FARMERS' INCOME GROWTH IN A NATURAL-SOCIO-ECONOMIC ENVIRONMENT FOR RELATIVELY POOR AREAS: EVIDENCE FROM GANZI, SOUTHWEST CHINA

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(Received 14th Oct 2024; accepted 4th Feb 2025)

Abstract. Policymakers and scholars around the world have grappled with the difficulties of reducing rural poverty. For China, although absolute poverty has been eradicated, considerable efforts are still required to address relative poverty and boost sustainable income growth among farmers. This study examines Ganzi Prefecture in Sichuan Province as a representative of China's relatively poor areas, analyzing the spatiotemporal dynamics of farmers' income and exploring the interactions between income growth, the natural environment, socio-economic progress, and rural support measures. The results indicate that, since 2014, both the internal income disparities of farmers in Ganzi and the income gap relative to the national average have converged. Our analysis provides robust evidence that socio-economic development and rural support have significantly increased farmers' income. The discussion of heterogeneity reveals that these positive effects vary across sub-income types and county categories. However, the impact of agricultural resources is not constant, and a "resource curse" effect is observed in more challenging counties, particularly in terms of hindering wage and salary income growth. Our findings advance scientific understanding of income growth challenges among farmers in relatively poor areas and highlight an integrated natural-social-economic perspective for analyzing this issue. These insights would provide new information for policymakers to formulate targeted follow-up assistance policies in the post-poverty era.
Keywords: *rural poverty reduction, rural supporting, resource curse, impoverished areas, China*

Introduction

Poverty has long been a significant global challenge and a persistent obstacle to socioeconomic development (Bapna, 2012; Adams et al., 2004; Tollefson, 2022; Li et al., 2023). In both developed and developing countries, the majority of the poor reside in rural areas (Bardhan, 2006; McAreavey and Brown, 2019; Wang et al., 2020), which is the focus of this study. Since the Declaration on Social Progress and Development first recognized poverty eradication as a communal mission in 1969 (UN, 1969), reducing rural poverty has remained a key focus of the global sustainable development agenda. However, the realities are not always encouraging. In 2013, 767 million people around the world living in extreme poverty (UN, 2015), down from 1.7 billion people in

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2303_38913915

1999; but chronically more than 70 percent of them lived in rural areas (IFAD, 2011). Currently, more than 700 million people are still living in extreme poverty (UN, 2023), of whom approximately 79% reside in rural areas (UN, 2019). The COVID-19 epidemic has effectively reversed years of progress in poverty reduction, compounding the already vulnerable position of the rural poor (UN, 2023, 2021).

Farmers' income is a fundamental measure of poverty status and its severity. Farmers' income growth is highly relevant to the United Nations 2030 Sustainable Development Goals (SDGs), such as "No Poverty" (SDG1), "Zero Hunger" (SDG2), and "Reduce inequality" (SDG10) (UN, 2015). Therefore, understanding the evolutions and determinants of farmers' income growth has attracts increasing attention from the general public, policymakers, and academics. Much work argued that rising farmers' income have been accompanied by varying changes in inequality across regions, and the issue of the factors influencing these changes always a focus. Researchers in fields such as economics, sociology, agricultural sciences, and geography have investigated the relationships between farmers' income growth and various factors — such as population growth (Parrado and Kandel, 2010), GDP growth (Augustin, 2017), public infrastructure (Charlery et al., 2015), agro-ecological environment and crop cultivation (Barbier and Hochard, 2016; Horlu, 2024), climate change (Quiroga and Suárez, 2016; Abid et al., 2016) and non-farm employment (Mager and Faße, 2024), considering the specific contexts of different countries and regions.

China used to face very serious rural poverty. In recent years, comprehensive anti-poverty campaign with targeted poverty alleviation launched, nearly 100 million rural inhabitants have been lifted out of poverty, achieving the milestone of eradicating absolute poverty. Despite these significant achievements, difficulties persist in narrowing the development gap between urban and rural and addressing relative poverty (Zhou et al., 2023; Liu et al., 2024; Huang et al., 2023). Achieving these objectives requires sustained efforts to raise the income level of farmers. Giving this background, the issue of Chinese farmers' income has long been the focus of academic attention, and scholars have conducted multidisciplinary and multifaceted research, which can be summarized in the following three aspects. First, the spatial and temporal patterns of farmers' income and poverty. Looking at the temporal trend, Chinese rural income has been increasing and rural poverty has been decreasing over recent decades (Chang et al., 2022; Luo et al., 2020; Yu and Li, 2021; Li and Sicular, 2014; Ravallion and Chen, 2007). Spatially, income distribution reveals an uneven pattern from the coast to the interior, with rural poor historically concentrated in the western and mountain area, particularly southwestern, regions (Liu et al., 2020, 2006, 2017; Ren et al., 2017). The second is rural income inequality and its evolution. In terms of spatial disparity, research shows that inter-regional inequality in farmers' income increased in the 1980s and 1990s (Luo et al., 2020; Ravallion and Chen, 2007), while has markedly decreased in the 21st century, particularly over the last decade (Wang et al., 2022; Yang et al., 2020). With regard to the urban-rural divide, studies at the national level have documented a persistent narrowing of the urban-rural income gap in the past more than ten years (Tang et al., 2022; Wang et al., 2024, 2023; Yao and Jiang, 2021); and similar trends are evident at the provincial level (Yang et al., 2023, 2022; Zhang et al., 2021). Additionally, researchers have also focused on income inequality between specific groups such as low-income farmers (Weng et al., 2024) and resettlers (Lo, et al., 2016) and their counterparts, middle- and high-income farmers and non-relocated farmers. Third, the factors and mechanisms influencing changes in farmers' income. Both the

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2303_38913915

natural environment and socio-economic development affect farmers' income. Research on natural factors often focuses on the associations between farmers' income and environmental variables, including climate conditions (Chen, 2014), cultivated land and its construction (Tang et al., 2013; Chen et al., 2023), vegetation growth status (Fan et al., 2022), natural hazards (Huang, 2022), natural reserves (Xu et al., 2023) and ecological restoration (Liu et al., 2010), payments for ecosystem services (Zhang et al., 2019; Wu and Jin, 2020), and more. On the socio-economic side, determinants of rural income taken into account are economic growth (Fan et al., 2022; Montalvo and Ravallion, 2009), urbanization (Ren et al., 2017; Zheng et al., 2015; Yang et al., 2023), industrial structure (Liu et al., 2021), digital technology access (Zhang and Li, 2024; Yin et al., 2021), support policy such as agricultural subsidies (Sun et al., 2024), infrastructure development (Zhang et al., 2023; Lu et al., 2023), and agricultural cooperatives (Lin et al., 2020), etc. Meanwhile, research focusing on high-quality rural development has also demonstrated that green agricultural technologies (Gao et al., 2024), agricultural scale management (Yin et al., 2024), integrated development of agriculture and tourism (Luo et al., 2023), and inclusive financial services and insurance (Liu et al., 2021; Lian et al., 2023; Bhuiyan et al., 2022) enhance income levels. These studies are both national-level studies with provinces as the study unit and case studies with rural households as the study unit. The data used are mainly from China statistical yearbooks (Yang et al., 2023; Liu et al., 2021); large-scale national surveys such as China Household Finance Survey (CHFS) (Huang, 2022), China Family Panel Studies (CFPS) (Zhang and Li, 2024; Zhang et al., 2023), and China Rural Development Survey (CRDS) (Wang et al., 2020); and targeted small-scale questionnaires and sample survey (Wu and Jin, 2020; Lin et al., 2020). The econometric research methods are most employed, such as Difference in Differences (DID) model (Chen et al., 2023; Sun et al., 2024; Luo et al., 2023), Panel fixed- and random- effects regression (Yao and Jiang, 2021; Liu et al., 2021; Lu et al.,2023), Probit regression (Weng et al., 2024), Multinomial logistic regression (Chen, 2014), Quantile regression (Zhang and Li, 2024), Vector auto regression (VAR) (Zheng et al., 2015; Yin et al., 2021), coupling coordination degree model (Yin et al., 2024).

