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Digital agriculture's equalization effect in the Yangtze River economic belt: An empirical study using difference-in-difference analysis

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Abstract: To achieve common prosperity in China, digital agricultural transformation is increasingly important in narrowing the income gap and promoting rural revitalization. Based on a quasi-natural experiment involving digital agriculture pilot projects in the Yangtze River Economic Belt, this paper systematically evaluates the impact of digital agriculture policies on common prosperity using data from the China Family Panel Studies (CFPS) from 2012 to 2022, employing a difference-in-difference (DID) approach. The study finds that digital agriculture policies significantly reduce residents' subjective perceptions of income inequality, with a particularly significant effect in the central and western regions and among households engaged in agriculture. Mechanism analysis suggests that the policies form a positive chain of pathways that mitigate income inequality by improving the modernization of agricultural production tools, optimizing resource allocation efficiency, and increasing farmers' income. Heterogeneity analysis reveals significant heterogeneity in policy effects across regions and population groups. The marginal utility of the policies is higher in the central and western regions due to their weak agricultural foundations, while the incremental effect is relatively limited in the eastern region due to its advanced agricultural modernization. This study provides empirical evidence for digital agriculture's contribution to common prosperity and offers a reference for policymakers to optimize digital agriculture promotion strategies and promote balanced regional development.

Keywords: *Agricultural digital transformation, Common prosperity, DID model, Regional heterogeneity, Yangtze River Economic Belt.*

1. Introduction

Driven by China's rural revitalization strategy and achieving common prosperity, agricultural modernization is a key path to addressing the "three rural issues" and narrowing the urban-rural gap [1]. Agricultural digital transformation, the in-depth application of modern information technology in agriculture, has promoted improvements in agricultural production efficiency and optimized the rural economic structure, but is also considered a key tool for narrowing the urban-rural income gap and achieving common prosperity [2]. In recent years, the Chinese government has attached great importance to agricultural digitalization development, proposing to accelerate the pace of agricultural and rural modernization and promote the widespread application of digital technologies in agriculture, providing important support for achieving rural revitalization and common prosperity.

The Yangtze River Economic Belt, a strategic region for China's economic development, has demonstrated exemplary national significance for its agricultural digital transformation. Spanning the eastern, central, and western economic zones, and encompassing 11 provinces and municipalities, including Jiangsu, Zhejiang, and Sichuan, the region boasts the richest agricultural resources and the highest concentration of agricultural populations. However, significant regional disparities exist in economic development levels and agricultural infrastructure [3, 4]. The upstream regions have a relatively low level of agricultural modernization, the midstream regions are in the process of structural

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adjustment, and the downstream regions have achieved a high degree of technological intensification [5]. Therefore, studying the impact of agricultural digital transformation on common prosperity in the Yangtze River Economic Belt provides empirical support for coordinated regional development and offers insights for optimizing agricultural digitalization policies nationwide.

In recent years, research on agricultural digitalization has steadily increased. Some scholars, taking a technological perspective, explore the application of digital technologies such as the Internet of Things, big data, and artificial intelligence in agricultural production and their impact on improving production efficiency [6-8]. Other studies focus on the impact of digital agriculture on farmers' income and rural economic development [2, 9]. However, the existing literature is deficient in three key areas: First, most studies focus on the economic benefits of digital agriculture, but less on its mechanisms of action in narrowing the wealth gap and promoting common prosperity. Second, empirical analysis of digital agriculture policies' regional adaptability and heterogeneous impact is relatively scarce. Third, the lack of rigorous econometric analysis based on causal identification makes it difficult to assess the "wealth-equalizing" effect of digital agriculture accurately.

This paper uses the digital agriculture pilot project in the Yangtze River Economic Belt as a quasi-natural experiment. It adopts the difference-in-difference (DID) method to systematically analyze the impact of digital agriculture transformation on common prosperity. Based on the China Family Panel Studies (CFPS) data from 2012 to 2022, this paper combines the characteristics of the policy implementation regions to construct a theoretical model and conduct empirical analysis. The research focuses on the following questions:

(1) Has digital agriculture significantly narrowed the gap between the rich and the poor?

(2) How can digital agriculture achieve the "equalization of wealth" effect through improving production efficiency and promoting industrial upgrading?

(3) Is there heterogeneity in the policy effect across regions and household types?

