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Agricultural production services and their influence on rural common prosperity: evidence from eastern China

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Common prosperity has emerged as a central focus in the global sustainable development agenda. Raising the total income of farmers and narrowing the income equality in rural areas are important ways to achieve common prosperity. This study utilized 368 micro-survey data of rural households in Jiangsu Province, China in 2016, to examine how agricultural production services (APS) promote common prosperity in eastern China through two mechanisms: narrowing the urban-rural income gap and reducing income inequality in rural areas. The results indicate that APS significantly increases per capita total income of rural households, thereby contributing to the narrowing of the urban-rural income gap by raising rural incomes. Moreover, APS has significantly reduced income inequality within rural areas. Notably, the positive effects of APS on agricultural net income are more pronounced for large-scale farmers, while for small-scale farmers, the services contribute substantially to increases in wage and business income. These findings suggest that it could generate larger common prosperity effect by tailoring the APS framework to overcome the distinctive constraints of small-scale farmers in order to compress intra-rural income inequality and rural-urban income inequality.

KEYWORDS

agricultural production services, income inequality, rural poverty, rural common prosperity, sustainable agriculture

1 Introduction

Common prosperity is a shared goal around the world, and one of its most important tasks is to eliminate poverty. According to the data released by the Ministry of Civil Affairs of China, 78% of the total number of poor people live in rural areas (Chen et al., 2021). This means that tracking rural poverty is essential for making real progress toward common prosperity. China Rural Statistical Yearbook reported that the net operating income and wage income occupied 36.06 and 41.14 of rural residents' disposable income in the recent 5 years on average, respectively, and 48.59% of this net operating income comes from agriculture on average. Therefore, based on the income structure of Chinese rural residents, it's important to develop agriculture and increase employment opportunities to reduce rural poverty (Liu et al., 2024).

However, it is noteworthy that Chinese agriculture, predominantly characterized by labor-intensive small-scale farming practices, heavily relies on family labor (Cook, 1999). From a global perspective, such family-based small-scale farmers commonly confront issues related to inadequate productivity and low income, particularly in developing countries such as Kenya (Kijima and Tabetando, 2020), South Africa (Baiyegunhi et al., 2019), and Vietnam (Tran and Goto, 2019). These persistent issues of inadequate productivity and low income pose significant challenges to global food security and sustainable agricultural development (Yang et al., 2025; Zhou et al., 2024). Therefore, this study is expected to offer valuable insights for policy formulation aimed at rural poverty alleviation and the achievement of common prosperity, both in China and other developing nations.

It should be noted that the Chinese rural society structure is changing. With the household registration system reform and urban economic development, increasing young and middle-aged rural laborers are carrying on off-farm work and/or move to live in cities. This implies Chinese agriculture faces farming labor and thus high labor costs. Taking account for agriculture development and this change, agricultural production services (APS) become promoted by the government in rural areas. China's 14th Five-Year Plan for Agricultural and Rural Modernization notes that APS is an important way to introduce modern production factors—technology, finance, and management—into smallholder operations. Therefore, over the next 5 years China will accelerate the expansion of APS systems to support smallholder farmers. Agricultural Production Services (APS) refer to a variety of trusteeship or outsourcing services provided by specialized operators across all stages of crop production (Tang et al., 2018; Huan et al., 2022). APS encompass fundamental agricultural tasks such as plowing, seeding, and harvesting; managerial functions like fertilization, spraying, and irrigation; as well as post-harvest services such as primary processing, transportation, and storage.

International research indirectly explored the role of APS in promoting common prosperity. Chen et al. (2023) posit that agricultural technology services enhance rural income through advanced agricultural production approaches. APS "slice" the operational capacity of large machinery through outsourcing and sharing, which decrease the indivisibility of agricultural machinery. This enables smallholders to also access the scale economies generated by mechanization, thereby lowering their unit operating costs (Foster and Rosenzweig, 2011; Yang et al., 2013; Wang et al., 2016). Using a dataset of Chinese rice farmers, Tang et al. (2018) demonstrated that APS help improve cost efficiency of agricultural production. APS reflect the specialized division of labor (Francois, 1990), through which farm households can replace relatively high-priced factor inputs with relatively low-priced ones to achieve cost savings and increased income (Benin, 2015; Qing et al., 2019; Peng et al., 2022). Nevertheless, it should be noted that some scholars contend that the potential benefits of APS are constrained by the limited resources endowment and relatively low skill levels of low-income rural households (Shita et al., 2020; Zeng et al., 2015; Otsuka, 2000). Therefore, previous literature has affirmed that there is the potential for APS to worsen income disparities and inequalities (Sang et al., 2023). Building on the current discourse surrounding rural development and income inequality, previous studies have primarily focused on the effects of households' participation in specific dimensions of APS, such as such as mechanized plowing, irrigation, or harvesting, on total household income or income distribution (Lyne et al., 2018; Mi et al., 2020). However, there remains a significant gap in comprehensively assessing the cumulative impacts of APS, including production, managerial, and post-production services, on total household income levels, income sources, and rural income inequality. Most existing studies offer only fragmented perspectives and fail to capture the multi-dimensional nature of APS and its broader socio-economic consequences (Chen et al., 2023; Shita et al., 2020). Moreover, prior research has paid limited attention to the heterogeneity in APS effects across different categories of farmers, particularly concerning farm size or operational scale. The income effects of APS are likely to vary between small-scale and large-scale farmers due to differences in capital, labor, and access to services (Qiu and Luo, 2021; Hu et al., 2022). Yet, the distributional impacts of APS across such diverse groups remain underexplored, limiting the potential for targeted interventions aimed at fostering inclusive rural transformation. To address these gaps, this study investigates the comprehensive effects of APS on rural household income and income inequality. Firstly, it assesses whether APS contribute to improves rural households' total income. Secondly, it investigates the heterogeneous impact of APS on two key income components (agricultural net income and wage-business income) among large-scale and small-scale farmers. Thirdly, the study evaluates the contribution of APS to rural income inequality using three widely recognized metrics: Gini index, Atkinson index, and Generalized entropy index within a village level. Based on these analyses, the study further seeks to explore the mechanism through which influence income inequality within rural communities.

