at distances less than 400 km, but not significant at distances greater than 400 km. Consequently, they concluded that the spatial spillover effect becomes negligible when the spatial distance between two cities exceeds 400 km. Following this finding, Lee et al. [57] also adopted 400 km as the matrix boundary in their investigation of the spatial spillover effects of green bond policies on green innovation and green spaces. In line with these findings, this study constructs a spatial weight matrix using the inverse of the squared distance between two counties, applying a 400 km threshold to determine the entries in the weight matrix. The resulting spatial weight matrix is presented as follows:

$$w_{ij} = \begin{cases} 0, & \text{if } D_{ij} > 400 \text{ km} \\ 1/(D_{ij})^2, & \text{if } 0 < D_{ij} \leq 400 \text{ km} \end{cases} \quad (14)$$

where D_{ij} is the distance between county i and county j.

4. Empirical Results and Analysis

4.1. Benchmark Regression

Table 5 presents the results of the benchmark regression analysis. Initially, the ordinary least squares (OLS) approach is utilized for the regression analysis. Columns (1) and (2) of Table 5 illustrate that the coefficient of *Int* is significantly negative, both before and after including the control variables. As OLS fails to account for the unobservable individual effects, it may lead to biased estimates. Thus, both the random effects (RE) and fixed effects (FE) models are employed for further regression analyses. When individual effects are considered, *Int* shows a significant positive coefficient. The Hausman test outcome, with a p-value below 0.001, indicates that the null hypothesis can be rejected and that the fixed effects (FE) model should be used with a 1% level of significance. Thus, this study utilizes

the FE model to quantify the impact of agricultural industry integration on the urban–rural income gap.

Table 5. The direct impact of agricultural industry integration on the urban income gap.

	(1) OLS	(2) OLS	(3) FE	(4) FE
Int	−6.050 ***	−1.153 ***	−2.646 ***	−0.907 ***
	(0.253)	(0.248)	(0.186)	(0.181)
Lnedu		0.130 ***		−0.035 ***
		(0.008)		(0.012)
Lnind		−0.073 ***		0.008 ***
		(0.005)		(0.003)
Lnwel		−0.051 ***		−0.000
		(0.006)		(0.004)
Lngov		0.076 ***		−0.081 ***
		(0.014)		(0.009)
Lnfin		0.025 **		−0.109 ***
		(0.010)		(0.008)
Lngdp		−0.285 ***		−0.073 ***
		(0.011)		(0.009)
Constant	2.560 ***	4.297 ***	2.384 ***	6.211 ***
	(0.014)	(0.138)	(0.018)	(0.144)
N	8976	8976	8976	8976

** 5%, *** 1%. Standard errors are in parentheses.

Columns (3) and (4) of Table 5 present the outcomes of the fixed effects (FE) model, both with and without incorporating control variables, respectively, after accounting for unobserved individual effects. The decline in the coefficients of Int on Gap further demonstrates the impact of unobserved individual effects in the OLS model on the estimated relationship between Int and Gap, highlighting the necessity of employing the FE model. Meanwhile, in both instances, the coefficients of Int on Gap are significantly negative, indicating that agricultural industry integration contributes to a reduction in the urban–rural income disparity after controlling for unobserved individual effects, which also enhances the credibility of the FE model results.

This result ties in well with those reported by Shen et al. [58], who argued that the integration of county-level agricultural industries can facilitate the diversification of farmers' revenue streams, thus narrowing the urban–rural income gap.

4.2. Robustness Test

4.2.1. Estimation of IV-2SLS

In addressing the potential reverse causality between agricultural industry integration and the rural–urban income gap, which could result in endogeneity bias and affect the reliability of the results, this study adopts an instrumental variable (IV) approach. Following the research of Zhou et al. [13], the lagged one-period agricultural industrial integration is selected as an IV and estimated through the two-stage least squares (2SLS) method:

$$\begin{aligned} \ln t_{it} &= \pi_0 + \pi_1 L.\ln t_{it} + \sum_{d=2}^{7} \pi_d controls_{it} + \eta_{it} + \delta_{it} \\ Gap_{it} &= \beta_0 + \beta_1 \widehat{\ln t_{it}} + \sum_{k=2}^{7} \beta_k controls_{it} + \omega_{it} + \varepsilon_{it} \end{aligned} \tag{15}$$

where $L.\ln t_{it}$ is lagged for one period of agricultural industry integration. η_{it} is the unobservable individual effect. δ_{it} is the error term. π_0 is the constant term. And π_d $(d = 2, 3, 4, \ldots, 7)$ are coefficients.