This study makes significant contributions by offering theoretical and practical insights into the role of digital agriculture in advancing common prosperity. First, it provides robust empirical evidence to support the argument that digital agriculture can effectively narrow income disparities and promote inclusive economic growth, addressing critical challenges in rural development. Second, it deepens understanding of how digital transformation impacts agricultural efficiency, resource allocation, and income distribution. These insights enrich the academic discourse on the intersection of digital technology and rural revitalization and have practical implications. The findings serve as a scientific foundation for policymakers to design and refine strategies that optimize digital agriculture initiatives, ensuring their alignment with regional characteristics and development needs. Moreover, by highlighting the heterogeneous effects of digital agriculture across different regions and population groups, this study offers actionable recommendations for fostering balanced regional development and achieving sustainable progress toward common prosperity.

The paper is structured as follows: Section 2 reviews the relevant literature, highlighting key theories and recent research on agricultural digital transformation and its relationship to common prosperity. Section 3 outlines the data sources, variable definitions, and research methodology. Section 4 presents the empirical analysis, examining the impact of digital agriculture through both mechanism and heterogeneity perspectives. Section 5 discusses the findings in detail, while Section 6 concludes with key insights and policy implications.

2. Literature Review

2.1. Digital Agriculture and the Yangtze River Economic Belt

The Yangtze River Economic Belt (YERB) is a core region for China's agricultural modernization and a key strategic area for developing the digital economy. Spanning the three major economic zones of east, central, and west, the region encompasses 11 provinces and municipalities, including Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, Chongqing, Sichuan, Yunnan, and Guizhou. Its unique geographical location and diverse agricultural resources give it a crucial role in the country's

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coordinated regional development strategy. The YERB not only supports over 60% of China's arable land and 50% of its agricultural population, but also contributes over 40% of its agricultural output, making it a crucial area for ensuring China's food security [10].

The regional characteristics of agricultural digital transformation in the Yangtze River Economic Belt exhibit significant gradient differences [3, 4]. With their developed economies and well-developed digital infrastructure, the downstream regions provide superior technological and resource conditions for agricultural digitalization. As major grain-producing areas, the midstream regions have demonstrated a strong demand for agricultural mechanization and informatization during the digital transformation, leveraging digital technologies to optimize agricultural production efficiency and resource allocation. Due to their complex terrain and relatively low economic development, the upstream regions have taken a later start in digital transformation, but they possess significant room for marginal improvement. Regional imbalances in digital infrastructure have become a major bottleneck restricting the development of agricultural digitalization in the upstream regions. However, the midstream and downstream regions have demonstrated a strong leadership role with their significant advantages in technology application and resource integration [11].

The digital transformation of agriculture has demonstrated significant success across the Yangtze River Economic Belt's production, processing, and distribution chains. Digital technologies have driven changes in agricultural production methods, significantly improving agricultural production efficiency and resource utilization through precision and intelligent approaches. In the processing sector, digital empowerment has promoted the extension and upgrading of the agricultural industry chain, driving the green transformation of agriculture and creating high added value [12]. In the distribution sector, information technology has improved the transparency and efficiency of the agricultural product supply chain, optimized resource allocation, and enhanced the competitiveness of agricultural products in domestic and international markets [13]. However, the uneven development of digital infrastructure, low technology penetration, and talent shortages remain significant challenges hindering the digital transformation of agriculture in the Yangtze River Economic Belt. This is particularly evident in upstream areas, where the contradiction between the fragmented management models of smallholder farmers and the difficulty of promoting digital technology is particularly prominent [11, 14].

Overall, the digital transformation of agriculture in the Yangtze River Economic Belt is vital in promoting agricultural modernization, optimizing urban and rural resource allocation, and fostering common prosperity. By tailoring development strategies to local conditions, optimizing digital infrastructure development based on regional characteristics, strengthening technology dissemination and talent development, and improving benefit-sharing mechanisms, we can further unleash the potential of digital agriculture and provide strong support for achieving high-quality development and common prosperity in the Yangtze River Economic Belt.

2.2. Digital Transformation of Agriculture

The digital transformation of agriculture is a crucial path to agricultural modernization. Its core lies in achieving systematic changes in production methods, organizational forms, and business models through integrating information technology and agriculture deeply. Existing research primarily explores the theoretical foundations of agricultural digital transformation from the perspectives of productivity improvement and transformation of production relations.