This study makes two contributions to the existing literature. Firstly, it proposes a new and comprehensive measure of APS by quantifying the proportion of households' payments allocated to all dimensions of APS relative to the total agricultural production costs. This indicator offers a more accurate assessment of the intensity of APS engagement and its potential influence on household income structures. Second, this study presents empirical evidence demonstrating the heterogeneous income effects of APS across farmer types. This empirical insight enhances understanding of the elusive consequences of APS on income inequality, an area that that remains insufficiently examined in existing empirical research.

2 Theoretical considerations

From an economic standpoint, the pursuit of common prosperity entails three key objectives: addressing income inequality within urban areas, narrowing income inequality in rural regions, and mitigating the income gap between urban and rural areas. First, APS do not reveal any significant correlation with the observed income inequality within urban areas. Consequently, the primary focus of this study does not revolve around addressing urban income inequality. Second, enhancing the income level in rural areas could potentially mitigate the urban-rural income gap. Accordingly, this research delves into the examination of APS's influence on the total income of farmers, with a particular emphasis on its potential role in narrowing urban-rural income inequality to a certain extent. Third, when analyzing the impact of APS on income inequality within rural areas, it is imperative to differentiate between various income sources and types of farmers. In the context of China, agricultural net income and wage-business income constitute the principal components of income for rural residents, as highlighted in the introductory section.

This survey findings indicate that these sources of income collectively contribute to 78% of the total household income among the sampled farmers within the survey area. Furthermore, income sources exhibit variations among different types of farmers. Notably, large-scale farmers predominantly derive their income from the agricultural sector, whereas small-scale farmers primarily rely on non-agricultural sectors for their earnings. Specifically, in this sample, agricultural net income accounted for 72% of the total income for large-scale farmers, while wage-business income accounted for 79% of the total income for small-scale farmers. It is important to note that APS play a direct role in household decision-making processes related to family labor allocation and agricultural production. Consequently, APS exert influences on both agricultural net income and wage-business income. These impacts are anticipated to be heterogeneous between large-scale and small-scale farmers, contributing to income inequality within rural areas. Hence, the central focus of this paper is to estimate the impact of APS on the total farm household income and income inequality within rural areas. In pursuit of this objective, this study establish a mechanistic framework to clarify the relationship between APS and agricultural net income as well as wage-business income. Additionally, this study estimate the contribution of APS to income inequality within rural areas (Figure 1). For clarity, this study distinguishes three income categories for farm households; (i) Total income: the sum of earnings obtained by every household member over a 1-year period, (ii) Agricultural net income: the net revenue generated accruing to the household from agricultural production and on-farm production activities, and (iii) Wage-business income: the financial earnings obtained by household members either through labor employment or non-agricultural business activities.

2.1 APS and agricultural net income

The utilization of APS has the potential to bolster agricultural net income through cost savings and improved agricultural productivity, thereby aligning with the objectives of increasing farmers' total income. The strength of APS may lie in the integration of advanced technologies into every stage of agricultural production, encompassing crop breeding and selection, soil testing for fertilizer formulations, pest control strategies, and grain harvesting techniques (Sahoo et al., 2021). On one hand, the application of these advanced technologies may contribute to a reduction in fertilizer usage (Chen et al., 2023) and labor input, thereby resulting in cost savings for agricultural production. On the other hand, the implementation of these advanced technologies has the potential to enhance agricultural output, consequently improving agricultural productivity. However, the improving-agricultural-net-income effect of APS may be heterogeneous at the farm household level. There are two theoretical considerations.

First, there exists discernible heterogeneity in terms of both timeliness and quality levels in the supply of APS, particularly when comparing large-scale farmers with small-scale farmers. This discrepancy may primarily be attributed to the substantial differences in land scale between these two types of farmer households. Notably, the likelihood of receiving timely and premium APS offerings is significantly higher for expansive and level farmland within the APS market. One fundamental rationale for this observation stems from the fragmentation of farmland, resulting in APS suppliers incurring elevated communication costs and service costs (such as those related to fuel expenditures, notably oil costs) when servicing multiple small-scale farmers at the same land scale level, in contrast to their large-scale counterparts. Consequently, APS suppliers may tend to prioritize large-scale farmers, as they offer greater profitability potential under the same APS pricing structure. Furthermore, it is noteworthy that large-scale farmers typically maintain farmland that exhibits greater uniformity and standardization when contrasted with their small-scale counterparts. This characteristic facilitates the implementation of standardized operations by APS providers for large-scale farmers, thereby enabling the provision of enhanced premium services.

Second, there exists heterogeneity in the technical content and quantity of APS adopted by large-scale farmers and small-scale farmers. In comparison to small-scale farmers, large-scale farmers typically possess a more substantial reservoir of human capital and financial resources at their disposal. This advantageous position equips them with the capability to cultivate a deep understanding of APS and the financial capacity to invest in advanced APS technologies. Moreover, it is worth noting that large-scale farmers frequently exhibit a higher degree of land consolidation and standardization. This characteristic augment their ability to effectively incorporate larger quantities of APS and readily adopt advanced APS technologies, including but not limited to machine transplanting and drone-based spraying. These technologies, in turn, contribute to improved agricultural productivity. Consequently, large-scale farmers are better positioned to achieve higher agricultural net income levels than small-scale farmers. In light of these considerations, this study proposes Hypothesis 1. Hypothesis 1 (H1): APS increase the total income of both large-scale and small-scale farmers primarily by boosting agricultural net income. However, the impact of APS on agricultural net income is expected to be greater for large-scale farmers compared to small-scale farmers.