The aforementioned research on Chinese farmers' income has yielded substantial findings, however, most studies primarily focus on the relationship between specific factors and farmers' income, lacking a comprehensive and systematic analysis of different influencing factors. Research tends to be conducted from a macro-level provincial and a micro-level household perspective, with limited attention to counties —the meso-level units essential for understanding regional dynamics in the national economy and governance. In addition, the most important point is that, in underdeveloped regions in terms of socio-economic development, especially the contiguous poverty-stricken regions, sustainable growth in farmers' income remains challenging despite alleviation of absolute poverty (Ren et al., 2017; Fan et al., 2022). These regions often overlap with ecological function zones and are remote from core economic and population centers, complicating data collection efforts. Existing research has inadequately addressed these complexities, limiting insights into the distinctive challenges of income growth in less developed areas. Ganzi Tibetan Autonomous Prefecture, was historically part of the "Three Regions and Three Prefectures" areas recognized for deep poverty, as well as a critical part of the ecological protection zone in the upper Yangtze River and the Northwest Sichuan Ecological Demonstration Zone, marked by fragile natural environments and a weak economic foundation (Yuan et al.,

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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2023). Recent policies, such as targeted poverty alleviation, have significantly accelerated farmers' income growth in Ganzi. However, compared to other regions, Ganzi continues to face substantial challenges in achieving rural revitalization. Its remote location, combined with the distinct characteristics of ethnic minority communities, creates a unique "natural laboratory" for studying income growth dynamics in underdeveloped minority regions. Despite this potential, very little research has been conducted on farmers' income in Ganzi. Considering this, this study aims to achieve three objectives: (1) to estimate the temporal and spatial dynamics of farmers' income in Ganzi, with a focus on contrasting income growth characteristics between Ganzi and the national level; (2) to analyze the multidimensional factors and mechanisms driving farmers' income changes from a comprehensive natural-social-economic perspective, and to identify the key determinants of income growth; and (3) Based on the above findings, to develop targeted and long-term policy recommendations to support stable income growth for local farmers. These insights are expected to provide valuable support for decision-making related to rural relative poverty governance and rural revitalization in China's "post-poverty alleviation era". Additionally, these insights may benefit other regions and countries with similar natural and socioeconomic contexts by informing strategies to increase farmers' income.

Materials and methods

Study area

This study was carried out in the Ganzi Tibetan Autonomous Prefecture (referred to as Ganzi), located in the western region of Sichuan Province in southwestern China, spans about 149,700 km^2, accounting for about 30% of Sichuan Province's total area (*Fig. 1*). Ganzi is an integral part of the Tibetan Plateau (TP), serves as a transitional zone between the TP, the Hengduan Mountains, Sichuan Basin, and the Yunnan-Guizhou Plateau; and its human-environment geographic pattern exhibits significant vertical distribution (Yuan et al., 2023; Wang et al., 2022).

Ganzi administers 18 counties, with a population of about 1.1 million, of which 68 per cent are rural residents, and is the administrative unit in Sichuan Province with the highest proportion of rural residents. There are 41 ethnic groups home there, with Tibetans comprising 78.97 per cent of the population. Ganzi was once a representative of deeply impoverished minority areas, where the poverty incidence had once been higher than 20 per cent, is the "main battlefield" for poverty alleviation. Since the implementation of targeted poverty alleviation, all 18 counties have withdrawn from the list of poor counties and realize absolute poverty eradication by 2020. However, due to the thin base of socio-economic development foundation, there is still a long way to go to solve the problem of unbalanced and inadequate development in rural areas and to fully realize rural revitalization.

Statistical analysis

Absolute and relative income

In this paper, the absolute income is the actual value of per capita disposable income in a specific region. The relative income is the level obtained by comparing the absolute income of one region to that of a benchmark (Arias and Wen, 2016; Fehr et al., 2021). This measure is affected not only by the income of the region but also by the income of

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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other people (the benchmark group), accurately reflecting income disparity and inequity among different regions, as measured by the ratio of the incomes of regions to that of benchmark groups.

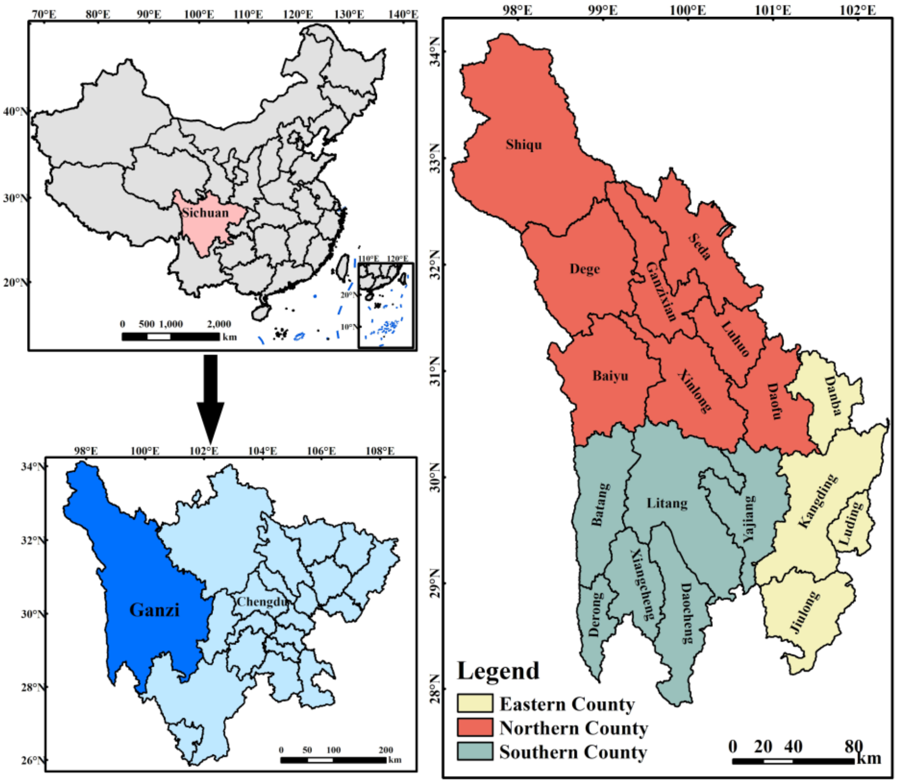

***Figure 1.** The study area map showing Ganzi's spatial locations and counties*

Convergence test

α-convergence implies that the deviation of income between different regions decreases over time. In this paper, the coefficient of variation (*CV*) is employed to examine the characteristics of α-convergence in the income between regions (Guo et al., 2024), which can be expressed by *Equation 1*, Where Y_i is the income of *i*-th region, *n* is the count of regions.

