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ORIGINAL ARTICLE

Economic benefits of climate-smart agricultural practices: empirical investigations and policy implications

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Abstract

Adopting climate-smart agricultural practices (CAPs) has the potential to mitigate the adverse effects of climate change and directly influence the well-being of households. Therefore, this research investigates the impact of CAP adoption intensity on household income, net farm income, and income diversity, using the 2020 China Rural Revitalization Survey data. We utilize the approach of two-stage residual inclusion (2SRI) to mitigate the endogeneity of CAP adoption intensity. The results show that CAP adoption intensity positively and significantly affects household income, net farm income, and income diversity. Heterogeneous analysis indicates that the impacts of CAP adoption intensity on household income increase across the selected quantiles, but the impacts on net farm income decrease across the same. In addition, CAP adoption intensity significantly improves income diversity only at the 20th quantile. Our findings suggest that enhancing farmers' CAP adoption intensity improves rural household welfare.

Keywords Climate-smart agricultural practices · Two-stage residual inclusion · Economic welfare · China

JEL classification D60 · O12 · Q01 · Q54

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1 Introduction

The interaction and exposure between climate-related hazards (e.g., frequency and intensity of occurrences and trends) and human systems result in climate-related risks (Wu et al. 2019), resulting in loss of livelihood and food insecurity, particularly in rural areas. Agriculture significantly contributes to the climate problem through GHG emissions and is also most vulnerable to the effects of climate change (CC). For instance, agriculture generates approximately 14% of total greenhouse gas (GHG) emissions (Stetter and Sauer 2022). This proportion will likely rise significantly as emissions from other sectors decline due to the clean energy transition (World Bank 2021). On the other hand, agriculture is highly susceptible to the impacts of CC (Habtemariam et al. 2020). For instance, a degree Celsius increase in average temperature would decrease wheat production by 6.0%, rice by 3.2%, maize by 7.4%, and soybean by 3.1% (Zhao et al. 2017). According to the Bluebook on Climate Change in China 2023, extreme weather events and the "climate risk index" take on an increasing trend.[1] The North-east China Plain, which stands as one of the most critical food production regions, has experienced a reduction in average regional precipitation levels throughout the crop-growing season of -1.72 mm/year during the last 40 years (Chen et al. 2022). Further, the average annual surface temperature increased by 0.23 ∘C every ten years since 1951 (Chen et al. 2022; Song et al. 2022). China's economic losses might double between 1.5 and 2.0 °C warming levels, and the population impacted by catastrophic floods could continuously rise (Wu et al. 2019). The short- and long-term effects of CC would diminish crop yields (Roy et al. 2019; Chaloner et al. 2021), damage livestock output (Wreford and Topp 2020), and challenge sustainable agricultural systems (FAO 2022), consequently leading to a rise in the population facing food insecurity (Pörtner et al. 2022).

Climate-smart agricultural practices (CAPs) employ comprehensive practices addressing CC and food security, which is critical to establishing a more sustainable and resilient agriculture system. Therefore, many studies have explored the factors that promote and inhibit farmers' decisions to adopt CAPs (Arslan et al. 2015; Sardar et al. 2021; Bazzana et al. 2022; Gikonyo et al. 2022; Musafiri et al. 2022). These studies have focused on individual and household factors (Musafiri et al. 2022), socioeconomic factors (Bazzana et al. 2022; Gikonyo et al. 2022), institutional factors (Sardar et al. 2021), and topography and climate-related factors (Arslan et al. 2015). For example, Zhu et al. (2021) found that compared with ties to retailers, ties to local farmers impeded farmers from actively combating CC in China. Sedebo et al. (2022) found that weather information significantly influences smallholder households' decisions to adopt CAPs in southern Ethiopia. Zhou et al. (2023) found that agricultural cooperatives are key to improving CAP adoption in rural China.

An increasing body of research has examined the impacts of CAPs on the three fundamental aspects (productivity, adaptation, and mitigation) of the climate-smart agriculture (CSA) systems (Lopez-Ridaura et al. 2018; Branca et al. 2021; Sedebo et al. 2022). However, most of these studies only consider one dimension of the implications of the CSA system, such as household income, agricultural outputs, and greenhouse emissions (Amadu et al. 2020; Bazzana et al. 2022; Israel et al. 2020). For example, Amadu et al. (2020) found that the maize yield of CAP adopters, who participated in the Agriculture for Life Advancement project in southern Malawi, is 53% higher than that of non-adopters.

[1] China Meteorological New Press. (2023). Blue Book on Climate Change of China unveiled. https://www.cma.gov.cn/en2014/climate/ClimateUpdate/202307/t20230719_5657000.html

Branca et al. (2021) revealed that transforming from conventional to climate-smart farming significantly enhances households' economic returns in Southern Africa. Bazzana et al. (2022) found that CAPs (water and soil management action and conservation practices) can greatly increase farmers' food security in rural Ethiopia, particularly for those with strong financial resources, extensive social networks, and entry to well-connected food markets.