2.2 APS and wage-business income

APS have the potential to enhance wage-business income by exerting influence on the labor market, and subsequently augment total household income. APS exert influence on the labor market through two distinct mechanisms. In the first instance, APS has the potential to augment labor supplementation. This phenomenon arises from the substitution of manual labor with machine-based engineering technology in the framework of APS (Wang et al., 2016). This substitution results in substantial reductions in agricultural labor inputs. The labor thus saved may subsequently be channeled back into the labor market, spanning both the agricultural and non-agricultural sectors. This may involve engagement in hired work at a nearby farm or agricultural enterprise, or the management of small retail establishments, among other possibilities.

Second, APS may have generated supplementary employment prospects within rural areas. It is pertinent to consider that APS play a pivotal role in broadening the array of employment opportunities available to the family labor force. These opportunities encompass various roles, including but not limited to those of agricultural machinery operators, agricultural machinery maintenance personnel, and transportation workers of agricultural products. Consequently, APS has the potential to lead to an increase in wage-business income for farm households. Nevertheless, the impact of APS on wage-business income improvement may vary at the level of farm households. As farm scale increases, factors such as marketing channels and farm management assume heightened significance in influencing agricultural net income. Consequently, the number of tasks for farmers tends to grow. Consequently, the time saved from reduced participation in agricultural production activities due to the adoption of APS is more likely to be allocated to performing these tasks. Essentially, this implies that large-scale farms have limited availability to engage in activities that generate wage-business income, while small-scale farmers possess relatively more time to dedicate toward pursuing wage-business income-generating endeavors. Therefore, this study proposes the Hypothesis 2.

Hypothesis 2 (H2): APS is expected to positively influence the total income of all types of farm households by promoting an increase in wage-business income. This positive effect is anticipated to be more pronounced among small-scale farmers compared to large-scale farmers.

2.3 APS and rural income inequality

The expected signs of the effect of APS on income inequality within rural areas are indeterminate. It is evident that APS have a more substantial positive influence on the agricultural net income of large-scale farmers compared to small-scale farmers. However, the positive effect on the wage-business income of large-scale farmers is relatively less pronounced when contrasted with that of small-scale farmers. Whether the net effect of APS on income inequality within rural areas is positive or negative is contingent upon empirical investigation. Therefore, this study proposes Hypothesis 3.

Hypothesis 3 (H3): *APS may exert an indeterminate effect on income inequality within rural areas.*

3 Data, model, and variables

3.1 Data source

The dataset employed in the empirical analysis was procured through a household survey conducted in the year 2017. The main purpose was to investigate the relationship between APS and the livelihood strategies of farmers within the framework of rural land reform. A multistage sampling procedure was applied to select the households. Initially, this study chose two typical counties in teams of both APS development and marketable grain production. They are Sheyang County, located in Yancheng City and Haian County, located in Nantong City. Subsequently, all townships within the aforementioned sample county were divided into high-, medium- and low-level groups based on the per capita agricultural net income level. Three townships were randomly selected from each group, and then 18 townships were included in the sample. Finally, all villages in each sample township were divided into high-, medium- and low-level groups according to the per capita agricultural income, two villages were selected from each group, and then 36 villages were selected. Finally, within each chosen village, a random sampling technique was used to select between 10 and 12 households for inclusion in the investigation. In total, the survey encompassed 368 households in the final dataset, after excluding households not actively involved in farmland cultivation. Of this sample, 355 households reported the utilization of APS practices in the year 2016, while the remaining 13 households confirmed the absence of APS adoption in the same year.

3.2 Model functions

3.2.1 The income generation function

To estimate the impact of APS on farm household income, this study establishes the income determination function. The functional form of the income determination function is expressed as follows:

$$\ln \mathbf{Income_{ki}} = \alpha_0 + \alpha_1 \mathbf{service_i} + \beta_2 \mathbf{type_i} + \mathbf{Z_i'}\varphi_1 + \mu_{1i} \quad (1)$$

$$\ln \mathbf{Income_{ki}} = \beta_0 + \beta_1 \mathbf{service_i} + \beta_2 \mathbf{type_i} + \beta_3 \mathbf{service_i}^* \mathbf{type_i} + \mathbf{Z_i'}\varphi_2 + \mu_{2i} \quad (2)$$

Model (1) is used to estimate the impact of APS on household income. Model (2) is used to identify if the relationship between APS and household income varies across different farmer types. Where $k = 1, 2, 3$, $Income_{1i}$, $Income_{2i}$, $Income_{3i}$ indicate i^{th} farm household's total income per capita, agricultural net income per capita, and wage-business income per capita, respectively; $service_i$ represents that the proportion of APS expenditure that is paid by the household i on this household's total agricultural production costs; $type_i$ is dummy variable that captures the type of farm households (1 = large-scale farmers, 0 = small-scale farmers); Z is the control matrix; α_0, α_1, β_0, β_1, β_2, β_3, φ_1 and φ_2 are the parameters to be estimated; μ_{1i} and μ_{2i} are the error terms.

The Ordinary Least Squares (OLS) method is employed to estimate the effect of APS and farm household types on households' income. However, some unobserved factors (e.g., the motivation to earn money) may influence both the decision on purchasing APS, APS expenditure, and income. Therefore, endogeneity may be present, which results in biased and inconsistent model estimation of the OLS method. To address this possible endogeneity, based on the approach applied by Feng et al. (2010), this study first employed a Tobit model to estimate the probability of whether farmers purchase APS and then got the predicted probability of purchasing APS. Second, this predicted probability was used as an instrumental variable for APS variables in Equations 1–3.