$$CV = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_i - \frac{1}{n}\sum_{i=1}^{n}Y_i\right)^2}{n}} \Bigg/ \frac{1}{n}\sum_{i=1}^{n}Y_i \tag{Eq.1}$$

Absolute β-convergence in this paper is defined as regions with lower farmers' income experiencing higher growth than those with higher incomes (Guo et al., 2024; Solow, 1956). This indicates a negative correlation between initial income levels and subsequent growth rates, leading to income level convergence across regions. The formula is as follows:

$$\ln(Y_{i,t+T}/Y_{i,t}) = \alpha + \beta\ln(Y_{i,t}) + \varepsilon_{i,t} \tag{Eq.2}$$

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where $Y_{i,t+T}$ and $Y_{i,t}$ is the income of region i of periods $t + T$ and t, respectively. T is the time span, $\varepsilon_{i,t}$ is the random disturbance term, α is a constant term. β is the coefficient of convergence to be estimated.

$$\begin{cases} if \ \ \beta > 0, & \text{non-convergence} \\ if \ \ \beta < 0, & \text{convergence} \end{cases} \tag{Eq.3}$$

The convergence speed can be expressed as:

$$\theta = -\ln(\beta + 1)/T \tag{Eq.4}$$

Kernel density estimation

Kernel density estimation is a non-parametric technique utilized to describe the distribution and dynamics of socioeconomic phenomena. In this paper, we investigate the income disparity and inequality among farmers across counties in Ganzi by examining the distribution and dynamic evolution through the extensibility and peak characteristics of the density curve (Pennino et al., 2017; Li et al., 2024). The formula for the density function is given by *Equation 5*:

$$f(x) = \frac{1}{nh} \sum_{i=1}^{N} K\left(\frac{X_i - x}{h}\right) \tag{Eq.5}$$

where $f(x)$ denotes the probability density function of income, X_i is the observed value, x is the mean value of the observations, n is the number of observations. $K(\ )$ is the kernel function. h is the bandwidth, the value of which determines the smoothness of the kernel density distribution.

Empirical strategy

The empirical strategy adopted in this study is the panel regression model. This approach offers several advantages by considering time series dependency and cross-sectional data heterogeneity, to enhance variable variability, reduce collinearity among variables and decrease estimation bias (Yao and Jiang, 2021; Liu et al., 2021; Hsiao, 2007).

Definition of variables

Explained variables

The explained variable is the farmers' income level, measured in terms of absolute and relative income levels, spanning observations for the period 2014-2022. The absolute income level (*AIL*) is defined by the logarithm of the Per capita disposable income of rural households, and the relative income level (*RIL*) is defined by the Per capita disposable income of counties compare to that of Sichuan Province.

In China, disposable income includes in-cash and in-kind income. Resident population is used in calculating rural households' income, who staying at home regularly or for over 6 months annually and integrated with the household economically and in terms of living. Population staying away from the household for over 6 months

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but keeping a close economic relation with the household by sending the majority of income to the household are still regarded as usual resident of the household.

Explanatory variables

Farmers' incomes are profoundly influenced by the complexity of natural-social-economic system, by drawing upon previous research, considering the field research conducted by this research team in Ganzi and data availability, and removing the potential covariance between variables, ultimately, we selected ten variables across four key dimensionalities to investigate the influencing mechanism on farmers' income, as follows:

Natural Environment. For the majority of farmers in Ganzi, agricultural production, particularly animal husbandry, is the primary source of income, heavily dependent on the natural environment. For one thing, the availability and quality of water resources, land, temperature, and ecosystem services largely determine agricultural production efficiency. On the other hand, the topography and geomorphology directly influence the construction of infrastructure, such as roads, which affects transportation costs and diversity of farmers' income sources. The Agricultural Resources (*AR*) (Liu et al., 2024; Tang et al., 2013; Fan et al., 2022; Bhuiyan et al., 2022) and Traffic Convenience (*TC*) (Ren et al., 2017; Zhang et al., 2023; Lu et al., 2023) are taken as explanatory variables to characterize the natural environment from above two perspectives.

Economic Development. The relationship between economic development and farmers' incomes is dynamic and influenced by a multitude of factors. The Per capita GDP (*PGDP*) is the most proximate indicator of economic growth, and higher per capita GDP typically correlates with more advanced technology, improved access to resources, and market integration, directly or indirectly boosting farmers' incomes. (Liu et al., 2020; Yao and Jiang, 2021; Fan et al., 2022; Montalvo and Ravallion, 2009). A group of researchers has asserted that regional industrial structures represents the stage of economic development encountered in a given region (Tang et al., 2022; Liu et al., 2021), significantly influence rural income; however, consensus on this matter remains elusive. We utilize the proportion of the primary industry in GDP as an indicator of industrial structure (*IS*) to test its potential impact on income of Ganzi's farmer. Since 2014 to 2022, this variable declined from 24.67 per cent to 17.85 per cent at prefectural level, which is much higher than that at both the Sichuan provincial and national levels. Additionally, the level of financial development (*FD*) is believed to positively affect farmers' income (Wang et al., 2023; Liu et al., 2021; Lian et al., 2023), therefore, we include it as an explanatory variable and expect an improvement in financial development would likewise to increase the farmers' income in Ganzi.

Social Progress. We choose the urbanization (Yao and Jiang, 2021; Zheng et al., 2015; Yang et al., 2023), employment (Yang et al., 2023; Lian et al., 2023), and tourism development (Luo et al., 2023; Yuan et al., 2023) as indicators of social progress, represented by the urbanization rate (*UR*), rural employment rate (*RE*), and tourist ratio (*TD*). These three variables have been shown in numerous studies to reduce farmers' poverty, enhance their skills, and diversify income sources. Especially tourism development for relatively poor areas as playing a large positive role in poverty alleviation and balanced urban-rural development. We therefore predict that the sign of their coefficients would be positive, indicating that social progress can significantly promote an increase in farmers' incomes.

Rural Supporting. Rural Supporting significantly influences farmers' incomes worldwide, which measured as the agriculture investment in fixed asset (*IFA*) (Yang et

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al., 2023, 2022; Bhuiyan et al., 2022) and financial supporting level (*FS*) (Wang et al., 2022; Chen et al., 2023) in this study. Investments in rural areas can stabilize and boost farmers' incomes with increasing agricultural productivity via rural infrastructure development and mechanization. The fiscal expenditure of agriculture, forestry, and water conservancy not only directly increase the natural and physical capital of farmers in poor areas, but also improve productivity and environmental sustainability thereby reducing losses caused by disasters. We suspect that in relatively poor areas like Ganzi, farmers' income is more affected by the rural supporting level than that in relatively affluent areas.

The labels, definitions and measurements of these variables are shown in *Table 1*.