Although it is widely acknowledged that farmers always adopt more than one type of CAP (Zakaria et al. 2020), most of the previous studies have used CAP adoption as a dummy variable in their estimations (Arslan et al. 2015). Only a few studies consider CAP adoption as an ordered or continuous variable when investigating its intensity on household welfare (Israel et al. 2020; Sardar et al. 2021). For example, taking CAPs as a continuous variable, Israel et al. (2020) found that CAP adoption (irrigation and water collection, soil conservation practices, and livelihood diversification) significantly reduces GHG emissions by 62.3% in Northern Ghana. Sardar et al. (2021) divided CAPs into different levels and found that the crop yields received by Pakistani farmers who adopted a full set of CAPs (water and nutrient management, adjusting planting dates, increasing crop varieties, and zero or minimum tillage) are 32% higher for cotton and 44% higher for wheat than non-adopters.

Despite the rich findings in the existing studies, there are important research gaps. First, while a growing body of research has explored the social, economic, and ecological effects of CAP adoption, little is known about whether and to what extent CAP adoption intensity affects income diversity. As a risk management strategy, income diversification can effectively address external shocks in production. Therefore, it is important to understand the relationship between CAP adoption intensity and income diversity. Second, previous studies have assumed that CAP adoption intensity has a homogeneous impact on household welfare. Nevertheless, CAP adoption intensity may affect rural households in the upper and lower levels of the distribution of household welfare indicators differently. This is not surprising because farmers are endowed with different personal characteristics (e.g., education and innate ability) and resource endowments (land and machinery). However, to the best of our knowledge, the potential heterogeneous effects of CAP adoption intensity on household welfare remain unexamined.

This study, therefore, examines the effects of CAP adoption intensity on household economic welfare. Our contributions are threefold. First, we consider seven types of CAPs (e.g., water-saving irrigation, organic fertilizer, farmyard manure, zero tillage, fallow cropping, crop rotation, and crop straw mulch) to capture the CAP adoption intensity. In particular, we categorized the farmers' CAP adoption intensity into four ordinal groups according to the number of CAPs they adopted. Second, this study considers multiple indicators, including household income, net farm income, and income diversity, to capture household economic welfare. Most studies only focus on specific household economic indicators, such as crop income and per capita consumption expenditure (Fentie and Beyene 2019; Sardar et al. 2021). Measuring household welfare from multiple dimensions provides a comprehensive understanding of the effects of CAP adoption intensity.

Third, we utilize a two-stage residual inclusion (2SRI) model to mitigate the endogeneity concern linked to CAP adoption intensity. Farmers self-decide whether or not to adopt CAPs. Both observable factors (e.g., age, gender, education, and family size) and unobservable factors (e.g., inner motivations and native ability) could affect their CAP adoption decisions. The fact leads to self-selection and omitted variable issues. Previous studies mainly employ the propensity score matching (PSM) model (Andati et al. 2023; Fentie & Beyene 2019) and inverse-probability-weighted regression adjustment (IPWRA) estimator (Israel et al. 2020) to mitigate the concerns related to selection bias. However, they can only control for the observed selection bias. Several studies used the endogenous switching regression model (Amadu et al. 2020; Akter et al. 2023), but it cannot solve the endogeneity issue of ordered explanatory variables (i.e., CAP adoption intensity). The 2SRI model can address the endogeneity of CAP adoption intensity by controlling for both observable and unobservable heterogeneities, thus producing more robust estimates. Additionally, we employ an instrumental-variable-based quantile regression (IVQR) model to explore the heterogeneous effects of CAP adoption intensity on household economic welfare. The findings of this study enrich the literature examining the effects of CAP adoption intensity on household welfare.

The subsequent sections of this paper are structured as follows: Section 2 offers a literature review, followed by an explanation of the estimation methodologies in Section 3. Section 4 introduces the data and provides descriptive statistics, while Section 5 presents and discusses empirical findings. The concluding section wraps up the paper and proposes policy implications.

2 Literature review

In the face of CC, farmers, particularly those in developing countries, have changed their traditional agricultural practices and adopted CAPs to reduce the adverse impact of changing climatic conditions (Nyasimi et al. 2017). These CAPs are diversified and need to be tailored based on different locations and conditions (Anugwa et al. 2022; Das et al. 2022; Morkunas and Volkov 2023). Previous studies mainly focused on the specific CAPs and taking CAP adoption as the dummy variable to explore its determinants and implications (Arslan et al. 2015; Bazzana et al. 2022; Israel et al. 2020; Musafiri et al. 2022). However, farmers are more inclined to implement a mix of CAPs rather than solely relying on a single CAP to tackle the obstacles presented by the impacts of CC (Zhou et al. 2023). Further, with the emphasis on the complementary effects of different CAPs (Harvey et al. 2014; Zheng et al. 2019; Antwi-Agyei et al. 2023), several research endeavors focused on the CAP adoption intensity, regarding it as the continuous or count variable based on the numbers of CAPs adopted by farmers (Sardar et al. 2021; Zakaria et al. 2020). In this study, we follow these studies to divide CAP adoption intensity into different levels and explore how CAP adoption intensity affects households' economic welfare, providing suggestions for CAP implementation in rural areas.