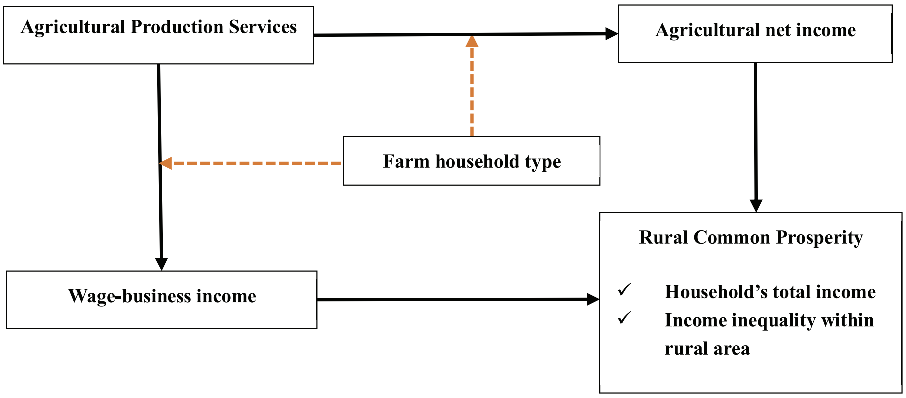

FIGURE 1
Framework for analyzing the relationship between APS and rural common prosperity.

3.2.2 The regression-based Shapley value decomposition

To estimate the impact of APS and farm household types on rural income inequality, this study adopts the regression-based Shapley value decomposition approach. Shapley value decomposition is an inequality decomposition method based on production input factors (Shorrocks, 1999), which has been widely used in previous studies related to income inequality (Morduch and Sicular, 2002; Fields and Yoo, 2000; Obayelu, 2014; Moute et al., 2015). Shorrocks (1999) proposed the Shapley value decomposition method involves a complicated iterative calculation process. Wan (2004) combined the Shapley value decomposition method with the ideas of Blackorby et al. (1981), Jenkins (1995) and Cancian and Reed (1998), resulting in a Shapley value decomposition method based on the income determination equation. This innovative approach offers two notable advantages. Firstly, it permits a reduction in constraints and facilitates the incorporation of additional control variables (Wan et al., 2007; Zhang and Wan, 2006). Secondly, it effectively addresses the contributions of constant and disturbance terms to income inequality (Wan, 2004).

The process for estimating the contributions of dependent variables to rural income inequality via the regression-based Shapley value decomposition approach involves three key steps. The initial step is to establish the income determination function (e.g., Equation 1). This function is estimated by OLS and then the coefficients of each variable in Equation 1 are estimated. The second step involves exponentiation of both sides of Equation 1, yielding Equation 3.

$$\mathbf{Income_{1i}} = \exp\left(\hat{\alpha_0}\right)\cdot\exp\left(\hat{\alpha_1}\mathbf{service_i}\right)\cdot\exp\left(\hat{\alpha_2}\mathbf{type_i}\right)\cdot\exp\left(\mathbf{X_i'}\hat{\gamma}\right)\cdot\exp\left(\hat{\alpha_i}\right) \quad (3)$$

Where $\exp\left(\hat{\alpha_0}\right)$, $\exp\left(\hat{\alpha_1}service_i\right)$, $\exp\left(\hat{\alpha_2}type_i\right)$, $\exp\left(X_i'\hat{\gamma}\right)$, and $\exp\left(\hat{\alpha_i}\right)$ is exponential form of α_0, $\alpha_1 service_i$, $\alpha_2 type_i$, $X_i'\gamma$, respectively.

In the third step, this study calculate the Gini index value of the fitted income value by Equation 3, denoted as G_0. This study then proceed to eliminate one independent variable at a time and calculate a new Gini index value, denoted as G_k. The contribution of the eliminated variable to the Gini index is quantified as $(G_0 - G_k)$. To mitigate any influence stemming from the order of variable elimination, this study average all the contributions of this variable to the Gini index across all possible orders. This averaged contribution represents the final contribution value of this variable. Within the framework of Shapley value decomposition, the contribution of the independent variables to income inequality mainly depends on two terms. The first one is the correlation coefficient between the variables and the income inequality, that is, the partial effect of the variables on the total income. Under a given distribution of the variables, a stronger correlation coefficient corresponds to a more substantial contribution to income inequality. The second one relates to the distribution of the variables themselves. Maintaining a constant correlation coefficient of these variables with respect to total income, a more unequal distribution of these variables results in a heightened contribution to income inequality.

3.3 Variable used for descriptive statistics

3.3.1 Dependent variables

In this study, common prosperity is measured by three farm household income indicators: per capita total income, per capita agricultural net income, and per capita wage-business income for the year 2016. Detailed definitions of these indicators are provided in Section 2.

3.3.2 Core independent variable

With reference to the methodology proposed by Geishecker and Görg (2008), APS is quantified as the ratio of expenses paid for APS to the household's aggregate agricultural production costs. During the 2016 household survey, farmers were asked to report (i) the amount paid for APS during the 2016 crop year and (ii) their overall agricultural production costs. APS payments cover fees for technical advisory services, irrigation management, and other items specified in the Section 1. Total agricultural production costs include expenditures on seeds, fertilizers, pesticides, other incidental expenses (including fuel and administrative fees), and—crucially—the APS payments themselves.

Farm households in this study are classified into two types: large-scale farmers and small-scale farmers. The classification of farm households by the Chinese central government is officially documented. In the National Bureau of Statistics of China (NBSC) (2017), a large-scale farmer is delineated as one that engages in crop farming for commercial purposes, with a cultivated land area of 100 mu or more when yielding one crop annually, or 50-mu or more when yielding two crops annually. Jiangsu, within our study region, is characterized by two crops per year. Accordingly, based on the definition made by the Third National Agricultural Census Program, this study classifies large-scale farmers as those who cultivated more than 50 mu (equivalent to 3.3 hectares) of farmland in 2016, and small-scale farmers as those who cultivated <50 mu of farmland. This classification aligns with the regional context, considering that the average cultivated land per household in Jiangsu province was 5.90-mu as of the end of 2016. The 50-mu threshold significantly exceeds the average cultivated land area in Jiangsu, representing more than eight times the regional average.