Table 1. *Description of variables*

Variable types	Dimensionalities	Variables	Labels	Definitions and measurements
Explained	Income level	Absolute Income Level	*AIL*	Logarithm of the per capita disposable income of farmers
Variables		Relative Income Level	*RIL*	The farmers' per capita disposable income of counties to that of Sichuan Province
Explanatory variables	Natural Environment	Agricultural Resources	*AR*	The interaction term between the normalized difference vegetation index (NDVI) and the per capita agricultural land area
		Traffic Convenience	*TC*	The interaction term between the reciprocal of relief degree of land surface and the road density (road length per km^2)
	Economic	Per Capita GDP	*PGDP*	Logarithm of the gross regional product divided by the population
	Development	Industrial Structure	*IS*	The proportion of the primary industry in gross regional production
		Financial Development	*FD*	Ratio of deposits and loans of financial institutions to the gross regional product
	Social	Urbanization Rate	*UR*	The proportion of a population living in urban areas compared to the total population
	Progress	Rural Employment	*RE*	Ratio of rural employed persons to the total rural population
		Tourism Development	*TD*	Ratio of tourists to the year-end resident population
	Rural Supporting	Investment in Fixed Assets	*IFA*	Logarithm of the agriculture, forestry, animal husbandry and fishery investment in fixed assets divided by the rural population
		Financial Support	*FS*	Logarithm of the expenditure of agriculture, forestry, and water conservancy divided by the rural population

Model setting

The panel regression model comprises three types: the Pooled OLS model, Fixed effects model (FE model), and Random effects model (RE model). Selecting the appropriate model depends on the characteristics of the variables and the specific research objectives.

To examine the relationship between farmers' incomes and the dependent variables across counties in Ganzi, a two-way fixed effects model was designed, which has the ability to account for the unique influences attributed to individuals and years changes, and to control for unobservable heterogeneity. The specific model settings are articulated as follows:

$$\begin{aligned} Income_{it} = {} & \alpha_0 + \beta_1 AR_{it} + \beta_2 TC_{it} + \beta_3 PGDP_{it} + \beta_4 IS_{it} + \beta_5 FD_{it} + \beta_6 UR_{it} \\ & + \beta_7 RE_{it} + \beta_8 TD_{it} + \beta_9 IFA_{it} + \beta_{10} FS_{it} + \delta_i + \gamma_t + \varepsilon_{it} \end{aligned} \quad \text{(Eq.6)}$$

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In *Equation 6*, i and t stand for county and year, respectively. $\beta_1 \sim \beta_{10}$ portray the coefficients of explanatory variables. α_0 is the intercept. δ_i and γ_t signify individual and time fixed effects, respectively. ε_{it} represents the error term.

Data sources

The research sample comprises 18 counties in Ganzi from 2014 to 2022. Data of disposable income of rural residents, economic development, social progress, and rural supporting dimensionalities are mainly taken from the *Ganzi Statistical Yearbook (2015-2023)*, supplemented and corroborated by the *Sichuan Statistical Yearbook* and the *China statistical Yearbook (County-level) (2015-2023)*. In natural environment dimensionality, the normalized difference vegetation index (NDVI) was derived from MODIS13A3 dataset produced by NASA (https://search.earthdata.nasa.gov/search), and the Relief Degree of land Surface data was sourced from Global Change Research Data Publishing & Repository (https://www.geodoi.ac.cn/) (You et al., 2018). The above data were cropped and calculated using the Ganzi administrative division data (https://cloudcenter.tianditu.gov.cn/administrativeDivision/) to obtain the values for each county.

Spatiotemporal dynamics of farmers' income

Trend of farmers' income of Ganzi and comparison with that of Sichuan Province and China

Figure 2 illustrates the changes in farmers' income of Ganzi Prefecture since 2014, considering both absolute values and relative levels. Following the implementation of the targeted poverty alleviation strategy, farmers' income in Ganzi exhibited a rapid growth trend, increasing from 7,341 yuan in 2014 to 16,363 yuan in 2022. This represents an average annual increase of 1,127.69 yuan, with an approximate growth rate of 10.54% (*Fig. 2a*).

The income of farmers of Ganzi experienced a significantly faster growth compared to that of Sichuan Province and China nationwide. In relative income level terms, the farmers' per capita relative income has increased from 78.5 to 87.6 percent of Sichuan's level, and from 69.9 to 81.3 percent of nationwide level (*Fig. 2b*), thereby narrowing the income inequality during 2014-2022 period. Furthermore, The *CV* in farmers' income between Ganzi & Sichuan, and Ganzi & China has consistently decreased and β-convergence is significant (*Table 2*), again confirming that the relative income gap has been steadily narrowing, and this gap may continue to decrease in the future.

It is noteworthy that, unlike the period before 2020 with a promising growth trajectory, the growth rates in 2021 and 2022 were comparable to or even slightly lower than those of Sichuan and the national average, which resulted in here was no increase in the relative income level of Ganzi's farmers during these two years, and halting the convergence of income gaps. This stagnation is consistent with the changes in farmers' incomes in many other relatively poor areas, primarily due to the famers' limited income sources effected by the COVID-19 pandemic, such as temporary closure of homestays and agritainment, overstocking and unsalable agricultural products, and reduction of opportunities for migrant workers (Huang, 2020; Li et al., 2021; Sinutok et al., 2021). In 2023, the famers' income growth of Ganzi once again surpassed that of

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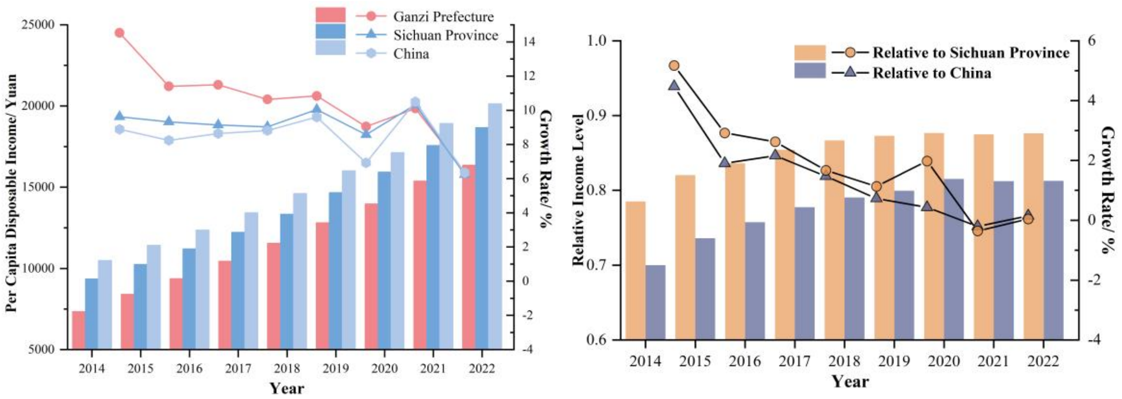
Sichuan and the national level, however, Ganzi still have a long way to go to catch up to and converge to the levels of relatively rich areas.