From the perspective of improving productivity, the foundation of agricultural digital transformation is centered on achieving a significant increase in agricultural production efficiency through technological advancements. In his book "Transforming Traditional Agriculture," Schultz [15] argued that the core of agricultural modernization lies in making a qualitative leap from inefficient to highly efficient production factors. By reshaping traditional production elements such as land, labor, and capital, digital technology can overcome resource limitations and propel agricultural production toward greater precision and intelligence, thereby significantly enhancing overall productivity [16]. This transformation can be understood through Baumol's "unbalanced growth theory," which suggests that

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agriculture, viewed as a traditional “stagnant sector,” can effectively overcome inefficiency through technological innovation [17]. For instance, adopting technologies such as precision irrigation, advanced agricultural machinery, and AI-powered pest and disease identification has allowed agriculture to shift from an experience-based model to a data-driven approach, providing systematic support for improving production efficiency.

From the perspective of changes in production relations, agricultural digital transformation has enhanced productivity and significantly influenced agricultural production relationships. According to Marxist political economy, data emerges as a new factor of production that fosters the deep integration of labor tools and the objects of labor [18]. The essence of agricultural digitalization lies in facilitating the reconfiguration of production factors and the reconstruction of value chains through technological innovation. Dayıoğlu and Turker [19] suggest that agricultural digitalization is experiencing a paradigm shift from a “technology-factor-industry” model to a data-driven “three-chain integration” model, which includes the industrial chain, innovation chain, and supply chain. This transformation optimizes resource allocation efficiency and encourages the expansion of the agricultural industrial chain alongside the upgrading of the value chain.

2.3. Agricultural Digital Transformation and Common Prosperity

Common prosperity is a central goal of China’s modernization, focusing on achieving shared and inclusive development outcomes. In the agricultural sector, digital transformation plays a crucial role in this modernization process and is closely tied to the goal of common prosperity. By enhancing agricultural production efficiency, optimizing resource allocation, and promoting integrated urban and rural development, digital transformation in agriculture can significantly reduce the urban-rural gap and provide strong support for realizing common prosperity.

Research indicates that agricultural digitalization is crucial in achieving common prosperity by enhancing production efficiency and increasing farmers’ incomes. Digital technology optimizes agricultural input structures and improves output efficiency, which leads to higher total factor productivity in agriculture. This, in turn, increases farmers’ incomes and promotes a more balanced allocation of resources between urban and rural areas Ouyang [18]. Liu and Liu [20] further show that advancements in agricultural productivity significantly reduce the income gap between urban and rural areas. Their findings reveal that the Theil index, which measures the urban-rural income disparity, gradually declines as agricultural digitalization progresses. This indicates that digital transformation has a substantial positive impact on achieving common prosperity.

Furthermore, the digital transformation of agriculture, by promoting the integration of the primary, secondary, and tertiary industries in rural areas, further deepens the virtuous cycle of “increased agricultural efficiency, increased farmers’ income, and urban-rural integration.” Digital technology empowers the extension of the agricultural industry chain, optimizes functional expansion paths, significantly increases the added value of agricultural products, and creates numerous non-agricultural employment opportunities [21]. For example, the application of e-commerce models in the digital transformation of agriculture not only integrates the production and marketing of agricultural products but also drives the transfer of rural labor by increasing product value and broadening market reach, thereby overall boosting the vitality of the rural economy and farmers’ income levels.

Agricultural digitalization’s role in promoting common prosperity varies significantly by region. In the Yangtze River Economic Belt, inland regions outperform coastal areas in agricultural modernization. While downstream regions benefit from advanced digital infrastructure, upstream areas, with weaker agricultural foundations, show greater potential for improvement Zhang, et al. [5]. Deng, et al. [22] also highlight that digitalization must reach a critical threshold to narrow the urban-rural income gap, particularly in central and western regions. Thus, pathways for agricultural digital transformation should consider each region’s economic development, agricultural resources, and digital infrastructure.

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Agricultural digitalization has excellent potential for promoting shared prosperity, yet current research has key limitations. There is a lack of studies on how digital policies can improve resource access for vulnerable groups. Additionally, analysis of the links between digitalization, green development, and shared prosperity is inadequate, particularly regarding how digital technologies can enhance agricultural efficiency and sustainability. Lastly, more exploration is needed to integrate international experiences with local practices in China. Specifically, addressing the unique characteristics of the Yangtze River Economic Belt for tailored digital transformation is a significant research gap.

This study examines the Yangtze River Economic Belt, a case study highlighting significant regional differences, to systematically investigate how agricultural digital transformation drives regional agricultural modernization and contributes to shared prosperity. The research analyzes the varied characteristics of digital transformation across different regions, revealing how digital benefits are distributed. Additionally, it explores pathways for the coordinated advancement of digitalization and green development, especially in ecologically fragile and underdeveloped areas. This research aims to provide both theoretical support and practical evidence for the comprehensive promotion of agricultural digitalization and the optimization of related policies.