Different CAPs bring about heterogeneous economic, social, and environmental effects on the three fundamental elements of the CSA system (Zakaria et al. 2020; Sardar et al. 2021; Akter et al. 2023). Adopting CAPs is an efficient pathway to ensure food security, which can be found in the positive effects of CAPs on households' agricultural productivity (Lopez-Ridaura et al. 2018; Sardar et al. 2021), food availability (Bazzana et al. 2022), and food consumption (Hasan et al. 2018). Further, CAP adoption significantly improves households' adaptability and resilience under various climatic conditions. For example, the prevalent agricultural adaptive strategies, such as diversifying crops, rescheduling farming, and changing crop structure are found positively influence crop yields (Arslan et al. 2015; Sedebo et al. 2022; Sargani et al. 2023), poverty alleviation (Habtewold 2021), crop income (Ahmad and Afzal 2020), and GHG emission mitigation (Zheng et al. 2019; Wang et al. 2020). CAP adoption is also imperative to improve gender equality in agriculture regarding ownership rights (Tsige et al. 2020) and knowledge and capacity (Hariharan et al. 2020). In this study, we focus on two pillars of the CSA system: productivity and adaptability. We use household income and net farm income as the proxy variable of productivity and use income diversity to indicate farmers' adaptability.

Therefore, to explore the economic impacts of CAP adoption, this study classifies CAP adoption behavior into four intensity levels based on the amount/number of CAP adoption behavior of the farmers and investigates its impacts on three dimensions of households' economic welfare. This comprehensive perspective helps us understand the potential synergistic effects of CAPs on household economic welfare.

3 Estimation strategies

3.1 Endogeneity issue and model selection

The adoption of CAPs is not random. Farmers self-determine whether to adopt CAPs and how many CAPs they should adopt. The intensity of CAP adoption depends on observable factors (e.g., age, gender, health status, and education) and unobservable factors (e.g., farmers' innate ability, risk preference, and motivation). This process of self-selection renders the intensity of CAP adoption endogenous. This endogeneity should be addressed to produce coherent estimations of the consequences linked to CAP adoption intensity on outcome variables. Both the two-stage residual inclusion (2SRI) approach and the two-stage prediction substitution (2SPS) approach can effectively tackle the issue of endogeneity associated with ordered explanatory variables (i.e., CAP adoption intensity in this study). Compared with the 2SPS approach, the 2SRI approach generated more accurate and reliable estimates (Terza et al. 2008; Basu et al. 2018; Zheng et al. 2023). Therefore, we adopt the 2SRI approach as the estimation strategy in this study.

3.2 The 2SRI approach

The 2SRI approach involves the estimation of two equations. The first equation investigates the factors influencing CAP adoption intensity. In the first equation, it is essential to incorporate at least one valid instrumental variable. Given that CAP adoption intensity is an ordered variable, we estimate the following ordered probit model in the first stage:

$$A_i^* = \alpha_i X_i + \beta_i IV_i + \varepsilon_i, A_i = \begin{cases} 1 \ if \ A_i^* \leq C_1 \\ 2 \ if \ C_1 < A_i^* \leq C_2 \\ \cdots \\ K \ if \ C_{K-1} \leq A_i^* \end{cases} \tag{1}$$

where A_i^* represents an underlying or latent variable depicting the CAP adoption intensity of household i; it is indicated by an observable categorical variable A_i. The latter is influenced by the unidentified cutoffs $C_1, C_2, \cdots, C_{K-1}$, which fulfills the requirement that $C_1 < C_2 < \cdots < C_{K-1}$. X_i denotes a set of control variables. IV_i refers to an instrumental variable (IV). α_i and β_i are parameters to be estimated, and ε_i is an error term.

An appropriate instrumental variable is a prerequisite for the 2SRI model to generate consistent estimates. Following previous research (Sang et al. 2023), we construct an IV based on the peer effect theory. Specifically, we use the average level of CAPs adopted by peers in the same village as the IV. Theoretically, the level of CAPs adopted by peers in the same village will motivate farmers to adopt more practices, but will not directly affect their economic welfare. We employed Pearson correlation coefficient analysis to statistically verify the validity of the employed IV (see Table 6 in the Appendix). The test results show that the correlation coefficient between the instrumental variable and CAP adoption intensity is 0.357, which demonstrates statistical significance at the 1% significance level. The results in Table 6 also show that the IV and outcome variables are not statistically significant. Hence, the instrumental variable (IV) fulfills the criterion of exhibiting correlation with the endogenous variable and non-correlation with the outcome variables, affirming the appropriateness of our chosen IV.