3.3.3 Control variables

Detailed definitions of these variables, along with their respective descriptive statistics, can be found in Table 1. The information on these six control variables is three-fold. First, agricultural production decision-maker (i.e., household head) characteristic variables include the age and the Communist Party of China (CPC) membership of the household head. The age of the household head is expected to be positively associated with their accumulated agricultural production experience (Manda et al., 2015), thereby resulting in a positive correlation with agricultural net income. However, it is also anticipated that age may exhibit a negative relationship with the propensity to adopt new and advanced technologies, potentially exerting an adverse influence on agricultural net income. Thus, the impact of age on agricultural net income is multifaceted. Moreover, while it is anticipated that older farmers may possess greater expertise and skills in non-agricultural production due to their prolonged engagement in the same occupation (Ma et al., 2018), it is crucial to acknowledge that advancing age is also accompanied by a decline in physical capabilities. This may consequently give rise to a mixed impact on the wage-business income. In summary, age is likely to yield mixed effects on the household total income. Farmers who hold membership in the CPC are likely to enjoy enhanced access to policy-related information (Zhang and Gao, 2024; Rosas, 2010). This access can facilitate their analysis of current economic conditions and developmental trends. Furthermore, it may enable them to secure government support, ultimately contributing to their income growth. Consequently, CPC membership has the potential to augment all three types of income.

Second, the household characteristics include the family size and the average educational attainment of the household members. On one hand, within the rural Chinese context, each member of a household contributes to the total income. For instance, individuals aged 65 and above participate in agricultural activities, while children assist with farming tasks during peak seasons. A larger family size may imply a greater number of income generators, thereby promoting the realization of economies of scale. Consequently, family size may yield a positive influence on total income. On the other hand, a larger family size incurs increased expenditures. Individuals often have the potential to earn higher incomes in non-agricultural vocations compared to agricultural ones (Zereyesus et al., 2017). Larger family units are more likely to allocate individuals possessing higher human capital or employ individuals with enhanced skills to generate income in non-agricultural sectors. Hence, family size is anticipated to have a positive impact on wage-business income while simultaneously exerting an adverse effect on agricultural net income. The educational achievements of family members serve as proxies for the human capital possessed within a household. As the mean level of educational attainment in farming households increases, there is a heightened propensity for the household to adopt APS or other advanced technologies to augment agricultural net income. Simultaneously, heightened levels of educational attainment may allocate the family's labor force toward off-farm employment, thereby securing wage-business income. This trend can be attributed to the premise that education plays a crucial role in enabling farming households to comprehend the advantages associated with the utilization of APS and analogous advanced technologies (Zou et al., 2023; Peles and Kerret, 2021), while also fostering a more supportive environment for non-agricultural labor participation. Consequently, it is anticipated that this variable will exert a positive influence on the three types of income. Third, the production characteristics include agricultural machinery assets and agricultural subsidies. These two variables are expected to have a positive effect on the agricultural net income and thus on the total income because they are beneficial to agricultural production. Finally, the township dummy variable is included in models to control the influence of unobserved differences among towns, particularly related to geographical characteristics, that might potentially affect income levels.

4 Results and discussion

4.1 Descriptive statistics

Table 1 displays the descriptive statistics of this sample. Among all the farm households included in this study, the average total income per capita in 2016 was 52,890 CNY. Of this, 52% was derived from agricultural production, while 37% came from off-farm business activities and employment. It indicates that the primary sources of farmers' total income are agricultural net income and wage-business income. On average, farm households' expenditure on APS accounts for 31.4% of the total costs of household agriculture production. The average age of agricultural production decision-makers was 58.85 years, with 20.1% of them being members of the CPC. The households had an average of 3.546 family members, received an average of 8.27 years of education, and possessed agricultural equipment valued at 126,180 CNY on average. In 2016, 91.3% of these households received agricultural subsidies.

TABLE 1 Variable definitions and descriptive statistics.

Variable	Variable definition and assignment	All observations (n = 368)		Large-scale farm households (n = 60)		Small-scale farm households (n = 308)		Means difference between small- vs. large-scale farm households
		Mean	S.D.	Mean	S.D.	Mean	S.D.	
Independent variables								
Total income per capita	The total income of farm households in 2016, divided by the number of household members (unit: 10,000 CNY)	5.289	11.312	22.133	20.925	2.009	1.603	−20.124***
Agricultural net income per capita	The net revenue from agricultural production and on-farm production activities in 2016, divided by the number of household members (unit: 10,000 CNY)	2.753	8.502	15.849	15.507	0.202	0.387	−15.647***
Wage-business income per capita	The financial earnings from labor employment or non-agricultural business activities in 2016, divided by the number of household members (unit: 10,000 CNY)	1.940	3.771	4.304	8.257	1.480	1.609	−2.825**
Core independent variables								
APS	The ratio of expenses paid for APS to the total agricultural production costs in 2016	0.314	0.151	0.209	0.158	0.334	0.142	0.125***
Farm household type	1 = large-scale farmers who cultivated more than 50 mu of farmland in 2016; 0 = small-scale farmers who cultivated <50 mu of farmland in 2016	0.163	0.370	/	/	/	/	/
Agricultural production decision-maker characteristic variables								
Age	Age of the agricultural production decision-maker in 2016	58.853	10.029	50.083	7.941	60.562	9.495	10.478***
CPC member	The agricultural production decision-maker is a CPC member (1 = yes; 0 = no)	0.201	0.401	0.167	0.048	0.208	0.023	0.041
Household characteristic variables								
Family size	Total number of household family members in 2016	3.546	1.483	4.150	0.159	3.429	0.086	−0.721***
Average education	Average schooling years of household family members	8.274	2.425	9.552	0.248	8.025	0.139	−1.527***
Production characteristic variables								
Value of agricultural devices	The present value of agricultural machinery and other agricultural facilities owned by the household in 2016 (unit: 10,000 CNY)	12.618	70.885	76.925	21.555	0.429	2.911	−76.496***
Agricultural subsidies	The household receives the government subsidy for agricultural production (1 = yes; 0 = no)	0.913	0.282	0.833	0.048	0.929	0.015	0.095**

*, **, *** indicate significance at the 10, 5, and 1% levels, respectively.