(a) (b)

Figure 2. *Chronological variation of farmers' absolute and relative income of Ganzi during 2014-2022. (a) Absolute income and its growth. (b) Relative income level and its growth*

Table 2. *Test results of α-convergence and absolute β-convergence for the farmers' income*

	α Convergence (*CV*)									**β Convergence (θ)**
Year	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2014-2022**
Ganzi & Sichuan	0.0189	0.0153	0.0137	0.0119	0.0107	0.0101	0.0097	0.0097	0.0096	0.0080***
Ganzi & China	0.0278	0.0236	0.0211	0.0190	0.0175	0.0165	0.0150	0.0151	0.0149	0.0079***

Spatiotemporal pattern and regional disparity evolution of farmers' income

Figure 3 maps the per capita income of farmers in each county-level unit of Ganzi to demonstrate the farmers' absolute income spatial heterogeneities and its evolutions. Taking 2014, 2018, and 2022 as the time cross-section, and using the method of natural breaks classification, the 18 counties are discretized into five groups according to the famers' absolute income: the high-income club, the slight-high-income club, the medium-income club, the slight-low-income club, and the low-income club. The regional disparity of farmers' income across counties in Ganzi is evident, ranking as the eastern > the southern > the northern counties. In the east-west direction, the eastern counties of Kangding, Jiulong, and Danba have consistently been high-income areas, while Batang and Baiyu in the west have consistently been medium-income counties. In the north-south direction, the income pattern in the south is stable, with Daocheng, Xiangcheng and Derong always being slight-high-income, medium-income and slight-low-income counties, respectively. The pattern changes in the central and northern regions are more complex. Specifically, in 2014, there were six low-income counties, accounting for 33 per cent of the total number of counties in Ganzi, namely Shiqu, Dege, Seda, Luhuo, Xinlong and Litang. By 2018, Xinlong was upgraded to a slight-low-income county, reducing the number of low-income counties to five. By 2022, Dege, Seda, and Litang were upgraded to slight-low-income counties, leaving only Shiqu and Luhuo as low-income counties, accounting for just 11.11 percent of the total number of counties. These indicate a narrowing of the income regional disparity.

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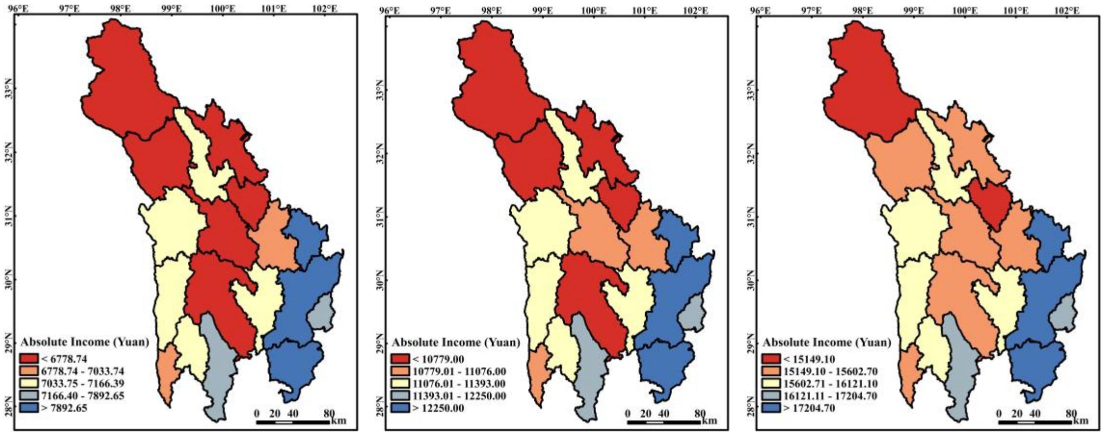

(a) 2014 (b) 2018 (c) 2022

Figure 3. *The spatial pattern of farmers' absolute income in Ganzi*

The kernel density distribution map (*Fig. 4*) illustrates the dynamic evolution of the relative income levels (in comparison with Sichuan Province) of farmers in counties of Ganzi. From 2014 to 2022, estimation curve shows a bimodal "M"-shaped distribution, characterized by one primary and one secondary peak. The continuous rise in the height of the primary peak suggests that despite some spatial polarization, there is a trend towards income equilibrium. Additionally, the kernel density curve keeps shifting to the right, especially in the rightward shift of the primary peak from 0.70~0.75 to 0.80~0.85, and the rightward shift of the secondary peak from 0.90~0.95 to 1.00~1.05. These indicate a continuous increase in the relative income levels of farmers in Ganzi.

Combining the spatiotemporal dynamics of farmers' absolute and relative income, it can be observed that the income of farmers in Ganzi has steadily increased and spatial disparities have gradually decreased, indicating an improvement of income equality.

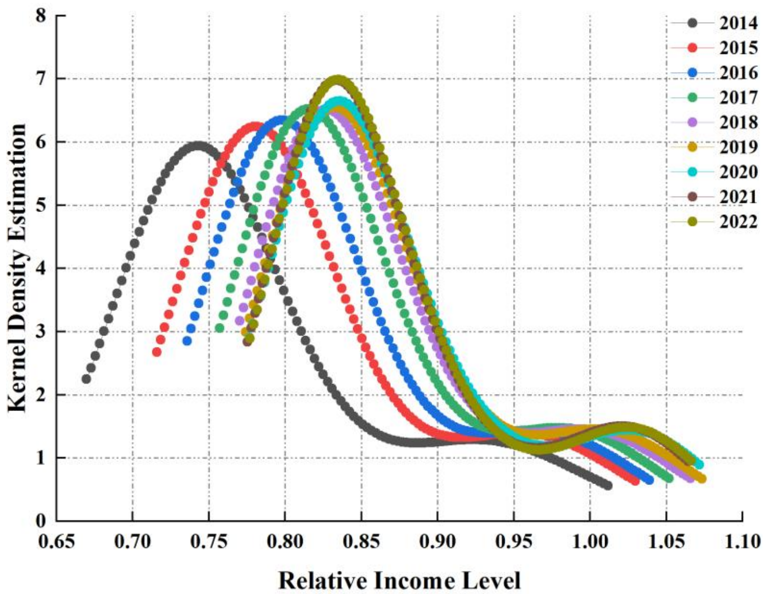

Figure 4. *Kernel density distribution map of farmers' relative income level in Ganzi*

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Natural-socio-economic Factors affecting farmers' income and their mechanisms

Benchmark regression results

Before conducting the formal panel regression analysis, several assessments were performed as follows: Initially, the correlations test for each explanatory variable was conducted, and the Person correlation coefficient matrix shown in *Table 3*. The absolute values of the correlation coefficients are all below 0.7, with most being below 0.5, indicating the absence of strong correlations between the variables. Furthermore, we employed the Variance Inflation Factor (VIF) to check for multicollinearity among variables, and the results show that the VIF re less than 10, and most of them are less than 5 (*Table 4*), suggesting that there are no significant concerns regarding multicollinearity. Subsequently, we performed a descriptive statistical analysis of the variables. As presented in *Table 5,* the median and mean values are closely aligned, and the absence of significant skewness underscores a high degree of concentration and stability within the dataset. These ensure the validity and accuracy of the empirical results.