The second equation examines the effect of CAP adoption intensity on a vector of outcome variables. The residual term forecasted through estimating the first equation is incorporated into the second equation as a regressor to mitigate unobservable selection bias. Specifically, the second equation of the 2SRI approach is specified as follows:

$$Y_i^J = \gamma_i A_i + \delta_i X_i + \eta_i Residual_i + \mu_i, J = 1, 2, 3 \tag{2}$$

where Y_i^J refer to J dependent variables, including household income ($J = 1$), net farm income ($J = 2$), and income diversity ($J = 3$). A_i and X_i are as defined earlier. $Residual_i$ is the residual term predicted after estimating Eq. (1). γ_i, δ_i and η_i represent parameters that need to be estimated. μ_i represents the error term.

3.3 The IVQR model

The estimation of Eq. (2) can provide homogeneous effects of CAP adoption intensity on outcome variables. Besides that, it is also interesting to understand how CAP adoption intensity influences the outcome variables at different distributions. For example, CAP adoption intensity may influence farming households with low and high household incomes differently. Therefore, we investigate the heterogeneous effects of CAP adoption intensity to enhance our understanding.

Some studies have utilized the conditional quantile regression (CQR) model (Ogutu and Qaim 2019; Zhang et al. 2020) and unconditional quantile regression (UQR) model (Khanal et al. 2018; Tran and Vu 2020) when investigating the heterogeneous effects of a program or intervention. Both of them consider all explanatory variables as exogenous. As discussed earlier, CAP adoption intensity is an endogenous variable. Therefore, we utilize the instrumental-variable-based quantile regression (IVQR) model to estimate the heterogeneous impacts of CAP adoption intensity. Unlike the CQR and UQR models, the IVQR model has the advantage of addressing the endogenous issue associated with the CAP adoption intensity variable. Following Chernozhukov and Hansen (2008), we estimate the τ^{th} quantile of the outcome variable, $Q_\tau(Y_i)$, as a linear equation involving the endogenous variable (A_i), a set of exogenous variables (X_i) and an error term (φ_i). It can be specified as follows:

$$Q_\tau(Y_i) = \theta_\tau A_i + \lambda_\tau X_i + \varphi_i \tag{3}$$

where $Q_\tau(Y_i)$ is independent of IV_i, θ_τ and λ_τ are parameters that need to be estimated at the quantile τ. We implement the estimator using the method of Machado and Santos Silva (2019).

4 Data and key variables

4.1 Data

This study employed data from the 2020 China Rural Revitalization Survey (CRRS), carried out by the Rural Development Institute at the Chinese Academy of Social Sciences. It contains rich information on agricultural production (e.g., CAP adoption), demographic factors (e.g., age, gender, education, health status, household size, and dependency ratio), and socioeconomic factors (e.g., income, farm size, and asset ownership). The 2020 CRRS utilized a multistage probability proportional to size (PPS) sampling technique to randomly select 3,833 households from 10 provinces in eastern, central, and western China. Since we are interested in the CAP adoption behavior of farmers growing grain crops such as maize, wheat, and rice, we dropped the samples of farmers growing other crops. We also deleted samples with missing information in dependent and independent variables. Finally, we obtained a sample size of 1,785 households.

In this study, we select three dependent variables to capture economic welfare outcomes: household income, net farm income, and income diversity. Household income refers to the collective earnings generated through agricultural activity, business investment, wages, property, subsidies, and remittances. Net farm income designates the difference between gross revenue derived from agricultural, forestry, animal husbandry, and fishery activities and production costs. The income diversity is quantified using the Simpson index, and we have considered eight types of income sources (i.e., agriculture, forestry, animal husbandry, fishery, business, salary, property, and transfer income).

4.2 Key variables

4.2.1 Dependent variables

Economic welfare, denoting the overall prosperity and living standards within an economy, remains a multifaceted concept (Fang 2011). Despite the various factors contributing to its measurement, there is still limited consensus on the definition of households' economic welfare in existing literature (Tankari 2017). In this study, we strategically chose three dependent variables to capture economic welfare outcomes: household income, net farm income, and income diversity. Household income, encompassing earnings from agricultural pursuits, business investments, wages, property, subsidies, and remittances, is a central and widely recognized measure of a household's economic well-being (Shahzad and Abdulai 2021). Net farm income is of great significance, representing the disparity between gross revenue from agricultural, forestry, animal husbandry, and fishery activities and production costs. Its role in directly measuring a household's financial success in agricultural endeavors has garnered broad acknowledgement.