3. Data and Methods

3.1. Variable Selection

This study analyzes the impact of agricultural digitalization policies on income inequality and shared prosperity, selecting a series of key variables. The explained variable is residents' subjective perception of the income gap. Data are from the China Family Panel Studies (CFPS), with the question asking, "How severe do you think the current income gap is?" Scores range from 0 (not severe) to 10 (very severe), measuring residents' subjective perception of regional income inequality. The income gap perception score reflects objective income disparity and incorporates factors such as a sense of social fairness and life satisfaction, which are important dimensions for measuring shared prosperity. Compared to purely objective income gap indicators, the income gap perception score better reflects the impact of policies on residents' subjective well-being and sense of social fairness.

To enhance the objectivity of this research, this article introduces two alternative indicators. The first is "regional relative income disparity," which objectively reflects regional income disparity by calculating the absolute difference between an individual's income and the regional average. The second is a "comprehensive indicator," which combines standardized measures of life satisfaction with perceived income inequality to create a comprehensive variable that more comprehensively reflects common prosperity. This combined analysis of these three variables allows for a more precise identification of the impact of digital agriculture policies on income inequality.

The core explanatory variable is the digital agriculture policy (DID), defined using the Difference-in-Differences (DID) approach as:

$$DID_{jt} = trial_j \times post_t$$

Here, $trial_j$ indicates whether the region is a pilot area for digital agriculture (assigned a value of 1 for pilot areas and 0 for non-pilot areas), and $post_t$ represents the policy implementation period (assigned a value of 1 for the years 2017 and beyond, and 0 otherwise). This variable is employed to identify the causal effect of digital agriculture policy on income disparity.

In addition, this paper introduces a series of control variables to reduce omitted variable bias. These variables include demographic characteristics (age, gender) and socioeconomic characteristics (urban or rural household registration type, marital status, years of education, health status, and medical insurance coverage). Table 1 shows a description of these variables.

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Table 1.
Variable Descrition.

Type	Variables	Definition
Explained variable	Wealth Gap (Y)	A scale from 0 to 10 indicates a mild gap at 0 and a severe gap at 10.
Explanatory variable	Digital Agriculture (DID)	If the respondent's location is a pilot area where the digital agriculture policy was implemented that year, the value is 1; otherwise, it is 0.
Control variables	Age	Natural logarithm of the respondent's age
	Gender	Male=1; Female=0
	Urban	Agricultural household registration = 1; non-agricultural household registration = 0
	Marriage	Spouse = 1; No spouse or widowed = 0
	Education	Years of education corresponding to the highest degree obtained by the respondents
	Medical insurance	Purchased medical insurance = 1; Not purchased medical insurance = 0
	Health	Unhealthy = 5; Average = 4; Somewhat healthy = 3; Very healthy = 2; Very healthy = 1

3.2. Data Sources

This study uses data from the China Family Panel Studies (CFPS), a comprehensive, nationwide, and continuous social panel survey covering 25 provinces, municipalities, and autonomous regions in mainland China, organized and implemented by the Institute for Social Science Survey (ISSS) at Peking University. CFPS data covers a wide range of information, including household and individual income, expenditure, demographic characteristics, and cognitive perceptions. The data are highly representative and reliable, providing a solid foundation for studying agricultural digitalization policies' economic and social impacts.

To ensure regional relevance, this study selected data from 11 provinces and municipalities within the Yangtze River Economic Belt (Shanghai, Jiangsu, Zhejiang, Anhui, Jiangxi, Hubei, Hunan, Chongqing, Sichuan, Yunnan, and Guizhou). The survey period covered six rounds, spanning 2012, 2014, 2016, 2018, 2020, and 2022. To ensure data integrity and validity, this paper implemented the following processing: first, samples with missing values for core variables were eliminated; second, continuous variables (such as income data) were winsorized with a 1% upper and lower bound to reduce the impact of extreme values on the results; and third, outliers and incomplete data were removed to ensure data quality.

After the above processing, the final sample contains 42,568 individual-year observations, covering a diverse range of regions and demographics within the Yangtze River Economic Belt. By controlling for regional and time fixed effects, this paper aims to use this data to evaluate the impact of digital agriculture policies on income distribution and common prosperity.

Table 2.
Descriptive statistical analysis.