Table 3. *Person correlation coefficient matrix of explanatory variables*

Variables	*AR*	*TC*	*PGDP*	*IS*	*FD*	*UR*	*RE*	*TD*	*IFA*	*FS*
AR	1									
TC	-0.677	1								
PGDP	-0.081	0.063	1							
IS	-0.204	0.176	0.666	1						
FD	-0.287	0.269	0.327	0.377	1					
UR	-0.369	0.278	0.590	0.553	0.606	1				
RE	-0.286	0.298	0.005	-0.024	0.041	0.168	1			
TD	0.033	0.117	0.555	0.506	0.412	0.445	0.141	1		
IFA	0.074	0.113	0.453	0.270	0.099	0.295	0.140	0.458	1	
FS	0.154	0.101	0.477	0.366	-0.115	0.236	0.068	0.366	0.521	1

Table 4. *Variance Inflation Factor (VIF) test results*

Variables	VIF	Tolerance	Variables	VIF	Tolerance
AR	2.602	0.384	*UR*	2.566	0.39
TC	2.285	0.438	*RE*	1.222	0.819
PGDP	6.057	0.165	*TD*	1.939	0.516
IS	4.961	0.202	*IFA*	1.760	0.568
FD	2.132	0.469	*FS*	2.000	0.500

Column (1) of *Table 6* reports the baseline regression results with the absolute income level (*AIL*) of farmers as the explanatory variable. Our analysis reveals that, in terms of Economic Development, there is a positive effect of *PGDP* on farmers' income and significant at the 0.001 level. specifically, a 1% increase in the *PGDP* corresponds to a 0.683% increase in the farmers' income, consistent with our expectation. Higher GDP per capita generally signifies a higher economic development, which can translate into increased farmers' incomes through several mechanisms, especially in transforming agricultural productivity and livelihood. At the same time, the economic development

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DOI: http://dx.doi.org/10.15666/aeer/2303_38913915

mode matters. Some studies have identified that economic growth in agriculture is much more effective in reducing poverty than growth in the non-agricultural sector (IFAD, 2011; Montalvo and Ravallion, 2009). However, the empirical result reveals a negative correlation between the proportion of agriculture in GDP and farmers' income. Although this correlation is not statistically significant, it suggests that in Ganzi, farmers' income growth are no longer primarily derived from traditional agriculture and animal husbandry. Additionally, the results indicate that financial development (*FD*) is a contributor for income growth. The coefficient is 0.057, and significant at the 0.001 level, suggesting that for every 1% increase in financial development, farmers' income increases by 0.057%, which is consistent with the findings of Liu et al. (2021) and Lian et al. (2023). This positive effect is through ways such as increasing access to formal credit facilities and affordable loans, and stimulating entrepreneurship, thereby enhancing agricultural productivity and enabling farmers to engage in non-farm activities with reducing cost of borrowing.

Table 5. *Descriptive statistics of variables*

Variables	N	Mean	Std. Dev	Median	Min	Max
AIL	162	9.331	0.274	9.340	8.784	9.878
RIL	162	0.849	0.080	0.826	0.699	1.051
AR	162	10.613	3.638	10.299	1.793	17.232
TC	162	0.048	0.0200	0.041	0.016	0.134
PGDP	162	10.207	0.475	10.196	8.960	11.450
IS	162	0.750	0.100	0.753	0.398	0.952
FD	162	2.494	0.897	2.243	1.185	5.434
UR	162	0.265	0.095	0.255	0.118	0.555
RE	162	0.570	0.041	0.572	0.443	0.660
TD	162	20.256	22.377	12.637	0.730	133.622
IFA	162	7.388	1.058	7.542	3.192	9.384
FS	162	9.047	0.506	9.119	7.308	10.112

Table 6. *Regression results of the benchmark model and robustness tests*

Variables	Model 1: *AIL*		Model 2: *RIL*		Model 3: *AIL*	
AR	0.004	(0.442)	-0.001	(-0.680)	0.003	(0.372)
TC	0.625	(0.811)	0.466***	(3.657)	0.744	(0.929)
PGDP	0.683***	(12.145)	0.034***	(3.672)	0.694***	(11.771)
IS	-0.143	(-0.753)	-0.139	(-0.462)	-0.216	(-1.056)
FD	0.057***	(3.037)	0.005	(1.603)	0.057***	(2.867)
UR	1.731***	(5.562)	0.241***	(4.685)	1.753***	(5.341)
RE	0.083	(0.326)	0.010	(0.237)	0.063	(0.235)
TD	0.001	(0.171)	0.001**	(1.981)	0.001	(0.472)
IFA	0.027***	(3.614)	0.001	(0.462)	0.024***	(2.964)
FS	0.044**	(2.021)	0.014***	(3.760)	0.049**	(2.109)
Time Fixed Effect	YES		YES		YES	
County Fixed Effect	YES		YES		YES	
N	162		162		153	
R^2	0.069		0.247		0.054	

***, **, and * represent the 1%, 5%, and 10% significance levels, respectively. The numbers in the parentheses are the t-statistics

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On the social progress aspect, Urbanization rate, rural employment, and tourism development have demonstrable positive effects on farmers' incomes, aligning with our expectations. The urbanization rate (*UR*), exhibiting a coefficient of 1.731—the highest among the explanatory variables, and significant at the 0.001 level, suggesting that a 1% increase in urbanization is associated with a 1.731% rise in farmers' income. Although the coefficients for rural employment (*RE*) (0.083) and tourism development (*TD*) (0.001) were not statistically significant, the three have a synergistic effect on farm income growth. Whether in China or in other developing countries (Yang et al., 2023; Arouri et al., 2017), urbanization often facilitates rural-urban labor migration, which, in turn, raises rural employment rates. These migrants frequently send remittances back to their families, bolstering rural households' incomes. Urbanization has also improved the rural-urban communication networks, particularly in regions with historically low urbanization rates, fostering a more integration of urban and rural industries, which in Ganzi has been reflected in the rise of rural tourism. The tourism development created employment opportunities in service industry, supported the operation of homestays and agritainments, and enhanced the market for local agricultural products, thereby diversifying and expanding income sources (Yuan et al., 2023; Wang et al., 2022).

Many studies have shown that the income of farmers especially those living in remote areas and smallholders, are more dependent on the natural environment than the income of people living in urban areas (Morton, 2007; Barbier and Hochard, 2018). The NDVI reflects the growth of crops and other vegetation, and the agricultural land area quantifies land resource input. The estimated coefficient of this interaction term is positive, but it is not statistically significant. Undoubtedly, greater agricultural resources (*AR*) generally correspond to higher agricultural yields and incomes, but they may also foster over-reliance on natural resources, reducing time and money investments in other activities, reducing incentives to develop other livelihood skills, and diminishing resilience to agricultural shocks, thereby largely offsets the positive impacts of agricultural resources (Barbier and Hochard, 2016; Horlu, 2024). The estimated coefficient of traffic convenience (*TC*) is positive, because the relief degree of land surface impacts farmers' income through infrastructure improvements such as roads, which are generally higher in regions with flat terrain and high road density (Zhang et al., 2023; Lu et al.,2023). However, this positive effect did not pass the test of significance in this study, probably due to there is not much difference in relief degree of land surface between the counties of Ganzi, and despite accelerated road construction, the increase in road density remains modest given the vast area.