Our sample comprises 60 large-scale farmers and 308 small-scale farmers. Significant differences are observed in the mean values of various variables across the two groups. Specifically, the average per capita total income of large-scale farmers exceeds that of small-scale farmers by 201,124 CNY. In terms of specific components, large-scale farmers exhibit an average per capita agricultural net income that is 156,470 CNY higher than that of small-scale farmers, along with an average per capita wage-business income that is 28,250 CNY greater. Furthermore, on average, the proportion of APS costs paid by large-scale farmers is 12.5 percentage points lower than that paid by small-scale farmers. In terms of other characteristics, the agricultural production decision-makers of large-scale farmers are, on average, 10.48 years younger and are 4.1% less likely to be members of the CPC when compared to small-scale farmers. Large-scale farmers, on average, comprise 0.72 more family members and receive 1.53 more years of education

TABLE 2 The impacts of APS on farm household income.

Variables	Model 1			Model 2		
	In (total income per capita)	In (agricultural net income per capita)	In (wage-business income per capita)	In (total income per capita)	In (agricultural net income per capita)	In (wage-business income per capita)
Core independent variables						
APS	4.437***	4.253***	2.260*	3.940***	3.685***	2.918**
	(1.09)	(0.78)	(1.37)	(1.11)	(0.79)	(1.39)
Farm household type	1.256***	1.776***	0.050	1.271***	1.794***	0.030
	(0.12)	(0.08)	(0.15)	(0.12)	(0.08)	(0.15)
APS * Farm household types	–	–	–	2.247**	2.573***	−2.979**
	–	–	–	(1.05)	(0.75)	(1.33)
Agricultural production decision-maker characteristic variables						
Age	−0.006**	−0.004*	−0.009**	−0007**	−0.004**	−0.008**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
CPC member	0.057	0.122***	−0.080	0.052	0.116**	−0.073
	(0.06)	(0.05)	(0.08)	(0.06)	(0.05)	(0.08)
Household characteristic variables						
Family size	0.037**	−0.037***	0.123***	0.032*	−0.043***	0.129***
	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)
Average education	0.058***	−0.014	0.089***	0.057***	−0.015	0.091***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Agricultural production characteristic variables						
In(value of agricultural devices)	0.236***	0.295***	0.034	0.282***	0.348***	−0.027
	(0.05)	(0.03)	(0.06)	(0.05)	(0.04)	(0.07)
Agricultural subsidy	0.279***	0.190***	0.187	0.306***	0.221***	0.150
	(0.10)	(0.07)	(0.12)	(0.10)	(0.07)	(0.12)
Township controls	Yes					
Constant	0.223	0.192	−0.212	0.262	0.236	−0.263
	(0.23)	(0.17)	(0.29)	(0.23)	(0.17)	(0.29)
R^2	0.729	0.882	0.332	0.732	0.885	0.339
Mean VIF	2.60	2.60	2.60	3.05	3.05	3.05
Observations	368					

Where Robust standard errors are shown in parentheses; *, **, *** indicate significance at the 10, 5, and 1% levels, respectively.

than small-scale farmers. Additionally, large-scale farmers are less likely to receive agricultural subsidies than small-scale farmers, and the value of agricultural equipment in large-scale farmers average 764,960 CNY more than that in small-scale farmers.

4.2 The impact of APS on farm household income

The estimated results of the income determination function are presented in Table 2. The results of Model 1 represent the baseline regression results. The empirical results indicate that APS has a significantly positive effect on both per capita total income and per capita agricultural net income, with significance levels of 1 and 5%, respectively. It's consistent with the inference of hypothesis H1. This finding suggests that households allocating a greater portion of their agricultural production expenditure to APS observe a corresponding increase in their total income and agricultural net income. Additionally, APS has a significant effect on per capita wage-business income, aligning with the expectations outlined in hypothesis H2. As household heads age, farm households tend to generate lower income across all three income types. If the household head is a member of the CPC, the household may

TABLE 3 The results of rural income inequality decomposition.

Variables	Contribution	Ranking
APS	−1.35%	9
Farm household types	51.91%	1
Age of household head	2.65%	5
Party member	0.69%	7
Family size	1.14%	6
Average education	20.05%	2
ln (value of agricultural assets)	19.45%	3
Agricultural subsidy	0.04%	8
Township dummies controls	5.43%	4

potentially realize enhanced financial returns from agricultural production. Nonetheless, there exists no statistically significant disparity in per capita total income and per capita wage-business income between households led by CPC members and those led by non-members. Furthermore, households with more years of education tend to report increased total income and wage-business income. An expanded family size is linked to heightened total income and wage-business income, concomitant with a decrease in agricultural net income. Additionally, Households possessing higher-value agricultural equipment or receiving agricultural subsidies tend to exhibit higher total income and agricultural net income.

This study uses the interaction term of APS and farm household types to examine the heterogeneous effects of APS on the three types of income between large-scale and small-scale farm households. To this end, Model 2 involves this interaction term based on Model 1. The outcomes of estimation indicate that, as the proportion of APS expenditure rises by one-unit, significant disparities emerge in three types of income between large-scale and small-scale farmers. Specifically, these findings demonstrate that large-scale farmers realize an increase of 224.7% in total income per capita and a 257.3% surge in agricultural net income per capita compared to their small-scale counterparts. This disparity likely arises because larger-scale farmers, endowed with superior human capital, are better able to identify and adopt APS packages that are optimally timed and tailored to their production conditions, thereby securing disproportionately higher returns. In addition, the scale economies of land amplify the marginal net agricultural benefits generated by APS interventions. These results align with the anticipated outcomes posited in hypothesis H1. Conversely, concerning wage-business income per capita, large-scale farmers experience a 297.9% reduction compared to small-scale farmers under the same conditions, consistent with hypothesis H2.