Utilizing the lagged one-period agricultural industrial integration as an IV satisfies the relevance criterion due to its association with agricultural industrial integration. Simultaneously, it adheres to the exogeneity requirement concerning control variables, including

Lneduit, Lnindit, Lnwelit, Lngovit, Lnfinit, Lngdpit. Simultaneously, the empirical results demonstrate the instrument's validity, with the Kleibergen–Paap rk LM statistic being significant at the 1% level. Additionally, the Cragg–Donald Wald *F* statistic registers at 71,192.95, exceeding the Stock–Yogo critical value threshold of 16.38 at the 10% significance level (Table 6). Furthermore, with the number of instruments matching the number of endogenous regressors, the model is exactly identified, eliminating any over-identification issues. Therefore, there is no under-identification or weak instrumental variables, which supports the choice of IV from an econometric perspective.

Even after accounting for endogeneity, the negative association between agricultural industry integration and the urban–rural income gap persists, significantly reinforcing the robustness of the above regression findings.

Table 6. Robustness test.

	IV-2SLS		**Alternative Measurements**	**Winsor**
	Int	*Gap*	*Gap*	*Gap*
l.Int	1.062 ***			
	(0.009)			
Int		−1.162 ***	−0.659 ***	−2.362 ***
		(0.267)	(0.180)	(0.391)
Lnedu	0.0002	0.124 ***	−0.102 ***	−0.088 ***
	(0.0001)	(0.010)	(0.017)	(0.015)
Lnind	0.0002 ***	−0.074 ***	0.017 ***	0.019 ***
	(0.0001)	(0.005)	(0.004)	(0.005)
Lnwel	−0.0003 ***	−0.050 ***	0.006	0.006 *
	(0.0001)	(0.006)	(0.004)	(0.003)
Lngov	0.001 ***	0.093 ***	−0.105 ***	−0.108 ***
	(0.0002)	(0.015)	(0.009)	(0.009)
Lnfin	0.00003	0.029 **	−0.112 ***	−0.097 ***
	(0.0002)	(0.012)	(0.008)	(0.007)
Lngdp	−0.001 ***	−0.285 ***	−0.032 ***	−0.025 ***
	(0.0002)	(0.012)	(0.010)	(0.008)
Constant	0.006 ***	4.084 ***	6.565 ***	6.237 ***
	(0.002)	(0.157)	(0.207)	(0.178)
Kleibergen–Paap rk LM	268.52 ***			
Cragg–Donald Wald F	71,192.95			

* 10%, ** 5%, *** 1%. Standard errors are in parentheses.

4.2.2. Alternative Measurement of Explanatory Variable

To ensure the robustness of the findings, this study further employs an alternative measure for the explanatory variable to verify the persistence of the impact of agricultural industrial integration on the urban–rural income gap. Drawing from the methodology adopted by Lai et al. [25], this study utilizes a dimensionless treatment to standardize the indicators of agricultural industrial integration. This standardization facilitates the re-examination of the effects of agricultural industrial integration on the urban–rural income gap, with the results presented in Table 6. The formula for the new standardized agricultural industrial integration indicator is as follows:

$$\text{Positive indicator } v_{tij} = \frac{x_{tij}}{\max x_{tij}} \tag{16}$$

$$\text{Negative indicator } v_{tij} = \frac{\min x_{tij}}{x_{tij}} \tag{17}$$

The findings indicate that, even after substituting the explanatory variable with a normalized measure of agricultural industry integration, the negative effect on the urban–rural income gap remains statistically significant at the 1% level. This consistency with the above findings not only corroborates the initial results but also addresses the robustness of

the benchmark regression analysis. The persistent negative relationship suggests that as agricultural industry integration increases, the urban–rural income gap tends to decrease, even if the measurements of the core indicators is replaced.