Variables	Obs	Mean	Std.	Min.	Max.
Wealth gap	42568	6.8026	2.3859	0.0000	10.0000
DID	42568	0.0173	0.1304	0.0000	1.0000
Age	42568	3.7763	0.4053	2.7726	4.4067
Gender	42568	0.4975	0.5000	0.0000	1.0000
Urban	42568	0.6778	0.4673	0.0000	1.0000
Marriage	42568	0.7946	0.4040	0.0000	1.0000
Edu	42568	1.7507	1.5957	0.0000	9.0000
Medsure	42568	0.9029	0.2962	0.0000	1.0000
Health	42568	3.1019	1.1758	1.0000	5.0000

Table 2 reports the descriptive statistics of the variables used in the empirical tests. The sample consists of independent individuals aged 16 and above. The treatment group includes 2,087 observations, accounting for approximately 4.9%. Regarding the characteristics of the income gap, the

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sample mean is 6.8026, indicating that the average income gap is above average. Effective planning and policy measures are needed to narrow the income gap.

3.3. Research model

3.3.1. DID Model

To evaluate the effectiveness of digital agriculture policy implementation, this study employed a difference-in-difference (DID) model to construct a quasi-natural experiment framework. The DID method compares changes in pilot and non-pilot regions before and after policy implementation, eliminating contamination from unobservable factors such as temporal trends and regional characteristics to identify the net effect of the policy.

$$Y_{ijt} = \beta_0 + \beta_1 DID_{jt} + \beta_2 X_{ijt} + \mu_j + \lambda_t + \epsilon_{ijt} \quad (1)$$

Among them, Y_{ijt} is the explained variable (such as farmer household income, regional income gap, etc.), DID_{jt} is digital agriculture policy variable (pilot region × after policy implementation), X_{ijt} is the control variable, μ_j is region fixed effect, λ_t is time fixed effect, and ϵ_{ijt} is random error term.

3.3.2. Heterogeneity Analysis Model

This study introduced heterogeneity analysis based on the baseline model to explore the differential effects of digital agriculture policies across different regions and groups. By interacting grouping variables (such as region type and household type) with policy variables, a heterogeneity analysis model was constructed to capture the differences in policy effects between agricultural and non-agricultural households and between the eastern, central, and western regions.

$$Y_{ijt} = \beta_0 + \beta_1 DID_{jt} + \beta_2 \left(DID_{jt} \times Group_j\right) + \beta_3 X_{ijt} + \mu_j + \lambda_t + \epsilon_{ijt} \quad (2)$$

Among them, $Group_j$ is the grouping variable; $\left(DID_{jt} \times Group_j\right)$ is the interaction term, used to capture group differences.

3.3.3. Robustness Test Model

This paper uses the DID method to analyze the impact of digital agriculture policies on the income gap between the rich and the poor. The validity of this method depends on the parallel trend assumption, which states that there should be no systematic differences in the income gap between the treatment and control groups before the policy implementation, and that both groups should show the same trends without the policy. To verify this assumption, the paper follows Jacobson, et al. [23] and utilizes the event study method to assess the consistency of time trends in both groups before the policy. In the dynamic effect model used for the parallel trend test, the variable yeark represents the time dummy for each year. In contrast, other variables correspond to those in the baseline model.

$$Y_{ijt} = \sum \delta_k treat_j \times year_k + \rho X_{ijt} + \mu_j + \lambda_t + \varepsilon_{ijt} \qquad (3)$$

4. Results

4.1. Benchmark regression analysis

Table 3 shows the results of the baseline regression analysis, focusing on the digital agriculture policy (DID) as the primary explanatory variable. The model in column (1) does not include control variables. The regression coefficient for DID is -0.1169, which is significant at the 5% level, indicating that the digital agriculture policy significantly reduced residents' perceptions of the rich-poor gap. Following the policy's implementation, the average perception score decreased by about 0.13 to 0.15 points (sample mean: 6.80), reflecting a 10% reduction in perceived inequality. These results suggest that the digital agriculture policy positively impacts perceptions of income disparity.

In the column (2) model, individual characteristics—such as age, gender, education, and health—were included to control for potential confounding effects. The results show that the difference-in-differences (DID) coefficient is still negative and significant at -0.1282, with a significance level of 1%.

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This indicates that digital agriculture policies significantly reduced the perceived wealth gap even after accounting for individual characteristics. Thus, promoting digital agriculture optimizes resource allocation and narrows the income gap between urban and rural areas by enhancing agricultural productivity and income levels.

In addition, according to the marginal effect analysis of the Logit model, the results of column (2) further show that the implementation of the digital agriculture policy has significantly reduced the probability of having a high score (≥8 points) on the perception of the wealth gap by 2.45 percentage points (the base rate is 25.78%). This change is equivalent to reducing the size of the high-perception group by 24,500 people per million RMB of fiscal investment, further highlighting the positive role of the digital agriculture policy in alleviating social differentiation.