Income diversity plays a key role in increasing household resilience and reducing economic risk (Li et al. 2020). In this study, the income diversity is quantified using the Simpson index and we have considered eight types of income sources (i.e., agriculture, forestry, animal husbandry, fishery, business, salary, property, and transfer income). Following previous studies (Vatsa et al. 2022), the Simpson index is measured as follows:

$$Simpson_i = 1 - \sum_{s=1}^{m} P_{i,s}^2 \tag{4}$$

where $Simpson_i$ refers to the Simpson index associated with household i. m is the total number of income sources for household i. $P_{i,s}$ refers to the proportion of income from sources s in total household income. The value of $Simpson_i$ is always between zero and one. If a household has only one source of income (e.g., agricultural), the value of $Simpson_i$ will be equal to zero. As the number of income sources increases, the value of $Simpson_i$ approaches one. Higher values of the Simpson index mean that households diversify their income using various sources.

4.2.2 Explanatory variables

The key explanatory variable is CAP adoption intensity. We choose seven practices reflecting CAP adoption intensity based on the grain crop production practices in China and existing literature on CAPs (Chen et al. 2022; Akter et al. 2023; Sattar et al. 2023), which includes: (1) water-saving irrigation, (2) organic fertilizer, (3) farmyard manure, (4) zero tillage, (5) fallow cropping, (6) crop rotation, (7) crop straw mulch.[2] Specifically, we categorize the farmers' CAP adoption intensity into four ordinal groups according to the number of CAPs they adopted: i.e., Adoption Level-0 (no CAPs have been adopted), Level-1 (Adoption of only one CAP), Level-2 (Adoption of two to three CAPs), and Level-3 (Adoption four to five CAPs). Each level represents the cumulative number of distinct practices adopted by a farmer. For example, a farmer classified under Level-1 means adopting any one of the seven specified practices, not limited to a specific one. Similarly, a farmer classified under Level-2 indicates choosing any combination of two to three practices from the set of seven. Our rationale for employing this ordinal coding approach rather than a multivariate analysis lies in our interest in understanding the cumulative impact of adopting a certain number of practices on specific outcomes. By categorizing farmers into ordinal levels, we aim to explore the relationship between the intensity of CAP adoption and outcomes in a structured and interpretable manner.

The control variables are selected based on previous studies on CAP adoption (Khan et al. 2022; Belay et al. 2023) and economic welfare (Ma et al. 2020; Ahmad and Jabeen 2023). These variables capture individual characteristics (household head's age, gender, education, and health status), household characteristics (household size, dependency ratio, farm size, and asset ownership), and location characteristics (eastern, central, and western China).

5 Results and discussion

5.1 Descriptive results

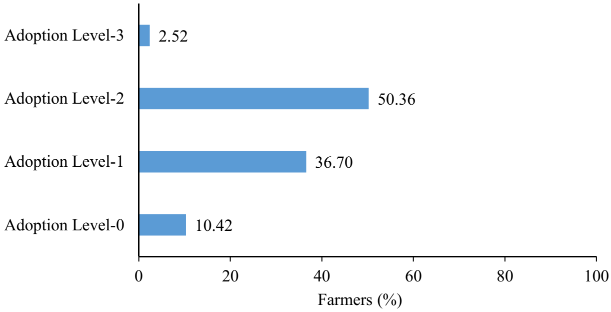
Table 1 presents the definitions and rates of adoption for each of the seven CAPs. The most popular practices adopted by farmers are crop straw mulch and organic fertilizer, accounting for 49% and 48%, respectively. The practices least popular among farmers are water-saving irrigation, zero tillage, and fallow cropping, representing 6%, 8%, and 8%,

[2] In this study, organic fertilizer refers specifically to commercial organic fertilizer, and farmyard manure refers to composted crop residues and animal manure.

Table 1 Definitions and descriptive statistics of climate-smart agricultural practices

Variables	Definitions	Mean (S.D.)
Water-saving irrigation	1 if water-saving irrigation technology is adopted, 0 otherwise	0.06 (0.24)
Organic fertilizer	1 if organic fertilizer is adopted, 0 otherwise	0.48 (0.50)
Farmyard manure	1 if farmyard manure is adopted, 0 otherwise	0.21 (0.41)
Zero tillage	1 if zero tillage is adopted, 0 otherwise	0.08 (0.27)
Fallow cropping	1 if fallow cropping is adopted, 0 otherwise	0.08 (0.27)
Crop rotation	1 if crop rotation is adopted, 0 otherwise	0.24 (0.43)
Crop straw mulch	1 if crop straw mulch is adopted, 0 otherwise	0.49 (0.50)

Fig. 1 Proportional distributions of adoptation intensity



respectively. Furthermore, around 24% and 21% of farmers have embraced crop rotation and farmyard manure, respectively.