4.2.3. Winsorizing the Variables

Considering the potential influence of sample outliers on the estimation results is crucial for ensuring the accuracy and reliability of statistical analyses. To mitigate the effects of outliers, a winsorization at 5% of the data is conducted before re-estimating the impact of agricultural industry integration on the urban–rural income gap (Table 6).

The re-estimation results show that the coefficient of agricultural industry integration remains significantly negative at the 1% level. This outcome is line with the above results, confirming that agricultural industry integration has a consistent negative relationship with the urban–rural income gap. The significance at the 1% level after winsorization further confirms the robustness of the benchmark regression results, suggesting that the relationship between *Int* and *Gap* is not affected by the presence of extreme values in the data.

4.3. Mechanism

In the preceding theoretical analysis, the mechanism by which agricultural industry integration affects the urban–rural income gap was analyzed from the perspective of agricultural green development. This section will test the mediating mechanism (Table 7).

The *Int* regression coefficient in Column (1) is 0.038, which is significant at the 5% level, suggesting that county-level agricultural industry integration promotes agricultural green total factor productivity. After incorporating agricultural green total factor productivity, the *Int* regression coefficient in Column (2) becomes −0.987, significant at the 1% level. This finding suggests that county-level agricultural industry integration may promote agriculture green development, reduce the use of polluting resource factors, such as chemical fertilizers, electricity, diesel and so on, and contribute to achieving agricultural green and sustainable development. Consequently, agricultural industrial integration could improve agricultural productivity, increase green income for farmers, and narrow the income gap between urban and rural areas.

Table 7. Indirect effects of agricultural industry integration on urban income disparities.

	(1) ***AGTFP***	**(2)** ***Gap***
Int	0.038 **	−0.987 ***
	(0.019)	(0.184)
Lnedu	−0.002 ***	−0.097 ***
	(0.001)	(0.017)
Lnind	−0.001 ***	0.018 ***
	(0.0001)	(0.004)
Lnwel	0.0003 *	0.006
	(0.0001)	(0.004)
Lngov	0.003 ***	−0.103 ***
	(0.0004)	(0.009)
Lnfin	0.002 ***	−0.109 ***
	(0.0003)	(0.008)
Lngdp	0.001 *	−0.030 ***
	(0.0004)	(0.010)
AGTFP		−0.267 ***
		(0.102)
Constant	0.960 ***	6.726 ***
	(0.008)	(0.223)
N	8976	8976

* 10%, ** 5%, *** 1%. Standard errors are in parentheses.

4.4. Heterogeneity Analysis

4.4.1. Geographical Heterogeneity

Due to China's extensive geographical area, there are significant differences in economic development levels and natural conditions across regions [13]. Significant distinctions are observed across regions, with the eastern region characterized by advanced economic progress, the middle region by plains conducive to large-scale agricultural cultivation, and the western region by a mountainous landscape that poses challenges to high-quality agricultural development. Nevertheless, as each region tailors its agricultural production to its specific conditions, there has been an increase in the overall level of agricultural integration.

To examine heterogeneity in the impact of agricultural industry integration on the urban–rural income gap across different regions, this study classifies the counties into three regions (eastern, middle, and western), based on their respective provinces and cities (Table 8). The analysis reveals that the impact of *Int* on *Gap* is more pronounced in the middle region than in the eastern region. The influence effect of *Int* on *Gap* in the western region is the smallest. Jiao [59] also found that the impact effect of agricultural industry integration was more significant in the middle region compared to both the eastern and western regions.

Table 8. Heterogeneity in the impact of agricultural industry integration on the urban income gap.