The results from the control variables indicate that most factors significantly influence the perception of the wealth gap. For instance, the negative coefficient for age (-0.6508) suggests that older individuals are less sensitive to the wealth gap. In contrast, education level and health status significantly positively affect the perception of the wealth gap. Additionally, the negative coefficient for urban versus rural household registration indicates that urban residents are less aware of the wealth gap issue than their rural counterparts. These findings are consistent with existing literature, providing further support for the model's validity and the reliability of the regression results.

Table 3.
Benchmark regression analysis results.

Variables	**(1)**	**(2)**
DID	-0.1169**	-0.1282***
	(-2.3843)	(-3.1643)
Age		-0.6508***
		(-16.1723)
Gender		0.1842***
		(7.2580)
Urban		-0.1251***
		(-3.2973)
Marriage		0.1165***
		(3.8249)
Education		0.0580***
		(3.5595)
Medsure		0.1270***
		(3.5217)
Health		0.0555***
		(4.8245)
District fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Obs.	42568	42568
R^2	0.0072	0.0155

Note: The t-statistics are in brackets. ***, **, and * are significant at the 1%, 5%, and 10% significance levels, respectively.

4.2. Mechanism Analysis

This study investigates how digital agriculture policies impact the wealth gap through three key mechanisms: modernization of agricultural tools, efficiency of agricultural inputs, and increased farmer income. Table 4 displays the regression results for each mechanism. These policies significantly improve the quality and efficiency of agricultural labor by promoting upgraded production tools.

The regression results show that digital agriculture policies significantly impact the level of agricultural equipment advancement. The DID coefficients are 0.1391 and 0.1555 in the models without control variables (Model 1) and with control variables (Model 2), respectively, both passing the 1% significance test. This indicates that policy implementation has promoted agricultural mechanization

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and technological upgrading, improved agricultural production efficiency, and promoted agricultural intensification and high-value-added development, laying the foundation for narrowing the wealth gap.

Digital agriculture policies enhance agricultural production efficiency by optimizing resource allocation. Tables 4 (3) and (4) indicate that the digital agriculture pilot significantly improved the agricultural input ratio, with DID coefficients of 0.0857 and 0.0813, both significant at the 5% level. This shows that these policies reduce resource waste through information technology, narrowing the efficiency gap between low-efficiency farming and large-scale modern agriculture. Consequently, resource efficiency improvements boost economic benefits and help decrease income disparities from uneven resource distribution.

The digital agriculture policy has boosted farmers' income by enhancing the added value of agricultural products. Regression results (5) and (6) in Table 5 show DID coefficients of 0.3168 and 0.2724, both significant at the 1% level. This indicates that digital technology has improved product quality, expanded markets, and increased competitiveness, leading to higher income for farmers. Consequently, this has alleviated some economic pressure on low-income groups and reduced the wealth gap.

Table 4.
Mechanism analysis results.

	Advanced Level of Agricultural Equipment		**Agricultural Production Ratio**		**Per Capita Income of Farmers**	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
DID	0.1391***	0.1555***	0.0857**	0.0813**	0.3168***	0.2724***
	(5.066)	(3.6447)	(2.0777)	(2.1226)	(4.094)	(3.2421)
Constant	0.6746***	0.1050	1.1623***	1.2198***	9.2844***	9.2381***
	(2908.55)	(1.3721)	(976.55)	(11.9399)	(6928.267)	(68.256)
Controls	No	Yes	No	Yes	No	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	13852	13852	24925	24925	42564	42564
R^2	0.2204	0.2926	0.1795	0.1852	0.1640	0.1902

Note: The t-statistics are in brackets. ***, **, and * are significant at the 1%, 5%, and 10% significance levels, respectively.

4.3. Heterogeneity Analysis

4.3.1. Heterogeneity of Agricultural Activities

This article examines the varying impacts of digital agriculture policies on households based on their involvement in agriculture and geographic location. Households engaged in agriculture benefit more from these policies, as they can directly use digital technologies to enhance production efficiency and increase product value. In contrast, non-agricultural households may experience limited benefits. Thus, a group analysis based on agricultural engagement is essential to clarify the policies' applicability and relevance.

Table 5 performs a grouped regression based on whether the household is engaged in agricultural activities. The results show that the impact of digital agriculture policies on non-agricultural households is not significant (columns (1) and (2), with DID coefficients of -0.0636 and -0.0782, respectively). This result indicates that implementing digital agriculture policies is less applicable to households whose primary source of income is non-agricultural, and their role in poverty reduction is limited.