We further present proportional distributions of CAP adopt intensity in Fig. 1. Most farmers adopted two to three practices (level-2) with a percentage of 50.36%, followed by farmers adopting one practice (level-1) with 36.70%. Only 10.42% of the farmers did not adopt any practice (level-0). In addition, 2.52% of the farmers adopted 4 to 5 practices (level-3).

Table 2 provides the definitions and summary statistics of the variables. The average per capita household income and per capita net farm income are 16.84 thousand Yuan and 7.03 thousand Yuan,[3] respectively. The average score for income diversity, as measured by the Simpson Index, is 0.36. The mean value of CAP adoption intensity is 1.45, indicating that the majority of households have a relatively low level of CAP adoption. On average, the household heads in the sample are 55 years old, and most (96%) are male. The average year of education is around eight years, and the mean health status is 4.22. There are about four persons in the sampled households on average. The mean dependency ratio is 0.26. The average size of farm size is 28.91 mu. Appropriately, 40% of households own agricultural machines. The proportions of farmers growing wheat, maize, and rice are 20%, 56%, and 24%, respectively. The percentages of farmers located in the eastern, central, and western regions are 18%, 35%, and 47%, respectively.

[3] On average, the net farm income per unit of land is 2.64 thousand Yuan.

Table 2 Variable definitions and summary statistics

Variables	Definitions	Mean (S.D.)
Dependent variables		
Household income	Total household income (1,000 Yuan/capita)[a]	16.84 (18.68)
Net farm income	The difference between gross revenue received from agricultural, forestry, animal husbandry, and fishery activities and production costs (1,000 Yuan/capita)	7.03 (15.06)
Income diversity	Measured by Simpson index	0.36 (0.21)
Key explanatory variable		
CAP adoption intensity	0 = no adoption; 1 = 1 practices; 2 = 2–3 practices; 3 = 4–5 practices	1.45 (0.71)
Independent variables		
Age	Age of household head (HH) (years)	55.10 (10.60)
Gender	1 if HH is male, 0 otherwise	0.96 (0.21)
Education	Education level of HH (years)	7.78 (3.09)
Health status	Self-reported health status: from 1 = very unhealthy to 5 = very healthy	3.55 (1.03)
Household size	Number of household members (persons)	4.22 (1.51)
Dependency ratio	Ratio of the number of residents aged less than 14 years and more than 64 years to household size	0.26 (0.26)
Farm size	Total farm size (mu)[b]	28.91 (87.78)
Asset ownership	1 if household owns agricultural machines, 0 otherwise	0.40 (0.49)
Wheat	1 if the main crop grown is wheat, 0 otherwise	0.20 (0.40)
Maize	1 if the main crop grown is maize, 0 otherwise	0.56 (0.50)
Rice	1 if the main crop grown is rice, 0 otherwise	0.24 (0.43)
Eastern	1 if household is located in eastern region, 0 otherwise	0.18 (0.39)
Central	1 if household is located in central region, 0 otherwise	0.35 (0.48)
Western	1 if household is located in western region, 0 otherwise	0.47 (0.50)
IV	Average level of CAPs adopted by peers in the same village	1.45 (0.42)
Observations		1,785

S.D. refers to the standard deviation; [a] Yuan is a Chinese currency (1 USD = 6.90 Yuan in 2019); [b] 1 mu = 1/15 ha

5.2 Determinants of CAP adoption intensity

Table 3 shows the effects of different factors on CAP adoption intensity estimated from Eq. (1). As previously mentioned, the ordered probit model was employed to estimate the CAP adoption intensity equation. Because the coefficient estimates of the ordered probit model are not straightforward in interpretations, we compute and present the results of the marginal effects estimates to facilitate our understanding.

The findings indicate that education, geographical location, and the average level of CAPs adopted by peers in the same village exert significant and positive marginal effects on CAP adoption intensity. Specifically, a one-year increase in the education level of the household head raises the probability of attaining CAP adoption intensity levels 2 and 3 by 0.7% and 0.1%, respectively. The findings indicate that the household heads with higher education are more likely to adopt more CAPs. The results are consistent with the findings of Sardar et al. (2021). Higher levels of education improve