	(1) **Eastern**	**(2)** **Middle**	**(3)** **Western**	**(4)** **Non-Major Crop-Producing**	**(5)** **Major Crop-Producing**
Int	−0.999 ***	−1.035 ***	−0.930 **	−0.820 ***	−1.062 ***
	(0.244)	(0.286)	(0.474)	(0.311)	(0.232)
Lnedu	−0.059 **	-0.001	−0.140 ***	−0.115 ***	−0.086 ***
	(0.025)	(0.033)	(0.032)	(0.028)	(0.022)
Lnind	0.033 ***	0.006	0.015	0.012	0.020 ***
	(0.005)	(0.006)	(0.016)	(0.008)	(0.004)
Lnwel	0.010 **	-0.007	0.011	0.004	0.013 ***
	(0.004)	(0.008)	(0.008)	(0.006)	(0.005)
Lngov	−0.105 ***	−0.060 ***	−0.155 ***	−0.110 ***	−0.087 ***
	(0.012)	(0.018)	(0.026)	(0.018)	(0.011)
Lnfin	−0.130 ***	−0.075 ***	−0.144 ***	−0.129 ***	−0.108 ***
	(0.012)	(0.013)	(0.018)	(0.015)	(0.009)
Lngdp	−0.006	−0.043 ***	−0.042	−0.085 ***	0.007
	(0.015)	(0.015)	(0.027)	(0.020)	(0.011)
Constant	5.851 ***	4.671 ***	8.325 ***	7.923 ***	5.442 ***
	(0.295)	(0.403)	(0.393)	(0.346)	(0.254)
N	3026	3054	2896	3600	5376

** 5%, *** 1%. Standard errors are in parentheses.

This phenomenon is primarily driven by the significant advantages of the eastern and middle regions in terms of workforce quality, land resources, and advanced technology. These factors facilitate the integration of the agricultural industry with secondary and tertiary sectors, thereby enhancing farmers' incomes and reducing the urban–rural income gap. Conversely, the western region's economic development is comparatively underdeveloped, with an uneven industrial foundation. The influence of its agricultural industry is somewhat limited, and a prevalence of smallholder economies exists. Consequently, the effect of agricultural industry integration on the urban–rural income disparity in the western region is less pronounced.

4.4.2. Functional Grain Area Heterogeneity

In addition, there are differences in the agricultural cropping structures across regions. Therefore, regions are further divided into major crop-producing areas and non-major crop-producing areas. In general, agricultural cultivation in major crop-producing areas

is superior to that in non-major crop-producing areas, resulting in differing impacts on the urban–rural income gap. Columns (4) and (5) in Table 8 delineate the effects of *Int* on *Gap* in non-major crop-producing areas and major crop-producing areas, respectively. The findings indicate a uniformly significant negative effect of *Int* on *Gap* in both major and non-major grain-producing areas, meaning that agricultural industry integration exerts a notable inhibitory influence on the urban–rural income disparity. However, the coefficient of influence in major grain-producing areas is slightly higher than that in non-major grain-producing areas.

This trend could originate from the strategic focus on centralizing grain production in China's primary agricultural zones, which possess more abundant agricultural resources [60]. This centralization is instrumental in fostering an integrated approach to high-quality agricultural development in these core grain-producing counties. The outcome of this approach is a diversified increase in local farmers' incomes and a gradual bridging of the income gap between urban and rural locales.

4.5. Spatial Spillover Effect

4.5.1. Spatial Autocorrelation Analysis

To examine the spatial autocorrelation of agricultural industry integration's impact on the urban–rural income gap, a Moran's I analysis is conducted, distinguishing between Global Moran's I for overall space and Local Moran's I for specific localities. This study uses Local Moran's I to identify and visualize local spatial variations ([61], see Table 9). Additionally, separate Moran's I analyses assess the spatial dependence between *Int* and *Gap* across counties. The results, showing a positive and significantly stable Moran index from 2014 to 2021 at the 1% level, indicate a significant spatial autocorrelation between *Int* and *Gap*, with the Moran index of *Int* declining over time, hinting at a decrease in spatial clustering and an improvement in agricultural industry integration across China's counties.