In contrast, the regression results for households engaged in agriculture (columns (3) and (4)) show DID coefficients of -0.1592 and -0.1725, respectively, both significant at the 5% significance level. This shows that digital agriculture policies have effectively improved the economic conditions of agricultural households by improving agricultural production efficiency, increasing the added value of agricultural products, and improving the market circulation channels for agricultural products, significantly

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alleviating their perception of the wealth gap. This result highlights the direct role of digital technology in promoting agricultural production.

Table 5.
Engaged in agriculture Heterogeneity results.

Variables	Non-engaged in agriculture		Engaged in agriculture	
	(1)	(2)	(3)	(4)
DID	-0.0636	-0.0782	-0.1592*	-0.1725**
	(-1.5526)	(-1.5640)	(-1.7739)	(-2.2507)
Controls	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Obs.	21443	21443	20629	20629
R^2	0.0083	0.0177	0.0045	0.0111

Note: The t-statistics are in brackets. ***, **, * and are significant at the 1%, 5%, and 10% significance levels, respectively.

4.3.2. Regional Heterogeneity

Significant differences exist in economic development levels, agricultural infrastructure, and resource endowments across regions, which can lead to significant variations in the effectiveness of digital agriculture policy implementation across regions. Therefore, geographically based group analysis can better reveal the applicability of policies across regions and provide a regional basis for policy optimization.

Table 6 presents a regression analysis of the samples grouped by eastern, central, and western regions. The results show that the impact of digital agriculture policies in the eastern region is not significant (columns (1) and (2), with DID coefficients of -0.0425 and -0.0851, respectively). This may be due to the relatively developed agricultural production technology and infrastructure in the eastern region, resulting in a weaker marginal effect of digital agriculture policies.

However, in the regression results for the central and western regions (columns (3) and (4)), the DID coefficients are -0.1803 and -0.1541, respectively, both significant at the 1% significance level. This indicates that digital agriculture policies have played a significant role in the central and western regions, where agricultural resource utilization efficiency is low and productivity levels are relatively backward. By optimizing resource allocation and improving production efficiency, the policies have significantly alleviated the problem of income inequality in these regions and promoted regional economic development.

Table 6.
Regional heterogeneity results.

Variables	Eastern region		Midwestern region	
	(1)	**(2)**	**(3)**	**(4)**
DID	-0.0425	-0.0851	-0.1803***	-0.1541***
	(-0.5614)	(-1.0805)	(-4。2725)	(-3.4008)
Controls	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Obs.	16949	16949	25619	25619
R^2	0.0041	0.0104	0.0070	0.0169

Note: The t-statistics are in brackets. ***, **, and* are significant at the 1%, 5%, and 10% significance levels, respectively.

4.4. Robustness Test

This paper employs a dynamic effect model to rigorously test the assumption of parallel trends, a critical requirement for the validity of the difference-in-differences (DID) approach. This model captures policy effects before and after the policy's implementation. By statistically examining the interaction coefficients for pre-treatment periods, the model assesses whether they significantly deviate from zero,

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thereby determining the validity of the parallel trends assumption. Additionally, the event study methodology visually represents the dynamic effects over time, offering further support for causal inference and identification of policy impacts [24].

Figure 1 presents the results of the parallel trends test, with the dashed lines denoting the 95% confidence interval. The interaction term coefficients for the pre-implementation periods fluctuate around zero and lack statistical significance, indicating the absence of systematic differences in wealth inequality levels between the treatment and control groups prior to the policy intervention.

This finding confirms that the DID estimation satisfies the assumption of parallel trends. Post-implementation, the interaction term coefficients are consistently negative and achieve statistical significance by the third year, demonstrating that the wealth equalization effect of digital agriculture is genuine and not attributable to unobserved systematic differences between the sample groups.