Table 3 First-stage estimation: determinants of CAP adoption intensity

		Marginal effects			
Variables	Coefficients	Adoption Level 0	Adoption Level 1	Adoption Level 2	Adoption Level 3
Age (c)	-0.001 (0.003)	0.000 (0.000)	0.000 (0.001)	-0.000 (0.001)	-0.000 (0.000)
Gender (d)	0.120 (0.132)	-0.020 (0.021)	-0.024 (0.027)	0.037 (0.040)	0.007 (0.008)
Education (c)	0.024 (0.009)***	-0.004 (0.001)**	-0.005 (0.002)**	0.007 (0.003)**	0.001 (0.001)*
Health status (c)	0.012 (0.026)	-0.002 (0.004)	-0.002 (0.005)	0.004 (0.008)	0.001 (0.001)
Household size (c)	0.015 (0.018)	-0.002 (0.003)	-0.003 (0.004)	0.005 (0.005)	0.001 (0.001)
Dependency ratio (c)	0.165 (0.108)	-0.027 (0.018)	-0.033 (0.022)	0.051 (0.033)	0.009 (0.006)
Farm size (c)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Asset ownership (d)	0.063 (0.059)	-0.010 (0.009)	-0.013 (0.012)	0.019 (0.018)	0.004 (0.003)
Wheat (ref rice) (d)	-0.061 (0.082)	0.010 (0.013)	0.012 (0.017)	-0.019 (0.025)	-0.003 (0.005)
Maize (ref rice) (d)	0.040 (0.069)	-0.006 (0.011)	-0.008 (0.014)	0.012 (0.021)	0.002 (0.004)
Eastern (ref western) (d)	0.119 (0.078)	-0.019 (0.013)	-0.024 (0.016)	0.036 (0.024)	0.007 (0.004)
Central (ref western) (d)	0.198 (0.066)***	-0.032 (0.011)**	-0.040 (0.013)**	0.061 (0.020)**	0.011 (0.004)**
IV	0.933 (0.078)***	-0.151 (0.014)***	-0.188 (0.015)***	0.286 (0.022)***	0.053 (0.007)***
Cut1	0.516 (0.269)*				
Cut2	1.830 (0.272)***				
Cut3	4.003 (0.291)***				
Log pseudo-likelihood	-1,730.378				
Wald χ^2 (12)	215.15, $p > \chi^2$=0.00				
Observations	1,785	1,785	1,785	1,785	1,785

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; Robust standard errors in parenthesis; The reference crop is rice; The reference region is western region; (c) Continuous variable (d) Dummy variable

Table 4 Second-stage estimation: impact of CAP adoption intensity on household income, net farm income, and income diversity

Variables	Household income	Net farm income	Income diversity
CAP adoption intensity	4.118 (2.014)**	4.297 (1.573)***	0.042 (0.023)*
Age (c)	-0.150 (0.042)***	-0.152 (0.035)***	0.002 (0.001)***
Gender (d)	-2.274 (2.110)	0.279 (1.912)	0.027 (0.024)
Education (c)	0.409 (0.152)***	-0.127 (0.108)	-0.001 (0.002)
Health status (c)	1.089 (0.377)***	0.286 (0.300)	-0.010 (0.005)**
Household size (c)	-0.932 (0.269)***	-0.989 (0.226)***	-0.009 (0.003)***
Dependency ratio (c)	-6.994 (1.451)***	-2.986 (1.132)***	0.064 (0.020)***
Farm size (c)	0.055 (0.019)***	0.039 (0.017)**	0.000 (0.000)
Aasset ownership (d)	0.075 (0.995)	1.971 (0.827)**	0.035 (0.011)***
Wheat (ref rice) (d)	1.155 (1.284)	2.225 (1.068)**	0.025 (0.015)*
Maize (ref rice) (d)	0.418 (1.137)	1.020 (0.962)	0.031 (0.013)**
Eastern (ref western) (d)	-1.815 (1.182)	-3.837 (0.833)***	-0.088 (0.015)***
Central (ref western) (d)	-3.778 (1.107)***	-2.216 (0.914)**	-0.037 (0.013)***
Residual	-2.924 (1.613)*	-2.627 (1.330)**	-0.026 (0.018)
Constant	19.598 (4.157)***	12.352 (3.530)***	0.211 (0.052)***
F test	11.56, $p > F$=0.00	11.10, $p > F$=0.00	8.16, $p > F$=0.00
Observations	1,785	1,785	1,785

***$p<0.01$, **$p<0.05$, *$p<0.1$; Robust standard errors in parenthesis; The reference crop is rice; The reference region is western region; (c) Continuous variable (d) Dummy variable

farmers' understanding of the benefits associated with CAPs, motivating them to adopt them. Haq et al. (2021) also found that better-educated farmers are more aware of the impacts of CC, so they take more CAPs to reduce production losses.

The results also show that relative to their counterparts residing in the western region of China (reference region), rural households residing in the Central region have a 6.1% and 1.1% higher likelihood of having CAP adoption intensity at level 2 and level 3, respectively. The main reason may be attributed to differences in agricultural structure. Agriculture in the central region primarily revolves around grain production, while the western region emphasizes poultry and livestock production. Finally, the coefficient of the IV representing the average level of CAPs adopted by peers in the same village is positive and significant, highlighting the importance of social interactions in the adoption of innovative technology. This finding is consistent with existing findings (Barnes et al. 2019; Pagliacci et al. 2020).