The distribution index of *Gap* mostly stays around 0.47, showing that the spatial aspect of the urban–rural income gap in Chinese counties remains unchanged. This stability is due to various factors like education [50], industrial development [51], welfare level [52], government expenditure [53], financial development [54], and economic development [55]. Despite the beneficial effects of agricultural industry integration on reducing the income gap, its influence is moderated by these factors, leading to no significant change in spatial distribution. This finding is consistent with the research of Zhao and Wang [62]. Therefore, this study controls for these influencing factors in its analysis of spatial spillover effects.

Table 9. Moran index of agricultural industry integration and rural–urban income gap by year.

Year	Int			Gap		
	Moran's I	*z* Value	*p* Value	Moran's I	*z* Value	*p* Value
2014	0.451	40.820	<0.001	0.454	41.152	<0.001
2015	0.309	28.108	<0.001	0.465	42.147	<0.001
2016	0.247	22.551	<0.001	0.475	43.076	<0.001
2017	0.211	19.277	<0.001	0.458	41.502	<0.001
2018	0.162	14.840	<0.001	0.495	44.837	<0.001
2019	0.147	13.475	<0.001	0.496	44.927	<0.001
2020	0.130	11.910	<0.001	0.491	44.472	<0.001
2021	0.122	11.128	<0.001	0.479	43.438	<0.001

4.5.2. Spatial Spillover Effects

This study determines the most suitable model among the spatial error model (SEM), the spatial autoregressive model (SAR), and the spatial Durbin model (SDM) using a sequence of tests, including the Hausman, Lagrange multiplier (LM), likelihood ratio (LR), and Wald tests (Table 10). The Hausman test leads to rejecting the null hypothesis at the 1% significance level for all three models, indicating a preference for a fixed-effects model. Both the LM and robust LM tests further confirm the presence of spatial lag and spillover effects,

suggesting SDM as the optimal choice. Additional LR tests reinforce SDM's advantages over SEM and SAR. The Wald test evaluates SDM's robustness, showing that SDM remains stable and does not reduce to SEM or SAR. Separate spatial Durbin models with individual fixed effects, time fixed effects, and double fixed effects are established, and LR tests are conducted. The LR values are, respectively, 97.48 and 18162.59, indicating that a spatial Durbin model should be used with both individual and time fixed effects.

Table 10. Results of spatial econometric model tests.

Test Methods Purpose	Statistic	*p* Value
LM-lag test	6078.726	<0.001
Robust LM-lag test	148.509	<0.001
LM-error test	7629.300	<0.001
Robust LM-error test	1699.083	<0.001
LR-spatial-lag test	234.39	<0.001
LR-spatial-error test	105.88	<0.001
Wald-spatial-lag test	122.08	<0.001
Wald-spatial-error test	212.91	<0.001

LM-lag test, Robust LM-lag test, LM-error test, and Robust LM-error test are used to test whether there are spatial lag and spillover effects to endorse the selection of SDM; LR-spatial-lag test and LR-spatial-error test are used to affirm SDM's superiority over SEM and SAR; Wald-spatial-lag test and Wald-spatial-error test are used to determine whether SDM would degenerate into SEM or SAR.

Columns (1) and (2) in Table 11 present the results of the SDM. The coefficients of *Int* and W**Int* are both significantly negative, suggesting that the development of county-level agricultural industry integration not only diminishes the local urban–rural income gap but also exerts a significant positive spatial spillover effect. Given that the estimated coefficient of ρ is significantly different from zero, the partial differentiation method is applied to disaggregate the effects into direct, indirect, and total effects [63].

Table 11. Spatial spillover effects of agricultural industry integration on urban income disparities.