The pivotal role of agriculture in China and its natural vulnerability determine the importance of support for rural, agriculture, and farmers. The estimated result reveals that both investment in fixed assets (*IFA*) and financial support (*FS*) are statistically significantly positively correlated with farmers' income ($p < 0.01$ and $p < 0.05$). A 1% increase in *IFA* and *FS* leads to a 0.027% and 0.044% increase in farmers' income, respectively. On a global scale, agricultural investment is argued is integral to the agricultural development strategies of numerous countries (Bhuiyan et al., 2022; Czubak et al., 2021). In Ganzi, farmers' limited capacity for self-development and investment underscores the critical need for external investment. Agricultural investments drive significant advancements in mechanization, agricultural technology R&D, and rural economies of scale. Agricultural financial expenditure also serves as a crucial funding source for rural development, advancing agricultural progress and improving livelihoods (Wang et al., 2022; Chen et al., 2023). Especially since the

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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Targeted Poverty Reduction Strategy, the proportion of fiscal expenditure allocated to agriculture has steadily increased, with more precise and effective distribution and usage. In Ganzi, these efforts have markedly enhanced the material conditions of production such as farmland and water conservancy, facilitating the transform from traditional farming and animal husbandry to modern agricultural practices, and boosting agricultural returns and farmers' net income. Amid sudden challenges, such as the COVID-19 pandemic, expanding agricultural fiscal expenditure has proven essential for stabilizing farmers' income.

Robustness test results

In order to reinforce the credibility of this study, the robustness testing is a critical step to ensure the reliability of the benchmark regression results, and conducted in the following two aspects.

Substitution of explained variables

To assess the potential impact of explained variable identification methods on estimation results, we re-estimated the regression model using relative income level (in comparison with Sichuan Province) as a proxy for absolute income level to measure farmers' income. The results of model 2, detailed in Column 2 of *Table 6*, reveal that apart from *AR* – which failed the significance test in both the benchmark regression and the robustness test – the signs of the remaining explanatory variables are consistent with those observed in the benchmark regression model. While minor variations in significance levels are present, the overall alignment with benchmark results underscores the robustness of the findings.

Change of research samples

Given the marked differences between Kangding, the capital of Ganzi, and other counties in socio-economic development and policy orientation – factors that could potentially bias the results, we excluded observations of Kangding City. A re-estimation was conducted using the subsamples comprising the remaining 17 counties, with the results detailed in Column 3 of *Table 6*. The subsample regression yielded coefficient signs and significance levels are identical to those of the benchmark model, suggesting that the regression results are not influenced by the exclusion of Kangding and further affirming the robustness of our findings.

Discussion on the differences of farmers' income influencing mechanisms

Differences in the influences of factors on different categories of income

In China, disposable income of residents is divided into four categories: Income from wages and salaries (*WI*), Net business income (*BI*), Net income from properties (*PI*) and Net income from transfer (*TI*) according to its source. To improve the accuracy and depth of this study, we further tested the impact of explanatory variables on different categories of income levels, with the objective of discussing the variability of impacts of these variables across income categories.

Table 7 demonstrates that, on the economic development, *PGDP* exerts a significant positive impact on all four income categories, indicating that economic growth has an

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DOI: http://dx.doi.org/10.15666/aeer/2303_38913915

all-encompassing effect on enhancing farmers' income. The proportion of the primary industry in GDP (*IS*) is negatively correlated with *WI*, *BI*, and *TI*; particularly with a statistically significant coefficient of -0.507 for wages and salaries (*WI*). The decrease in the proportion of primary industry corresponds to the increase in the share of secondary and tertiary industry, significantly bolstering the non-agricultural sectors in the rural economy, and most evident in the change in *WI* (Tang et al., 2022). Financial development is positively correlated with both *WI* and net business income (*BI*), in line with findings from previous studies (Lian et al., 2023).

In terms of social progress, similar to the benchmark regression results of factors influencing total income, the positive associations between urbanization and all four categories of income pass the significance test, while the effects of rural employment and tourism development do not achieve statistical significance.

Regarding the natural environment, the coefficients of the agricultural resources and traffic convenience on the four income categories have different signs and none of them passes the test of significance. These, once again, confirmed the bidirectionality of agricultural resources on farmers' income, as argued before, particularly in its negative coefficient on *WI*; and, the positive coefficient on traffic convenience on *BI*, suggesting that there is a favorable effect on farmers' business activities.

For rural support, agriculture investment in fixed assets and fiscal expenditure positively influence all income categories, with the most pronounced effects on business and transfer income. These effects are attributed to investment in fixed assets and fiscal expenditure on agriculture creating better conditions for farming and animal husbandry, as well as fiscal expenditure playing a moderating role in the redistribution of income.

The discussion across the four income categories indicates that estimates for *BI* most closely align with the benchmark results, underscoring its consistent role as the primary contributor to farmers' income, comprising over 60% of the total. The least significant influence is found for *PI*, likely due to two main reasons: first, the property income of farmers in Ganzi is markedly low, with a large gap between it and the other three categories of income; second, *PI* is inherently derivative, relying on the coordinated development of multiple income sources, and its acquisition mechanism differs substantially from other income.

Table 7. *Estimation results of influencing factors on different categories of income*

Variables	Model 4: *WI*		Model 5: *BI*		Model 6: *PI*		Model 7: *TI*	
AR	-0.015	(-1.017)	0.008	(0.939)	-0.019	(-0.290)	0.002	(0.124)
TC	0.141	(0.100)	1.080	(1.307)	-1.029	(-1.630)	-0.223	(-0.169)
PGDP	0.909***	(8.794)	0.625***	(10.364)	1.633***	(3.549)	0.673***	(6.970)
IS	-0.507*	(-1.660)	-0.060	(-0.296)	0.300	(0.193)	-0.294	(-0.902)
FD	0.091***	(2.639)	0.052***	(2.591)	-0.093	(-0.604)	0.019	(0.576)
UR	2.772***	(4.843)	1.166***	(3.494)	3.755**	(2.791)	1.877***	(3.513)
RE	0.564	(1.208)	0.256	(0.942)	5.795	(1.474)	0.157	(0.360)
TD	0.001	(0.072)	0.002	(0.699)	0.006	(1.272)	-0.001	(-0.997)
IFA	0.022	(1.569)	0.030***	(3.664)	0.013	(0.206)	0.033***	(2.595)
FS	0.004	(0.103)	0.052**	(2.195)	0.052	(0.289)	0.076**	(2.007)
Time Fixed Effect	YES		YES		YES		YES	
County Fixed Effect	YES		YES		YES		YES	
N	162		162		162		162	
R^2	0.125		0.109		0.102		0.066	

***, **, and * represent the 1%, 5%, and 10% significance levels, respectively. The numbers in the parentheses are the t-statistics

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2303_38913915

Differences in the influences of factors in different categories of county

The vast area of Ganzi and the uneven development of its natural-socioeconomic systems across counties suggest that the determinants of farmers' income may vary significantly by region. Therefore, we classify the 18 counties into two groups based on official criteria for remote and challenging areas: Category I, comprising 11 relatively less challenging counties; and Category II, consisting of 7 more challenging counties (Shiqu, Seda, Litang, Yajiang, Ganzixian, Daocheng, and Derong) for regional heterogeneity analysis, and the results of the regression are shown in *Table 8*.