4.3 The impact of APS on rural income inequality

The results of income inequality decomposition are presented in Table 3. Based on the results reported in the first line of Table 4, the income determination function can explain 72.98% of the income inequality generation. This indicates that the variables involved in the income determination function can explain the income inequality well. The focus of this study lies in the effect of APS on rural income inequality. The decomposition results reveal that the contribution of APS to income inequality is −1.35%. This finding suggests that APS has the potential to narrow rural income inequality, albeit with potential limitations on its effectiveness. Considering the results from Model 2, a plausible explanation emerges: the incremental improvement brought about by APS on the agricultural net income of large-scale farmers is less pronounced than its impact on the wage-business income of small-scale farmers.

Farm household types contribute over 50% to rural income inequality, ranking highest among contributing factors. According to the definition of farm household types in this paper, this finding implies a pivotal role for cultivated farmland size in the widening of rural income inequality. However, alternative explanations for this phenomenon may exist. For instance, research suggests that differences in available resources and skill levels among farm households of varying operational scales may result in disparate impacts of income improvement through the adoption of new technologies, thereby potentially exacerbating rural income inequality (Shita et al., 2020). Section 4.1 establishes significant distinctions in characteristics between large-scale and small-scale households. Nevertheless, further research is required to ascertain whether and why these differences in characteristics influence rural income inequality. Among the other factors in the decomposition model, factors such as agricultural devices and the average education level of family members emerge as noteworthy contributors to rural income inequality, with respective shares of 19.45 and 20.50%. These findings suggest that agricultural devices and human capital play a significant role in shaping rural income inequality. The aforementioned finding once again underscores the significant influence of education on income inequality, aligning with the findings of Morduch and Sicular (2002). The remaining factors are beyond the scope of this study; thus, this conclusion is presented without providing detailed explanations. The variables of township dummies controls, age of household head, family size, CPC membership, and agricultural subsidy exhibit a relatively smaller impact on income inequality.

4.4 Robustness test

Given the grounding of variable selection in prior literature and local context, the representativeness of farm household types and income inequality variables necessitates meticulous attention. To assess the robustness of regression outcomes, this study employs a new measurement methodology for both farm household types and income inequality in robustness testing. For the classification of farm household types, this study adopts the categorization system established by the Food and Agriculture Organization of the United Nations (FAO). This system utilizes a delineation threshold of 30 mu (2 ha) to demarcate distinct categories among farm households. This methodological adjustment aims to enhance the precision and robustness of the analysis by aligning with internationally recognized standards in the characterization

TABLE 4 The proportion that the rural income inequality can be explained.

Index of rural income inequality	Values of rural income inequality			Explained proportion (%)
	Total value	Independent variables	Error term	
Gini index	0.668	0.487	0.180	72.983
Atkinson index	0.372	0.278	0.094	74.675
Generalized entropy index	0.830	0.622	0.208	74.981

TABLE 5 The impacts of APS on farm household income after changing the measurement of farm household type.

Variables	ln (total income)	ln (agricultural net income)	ln (wage-business income)
APS	3.951***	3.813***	2.779**
	(1.09)	(0.80)	(1.39)
Farm household types (2)	1.279***	1.726***	0.125
	(0.11)	(0.08)	(0.14)
APS * Farm household types (2)	2.218**	2.175***	−2.541*
	(1.03)	(0.76)	(1.32)
Control variables	Yes	Yes	Yes
R^2	0.738	0.880	0.338
Mean VIF	3.04	3.04	3.04
Observations	368	368	368

Where robust standard errors are shown in parentheses; *, **, *** indicate significance at the 10, 5, and 1% levels, respectively.

of farm households. Table 5 reports the results of Model 2 subsequent to the alteration in the measurement of farm household types.

These findings align consistently with the empirical results. For the income inequality variable, this study employs two additional widely acknowledged indicators of income inequality, namely the Atkinson index and the Generalized entropy index. These new income inequality indicators are used in Equation 3. Table 4 reports the explanatory capacity of variables involved in the income determination function on the income inequality generation.

Notably, these variables exhibit a robust explanatory capacity for income inequality. Moving forward to Table 6, this study elucidate the contributions of variables to income inequality subsequent to the alteration in the measurement of income inequality. The revised ranking of variables in Table 6 maintains congruence with empirical findings.

Based on the aforesaid discussion, the study findings reinforce the global relevance of APS in advancing equitable agricultural growth. National strategies like China's land trusteeship and international examples such as CHCs in India or service cooperatives in Africa exemplify scalable models (Attipoe et al., 2021; World Bank, 2023). To realize the full potential of APS in promoting common prosperity, targeted policy support, investment in rural infrastructure, and institutional innovations are needed globally.

These findings indicate that it could generate larger distributional dividends by tailoring the APS framework to overcome the distinctive constraints of smallholders in order to compress intra-rural inequality and rural-urban income divide. However, constrained by remote location (Megerssa et al., 2020; Lusike et al., 2023), underdeveloped agricultural infrastructure (Ai et al., 2023), digital divide and limited agronomic expertise (Yang et al., 2023; Zhou et al., 2023), and weak market leverage (Agholor et al., 2023), small-scale farmers confront multiple barriers to APS utilization, ranging from constrained access channels and difficulties in locating or bargaining with service providers to highly variable service quality. Consequently, the anticipated role of APS in advancing common prosperity remains largely unrealized.