Variables	(1) Main	(2) Wx	(3) Direct Effect	(4) Indirect Effect	(5) Total Effect
Int	−0.302 **	−1.252 **	−0.386 **	−3.672 ***	−4.058 ***
	(0.151)	(0.504)	(0.157)	(1.205)	(1.245)
Lnedu	−0.003	−0.247 ***	−0.019	−0.622 ***	−0.640 ***
	(0.015)	(0.035)	(0.014)	(0.081)	(0.082)
Lnind	−0.001	−0.021 ***	−0.002	−0.054 ***	−0.056 ***
	(0.004)	(0.008)	(0.004)	(0.018)	(0.018)
Lnwel	0.002	0.016 **	0.003	0.042 **	0.045 **
	(0.003)	(0.008)	(0.003)	(0.018)	(0.018)
Lngov	0.007	0.006	0.007	0.026	0.033
	(0.101)	(0.025)	(0.010)	(0.057)	(0.058)
Lnfin	0.034 ***	0.058 ***	0.039 ***	0.193 ***	0.232 ***
	(0.009)	(0.020)	(0.008)	(0.046)	(0.048)
Lngdp	−0.012	0.045 ***	−0.010	0.097 **	0.087 **
	(0.010)	(0.017)	(0.010)	(0.038)	(0.038)
Spatial ρ	0.614 ***				
	(0.00)				

** 5%, *** 1%. Standard errors are in parentheses.

Columns (3) and (4) present the direct and indirect effects. The coefficient of the direct effect is −0.386, which demonstrates that agricultural industry integration can reduce the urban–rural income gap in the county. The indirect effect's coefficient is −3.672, significant at 1%, indicating that integration reduces the income gap in adjacent areas. Clearly, the direct effect's coefficient is smaller than the indirect effect's. Chen and Yu [64] also found the indirect (spatial spillover) effect to be larger than the direct, indicating a

greater impact on neighboring regions. This may be because these regions adapt and innovate upon the local model, leveraging competition and motivation to learn, leading to more significant benefits.

Column (5) displays the results of the total effect. The estimated coefficient of the total effect is −4.058, exhibiting significant negativity at the 1% level. This indicates that, whether considering the direct or indirect impacts, agricultural industry integration can effectively narrow the urban–rural income disparity. Zhou et al. [65] analyzed the spatial effect of agricultural industry integration on farmers' income based on 30 provinces in China from 2011 to 2020. They also found that agricultural industry integration had positive spatial spillover effects, which not only had a significant income-generating effect on local farmers, but also promoted the income-generating effect of farmers in other regions, contributing to the overall income-generating effect.

5. Conclusions

5.1. Conclusions

Prior research has underscored the potential of agricultural industry integration to augment farmer incomes and ameliorate income disparities. Nonetheless, scant analysis has been devoted to exploring the specific mechanisms by which integration at the county level alleviates the urban–rural income divide, especially its spatial dynamics. Moreover, the intermediary role of agricultural green total factor productivity (AGTFP) in bridging the income gap through agricultural industry integration remains underexplored. This study leverages data from 1122 Chinese counties to shed light on how agricultural industry integration impacts this income gap. Based on extensive theoretical frameworks and empirical evidence, our investigation delineates the effects of agricultural industry integration on urban–rural income disparity through four key dimensions: direct impact, regional heterogeneity, AGTFP's mediating effects, and spatial consequences.

Our findings reveal that agricultural industry integration significantly diminishes the urban–rural income gap. Notably, this impact is observed consistently across diverse county frameworks, with a more marked effect in central regions and principal grain-producing areas. Moreover, we uncover that agricultural industry integration may indirectly narrow the urban–rural income gap by fostering improvements in AGTFP. Importantly, our analysis also identifies a substantial positive spillover effect—successful integration in one county not only benefits the local area but also neighboring counties to narrow the urban–rural income gap. Considering both the direct effects and the spillover effects, the overall influence of agricultural industry integration on the urban–rural income gap is still negative and significant.

5.2. Policy Recommendations

Based on the above analysis, policy recommendations are provided to further improve agricultural industry integration development and thereby reduce the urban–rural income gap.