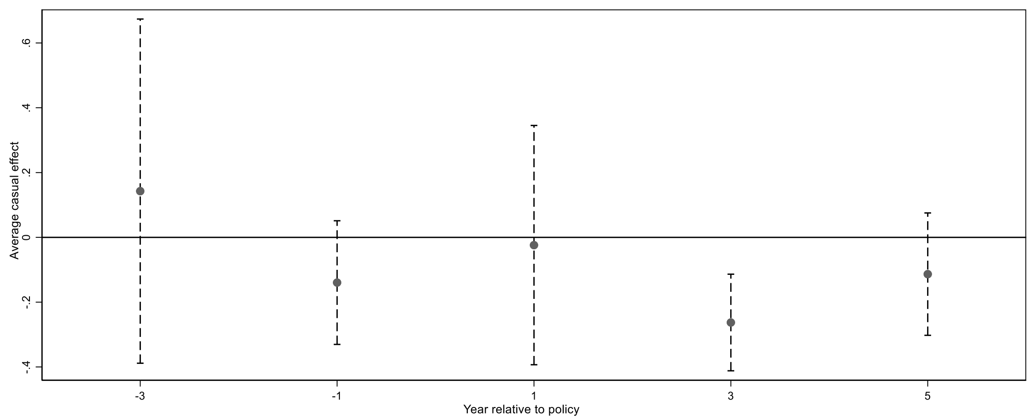

Figure 1.
Parallel trends test result.

5. Discussion

This study utilizes a quasi-natural experiment of digital agricultural transformation in the Yangtze River Economic Belt, applying the Difference-in-Differences (DID) method to systematically evaluate the impact of digital agriculture policies on reducing income inequality and promoting common prosperity.

The findings indicate that digital agriculture policies significantly reduce residents' subjective perception of income inequality, with more pronounced effects observed among households in the central and western regions and those engaged in agricultural activities.

These results demonstrate that digital agriculture can effectively mitigate resource mismatches between regions and social groups by improving agricultural productivity, optimizing resource allocation, and increasing rural household income.

This aligns with existing research that highlights the role of technology in stimulating rural economic development and revitalization [6-8].

Specifically, digital agriculture enhances agricultural productivity through intelligent production tools, precision resource allocation, and efficient supply chain flows. These technologies offer viable solutions to address the issue of low productivity in the central and western regions while creating new employment opportunities for rural households.

Mechanism analysis further underscores the critical role of value chains in digital agriculture policies. By modernizing agricultural production processes and raising efficiency, digital agriculture optimizes the scale and intensity of resource utilization and reduces costs. Additionally, it extends industrial chains, improves market competitiveness, and adds value to agricultural products.

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These mechanisms collectively form the foundation for digital agriculture's potential to narrow income inequality. Furthermore, the success of these policies depends on the development of digital infrastructure and citizens' ability to adopt and utilize technology.

This finding aligns with existing studies on the interplay between technological advancement and policy effectiveness [18, 19].

Thus, future policies should prioritize investments in digital infrastructure, enhance technical training for farmers, and improve farmers' digital literacy and adoption capacity. A comprehensive design of these policies can ensure their effectiveness across diverse regions. Policies should address structural barriers to productivity and economic development for the central and western regions, where agricultural modernization lags.

At the same time, the eastern region, which has relatively advanced agricultural technology, should leverage digital agriculture to enhance market competitiveness and industry value chains further. In summary, future policy design should strive for resource allocation strategies tailored to the distinct needs of the central and western regions. This would ensure balanced regional development, maximize the benefits of digital agriculture, and contribute to the broader goal of achieving common prosperity.

6. Conclusions

This study leverages a quasi-natural experiment of digital agriculture pilot projects in the Yangtze River Economic Belt. It employs the Difference-in-Differences (DID) method to systematically evaluate the impact of digital agriculture policies on achieving common prosperity.

The findings reveal that digital agriculture policies significantly reduce residents' subjective perceptions of income inequality, with the effects being particularly pronounced among households in the central and western regions and those engaged in agricultural activities.

By enhancing agricultural productivity, optimizing resource allocation, and increasing rural household income, these policies contribute to narrowing the urban-rural income gap and serve as a critical tool for promoting common prosperity.

Mechanism analysis further demonstrates that digital agriculture policies improve the modernization of production tools, enhance the efficiency of agricultural input utilization, and increase the value-added of agricultural products, leading to the effective reduction of income inequality. These mechanisms form the foundation of the policies' efficacy and highlight the pivotal role of digital technologies in advancing agricultural modernization.

Additionally, the study uncovers significant heterogeneity in policy effects across regions and demographic groups. Households in the central and western regions, as well as agricultural families, benefit more significantly, while the effects on non-agricultural families and those in the eastern region are relatively weaker.

This research contributes to a deeper understanding of the potential of digital agriculture to promote common prosperity and provides practical guidance for optimizing digital agriculture policies. Nevertheless, the study also identifies certain limitations. For instance, the long-term effects of policies and their sustainability remain unexplored.

Future studies could leverage more extensive and longitudinal data to examine the interplay between digital agriculture and sustainable development, as well as the integration of agriculture with urbanization and other related domains. Such research would provide a more comprehensive foundation for achieving the overarching goal of common prosperity.

Transparency:

The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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