This study offers critical policy insights on the need to widely promote APS to advance global common prosperity. According to the 2020 report by the International Land Coalition and Oxfam, 2.5 billion agricultural smallholders operate under stark land disparities. Moreover, 1% of the largest farms control over 70% of global agricultural land, while 80% of smallholder operate <2 hectares. Given the limited purchasing power of smallholder farmers, price signals alone cannot be relied upon to induce the market to supply them with high-quality APS. Consequently, constructing an APS system that is genuinely smallholder-friendly becomes a policy imperative, particularly in most of Asia and Africa, where smallholders constitute the majority of agricultural producers and are simultaneously exposed to entrenched poverty and heightened risks of re-impoverishment, such as China, Ethiopia, Kenya, South Africa. Therefore, targeted policies are essential to ensure that smallholders in these regions can access APS effectively. On the whole, smallholders are primarily constrained by a triad of deficits: (i) reliable information channels, (ii) advanced domain-specific expertise coupled with digital literacy, and (iii) conventional endowments of capital and natural assets—namely agricultural infrastructure, irrigation water, arable land, and financial reserves. Consequently, governmental integration strategies must proceed along two mutually reinforcing tracks. First, the architecture of the APS framework must be deliberately calibrated to the heterogeneous characteristics of smallholders. Second, this framework must be co-deployed with a policy portfolio that encompasses fiscal support instruments, infrastructure upgrading programs, soil and water resource governance schemes, and targeted capacity-building initiatives in professional training. Concretely, governments can construct a smallholder-friendly APS framework along four interlocking axes.

TABLE 6 The results of rural income inequality decomposition in the robustness test.

Variables	Contribution		Ranking	
	Atkinson index (%)	Generalized entropy index (%)	Atkinson index	Generalized entropy index
APS	−2.88	−3.03	9	9
Farm household types	57.99	57.32	1	1
Age	2.25	2.33	5	5
Party member	0.21	0.21	7	7
Family size	0.27	0.26	6	6
Average education	16.28	16.42	3	3
In (value of agricultural assets)	21.97	22.46	2	2
Agricultural subsidy	−0.48	−0.51	8	8
Township dummies controls	4.38	4.53	4	4

First is informational framework. APS will turn smart, precise, and green. Big-data and AI will map smallholders' information gaps-water, soil, weather, markets (Kumar et al., 2017). These information technologies algorithmically translate the resulting insights into bespoke agronomic prescriptions, context-sensitive production services, and evidence-based managerial guidance, thereby strengthening smallholders' adaptive capacity to climatic variability and market volatility.

Second is organizational framework. The emerging APS is best conceived as a "platform-plus-network" configuration that aggregates and reallocates agricultural resources and knowledge. Governments should (a) deploy 5G, cloud computing, and the internet of things to build a digital service platform that seamlessly links smallholders with technology, finance, and markets, enabling resource pooling and optimal allocation (Zhang et al., 2022), and (b) institute a collaborative organizational matrix in which agricultural service providers, intermediary organizations, and farm households form a triangular relationship centered on service delivery, cost minimization, and benefit sharing (Yang et al., 2024). Exemplary of this model are Poland's Agricultural Chambers, which function as bidirectional conduits for transmitting farmers' opportunities and constraints to policymakers while simultaneously disseminating policy information downward (Kasprzyk et al., 2024).

Third is precision-oriented training services. Smallholders juggle subsistence. They often overlook regional crises—climate shocks (Ohenhen et al., 2024), aquifer depletion (Gupta et al., 2022a), chemical runoff (Gupta et al., 2022b). These messages travel digitally. Low digital literacy locks smallholders out. Such unawareness dulls their interest in eco-friendly APS. Therefore, governments should deliver grounded, demand-driven training programs—most notably, capacity-building in digital literacy for smallholders and widespread diffusion of the modern agricultural technologies embedded within APS.

Fourth is aligned fiscal and financial instruments. Fiscal and financial policies must be synchronized with agricultural development and land-use policies to generate coherent policy synergy (Zou et al., 2023). Governments can deploy targeted subsidies and institutional incentives to induce financial institutions to extend concessional loans to both smallholders purchasing APS and the service organizations supplying them (Qiu et al., 2023). Additionally, the introduction of index-based insurance mechanisms can help service providers hedge against natural-disaster risks, thereby stabilizing their operations (Lydiah et al., 2023).

This study is limited by its regional scope and dataset size. It does not fully capture the broader dimensions of common prosperity such as urban-rural income divide or the differential impacts of APS on various income sources across farm types. Future research should leverage large-scale macroeconomic and cross-national data to deepen understanding of APS impacts across diverse socio-economic and agro-ecological contexts.

5 Conclusion and way's forward

This study offers robust empirical evidence on the impact of agricultural production services (APS) on rural household income and income inequality, highlighting the heterogeneous effects across different farm household types. The study results confirm that APS significantly enhance per capita household income, and indicate their potential to narrow the income gap between rural and urban areas. Moreover, the regression-based Shapley value decomposition reveals that APS contribute negatively to income inequality in rural areas and underscoring their redistributive potential. The analysis further shows that APS have a more substantial positive effect on the agricultural net income of large-scale farmers, while the benefits to wage-business income are greater for small-scale farmers.

Future policy efforts should aim to expand the inclusive potential of APS by improving access for small-scale farmers, especially in resource-poor regions. Diversifying service delivery models through digital platforms, cooperatives, and public-private partnerships can enhance both reach and effectiveness. Strengthening capacity-building initiatives will be essential to equip farmers with the skills necessary to fully utilize APS. Regular monitoring and evaluation of APS programs should be institutionalized to inform adaptive policymaking based on evolving socio-economic conditions.

Data availability statement

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

Author contributions

ZY: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Software, Writing – original draft. CG: Conceptualization, Formal analysis, Methodology, Project administration, Supervision, Validation, Visualization, Writing – review & editing. PZ: Investigation, Project administration, Resources, Supervision, Validation, Writing – review & editing.

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Conflict of interest

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

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

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