Firstly, regarding the outcomes of the direct and indirect effects, the substantial development of county-level agricultural industry integration is important in reducing the urban–rural income gap. Consequently, it is imperative to further strengthen the integration of the county-level agricultural industry. This initiative should include guiding migrant workers to return to their home counties for employment opportunities, as well as aiding local laborers in achieving higher productivity and income. Concurrently, during the advancement of agricultural industrial integration, relevant authorities should emphasize green and sustainable practices. This can involve streamlining the use of production inputs and curbing the utilization of pollutants, such as chemical fertilizers, electricity, and diesel, which contribute to carbon emissions in agriculture. By bolstering green productivity within the agricultural sector, counties may advance toward greener, low-carbon, and high-quality agricultural industry development, ultimately enhancing green income for farmers, further narrowing the income gap between urban and rural areas.

Secondly, considering the findings of the heterogeneity analysis, the impact of agricultural industry integration on the urban–rural income gap depends on the availability of natural resources, and other factors. It is crucial to focus on areas with scarce resources and less developed economies to improve integration by enhancing infrastructure and social services. Specifically, in the western region, with its mountainous terrain, the integration of the agricultural industry has been slow. In order to accelerate the process of integration of the agricultural industry, localities can adopt modern technology to develop agriculture, especially the cultivation of specialty crops, so as to improve the utilization rate of land resources. In addition, localities can develop live e-commerce, create a regional circulation system for agricultural products, and broaden the sales market for agricultural products.

Finally, considering the spatial effect results, to integrate agricultural employment locally and enhance labor resource allocation efficiency, it is prudent for counties to tailor agricultural industry development to their unique circumstances. In the context of 'one county, one industry', counties must fortify collaboration with adjacent counties, pool inter-county resources, and leverage mutual strengths. By capitalizing on the positive spillover effects of agricultural industry integration on the urban–rural income disparity, this initiative aims to fuel collective agricultural growth in neighboring counties, co-advancing rural income enhancement, and ensuring shared prosperity resulting from the integration's progress.

5.3. Limitations and Prospects

Although this study fills the gaps in the existing literature by providing a detailed discussion of agricultural industry integration, agricultural green total factor productivity, and the urban–rural income gap at the county level, there are still some shortcomings that need to be further researched and improved.

Firstly, the variable weights in agricultural industry integration indicate that Taobao villages carry the highest weight compared to other variables, such as agricultural cultivation, agricultural output, agricultural machinery, and facility agriculture. Due to the absence of Taobao villages in many counties, the number of Taobao villages better reflects the integration of agricultural industries. Therefore, in future research on agricultural industry integration, greater emphasis could be placed on measuring Taobao villages, and even considering Taobao villages as one of the proxy indicators for agricultural industry integration. The high weight of Taobao villages may also be attributed to the limited selection of integration indicators. Considering data availability and completeness, we selected only five indicators to measure the integration of agricultural industries in county areas. Other researchers have also considered the gross output value of agriculture, forestry, animal husbandry, and fishery services, the gross output value of the primary industry, and the urbanization rate as measurement indicators [25,31]. Thus, future studies could measure the integration of agricultural industries at the county level using more dimensions and uncover more intriguing relationships.

Secondly, with respect to missing data issues, the gathering and statistical representation of county-level data may be incomplete or missing, potentially restricting comprehensive analysis of the urban–rural income disparity. For example, in measuring the urban–rural income gap, this study directly addresses it solely through the ratio method. The most commonly used Theil index, influenced by both the average income and its distribution, offers a more holistic approach to considering the urban–rural income divide. Nevertheless, since the statistical yearbooks of many counties omit resident population figures, quantifying the urban–rural income gap and affirming result robustness with alternative metrics is unfeasible. Moreover, labor constitutes a critical component of agricultural production when measuring green total factor productivity in agriculture. However, it is not included as an input indicator due to incomplete data.

Finally, agricultural industry integration unfolds over an extended period. This study considers the inclusion of Taobao villages within agricultural industry integration indices to signify the use of agricultural technology in agricultural marketing, with data collection

commencing in 2014. Consequently, the analysis is confined to the 2014–2021 timeframe. Future investigations ought to concentrate on the enduring impact of agricultural industry integration in narrowing the urban–rural income gap. Moreover, the applicability of the conclusions across different contexts is limited due to the complexities inherent across various regions of the country, which makes generalization of the findings from a singular model to all regions challenging.

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