Table 8. *Estimation results of influencing factors in different categories of county*

Variables	Model 8		Model 9	
AR	0.018***	(2.917)	-0.022***	(-3.535)
TC	1.580***	(3.109)	0.178	(0.091)
PGDP	0.845***	(11.720)	0.470***	(4.721)
IS	-0.150	(-0.511)	-0.044	(-0.206)
FD	0.180***	(6.556)	-0.035	(-0.809)
UR	1.547***	(4.168)	2.311***	(3.808)
RE	0.542**	(2.314)	-0.826	(-0.940)
TD	0.001	(1.092)	-0.001	(-0.993)
IFA	0.017*	(1.841)	0.033***	(3.405)
FS	0.009	(0.390)	0.080*	(1.803)
Time Fixed Effect	YES		YES	
County Fixed Effect	YES		YES	
N	99		63	
R^2	0.026		0.032	

***, **, and * represent the 1%, 5%, and 10% significance levels, respectively. The numbers in the parentheses are the t-statistics

The results for Model 8 and Model 9 correspond to samples category I and category II counties, respectively. It can be seen that GDP per capita, urbanization rate, and agriculture investment in fixed assets are significantly and positively correlated with farmers' income in both categories. Traffic convenience and agriculture financial expenditure also have a positive influence on income of rural residents, with the impact of traffic convenience being more pronounced in "relatively less challenging counties" while agriculture financial expenditure has a greater effect in "more challenging counties", which means that the stimulating effect of increased financial support is more effective in enhancing farmers' income in less developed regions. The coefficient of agricultural resources is 0.018 in model 8 and -0.022 in model 9, both significant at the 0.01 level, which is attributed to the different mechanisms by which agricultural resources affect farmers' income in different regions. In "relatively less challenging counties", agricultural resources work synergistically with other socioeconomic factors, whereas in "more challenging areas", inefficiencies in resource utilization may lead to a "resource curse" effect that inhibits farmers' income growth and rural development.

Differences between this study with previous studies

Our study supports that farmers' income in historically impoverished areas, such as Ganzi Prefecture, are growing faster, and that the relative gap with the national average

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is narrowing, which is consistent with previous studies (Liu et al., 2024; Ren et al., 2017; Wang et al., 2022). Benefiting from a further disaggregation of farmers' disposable income, we find that, in Ganzi, the income from properties of farmers is a marked "weakness". This is a detailed though not by any means unimportant finding, which is potentially helpful to the local government in formulating targeted follow-up rural support policies.

The influences of economic and social factors on farmers' income in Ganzi remain largely consistent with our expectations and previous researches. However, we observed that the income-boosting effect on farmers of urbanization is more pronounced in Ganzi than that of other factors, which might be explained by the fact that urbanization has a short-term and more rapid income-uplifting effect on farmers in relatively poorer areas with a thinner base of socio-economic development and employment opportunities, not only in terms of its direct effect, but also through the intermediary effect which that contribute to the overall progress of both city, town, and rural (Yao and Jiang, 2021; Yang et al., 2023).

As for the natural environment, the large agricultural resources in Ganzi has not been effectively converted into livelihood resources for farmers and herders, and its contribution to the income is limited, and the "resource curse" effect even occurs. In China, this effect has been identified for water resources in agriculture production (Liang et al., 2019; Zhao and Jia, 2016), and this study reveals that the "resource curse" also appears to occur for ecological and land resources. Globally, the detrimental impact of the resource curse on rural development occurs not only in relatively poor areas but also in developed countries (He and Chen, 2024), impeding the sustainable growth of farmers' income.

Conclusions and implications

Main conclusions

Farmers' income growth was always a critical area of academic inquiry. Here, we examine Ganzi Prefecture in Sichuan Province, a representative of China's relatively impoverished regions, to analyze the dynamic evolution of farmers' income. We assess the impacts of natural environment, socio-economic development, and support policies; and discuss the heterogeneity of these influences. The following salient conclusions were drawn:

First, higher annual growth rates have driven a convergence in the income gap between farmers in Ganzi and the national average. Simultaneously, spatial income disparities within Ganzi have diminished. The *BI* is the principal contributor to total income growth, whereas *PI* continues to represent a major constraint.

Second, regarding natural environment, agricultural resources have influences that align with the "resource curse" hypothesis, limiting income growth in more challenging counties by suppressing *WI* expansion. In contrast, the benefits of enhanced traffic convenience are more pronounced in less challenging regions.

Third, on socio-economic development, increasing *PGDP* and urbanization rate were the most effective driver of growing farmers' total and dis-category incomes. The industrial upgrading correlated with *WI* growth, and financial development was corresponded to increases in both *WI* and *BI*.

Fourth, concerning rural supporting policy, the investment in fixed assets and financial support significantly enhance income growth, notably in *BI* and total income *TI*. These effects are greater in the more challenging counties.

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Policy implications

From the conclusions drawn in this study, we propose several policy suggestions that may not only help to address relative poverty, but also advance rural revitalization and rural sustainable development in China's post-poverty era:

(1) Accelerate the construction of rural transportation and communication infrastructures, particularly in remote pastoral regions. Facilitate the flow of capital, technology and information into villages to increase employment and entrepreneurial opportunities for farmers and to expand the potential for income growth.

(2) Enhance the rural financial services and reduce financial exclusion. Provide affordable credit, financing guarantee, and agricultural insurance to address he funding problems of farmers' business operations, strengthen market competitiveness and risk-resistance, and promote sustainable income growth.

(3) Modernize the rural industrial structure. Cultivate new occupations such as agro-processing and rural tourism, coupled with e-commerce and skill training, thus achieving the synergistic effect of improving natural resource utilization efficiency and diversifying farmers' income.

(4) Guide counties to formulate rural development strategies in accordance with their comparative advantages. However, whether in less or more challenging counties, agricultural investment and rural supporting should at least be maintained at an undiminished level in the post-poverty era.

(5) Last but by no means least, relatively poor areas often overlap with ecologically vulnerable zones, and it is essential to foster a positive interaction between farmers' income growth and eco-environmental protection. Measures such as ecological compensation, relocation, and solar photovoltaic poverty alleviation should be implemented to achieve this balance.

Limitations of this study and prospects

There are several limitations of this study that should be acknowledged.

(1) This study identifies income as the key metric for assessing farmers' livelihoods, but a comprehensive understanding requires incorporating additional indicators, such as consumption expenditure. The lack of county-level Consumer Price Indices (CPI) limits adjustment for income inflation, potentially risking over- or under-estimating actual income changes. And, important factors influencing farmers' income like agricultural technology and educational attainment were not included in the analysis and warrant further research.

(2) This study examines changes in farmers' income at the county level and we have also been reminded extending comparative analyzes of urban-rural disparities to determine whether rural poverty has declined more faster than urban poverty. Furthermore, micro-level household surveys aiming provide insights into family and individual strategies for vulnerable populations should be paying special attention in the future.

(3) We propose policy suggestions to support farmers' income sustainable growth for a China's relatively impoverished area –Ganzi. Future research should broaden the geographical scope to examine the regional heterogeneity of the impact of the natural-socio-economic environment on farmers' income. Furthermore, assessing the applicability of these proposed anti-poverty measures to Chinese diverse regions and even different countries is critical for informing effective global strategies to reduce rural poverty.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2303_38913915

Acknowledgements. This study was supported by the Strategic Priority Research Program of Chinese Academy of Sciences [grant number: XDA23060704].

Conflict of Interest. The authors have no competing interests to declare that are relevant to the content of this article.

Data availability. The data presented in this study are available on request from the corresponding authors.

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