5.3 Homogeneous impacts of CAP adoption intensity

Table 4 presents the results regarding the effects of CAP adoption intensity on economic outcomes estimated from Eq. (2). The coefficients of residuals predicted from the first stage of the 2SRI model are negative and statistically significant in columns 2 and 3. These results indicate the potential presence of endogeneity issues arising from unobserved factors, which supports the utilization of the 2SRI model (Ma and Zhu 2020).

5.3.1 Impacts on household income

The results in column 2 of Table 4 reveal that the coefficient of the CAP adoption intensity variable is positive and statistically significant, indicating that enhancing CAP adoption is linked to a rise in household income. This finding is consistent with previous studies (Makate et al. 2019; Jamil et al. 2021). For example, Makate et al. (2019) demonstrated that adopting the complete CSA package significantly influenced household income more than other packages.

Our estimates show that household income is also affected by other control variables. For example, the age variable exerts a negative and statistically significant impact on household income. This is because elderly individuals are reluctant to learn new techniques and stick to their production habits (Huang et al. 2020). The coefficient associated with the health status variable is positively significant, implying that farmers in good health are more inclined to achieve higher income levels. Better health conditions help farmers engage in non-agricultural employment, contributing to higher household incomes (Ma et al. 2022).

5.3.2 Impacts on net farm income

The results in column 3 of Table 4 indicate that CAP adoption intensity significantly increases net farm income. Implementing CAP can effectively mitigate the negative consequences of CC, enhance resilience, and ultimately lead to improved productivity, resulting in higher net farm income (Azadi et al. 2021). The findings are similar to the results of previous studies (Khan et al. 2021; Pangapanga-Phiri and Mungatana 2021). For example, Khan et al. (2021) found that farmers who adopted multiple CAPs had higher profits than those who adopted few.

The results show that other exogenous factors also influence net farm income. For example, the variable of farm size exerts a positive and statistically significant impact on net farm income. Larger farm sizes may provide a chance to enjoy economies of scale in agricultural production, leading to higher farm income. This finding is consistent with previous studies such as Noack and Larsen (2019) for Uganda and Hussain et al. (2020) for Pakistan. The coefficient of asset ownership is positive and statistically significant, indicating that agricultural machines can help farmers lower production costs and increase yields and net returns (Zhou and Ma 2022).

5.3.3 Impacts on income diversity

Column 4 of Table 4 shows the impact of CAP adoption intensity on income diversity. As discussed earlier, we employ the Simpson Index to measure income diversity. The results reveal that increasing farmers' adoption of CAPs promotes income diversity. CAP adoption saves farm labor and time, thus facilitating farmers to reallocate the saved time to engage in non-farm activities (Ngwira et al. 2013). In addition, the government also provides subsidies to farmers who adopt CAPs, thereby increasing their transfer income (Xie et al. 2022).

The results also offer valuable insights into the influence of control variables on income diversity. For example, the health status variable significantly and negatively affects income diversity. The possible reason is that farmers in good health tend to concentrate on non-agricultural employment to optimize their earnings, potentially

Table 5 Impact of CAP adoption intensity on household income, net farm income, and income diversity: IVQR model estimation

	IVQR model estimation			
Variables	20th	40th	60th	80th
	Dependent variable = household income			
CAP adoption intensity	0.136 (0.165)	0.211 (0.122)*	0.265 (0.104)**	0.325 (0.103)***
Control variables	Yes	Yes	Yes	Yes
Observations	1,785	1,785	1,785	1,785
	Dependent variable = net farm income			
CAP adoption intensity	1.217 (0.521)**	0.978 (0.293)***	0.854 (0.205)***	0.733 (0.184)***
Control variables	Yes	Yes	Yes	Yes
Observations	1,785	1,785	1,785	1,785
	Dependent variable = income diversity			
CAP adoption intensity	0.058 (0.035)*	0.042 (0.027)	0.028 (0.024)	0.018 (0.026)
Control variables	Yes	Yes	Yes	Yes
Observations	1,785	1,785	1,785	1,785

Household income and net farm income are log-transformed. ***$p<0.01$, **$p<0.05$, *$p<0.1$; Standard errors in parenthesis

diminishing income diversification. The dependency ratio variable affects income diversity positively and significantly, indicating that rural households with elevated dependency ratios lean towards diversifying sources of income, thereby alleviating the burdens of life.

5.4 Heterogeneous impacts of CAP adoption intensity

The results for the IVQR estimates on the impacts of CAP adoption intensity on the economic outcomes are presented in Table 5. The results show that the impacts of CAP adoption intensity on household income are uniformly positive across the selected quantiles, except at the 20th quantile. The magnitudes of the coefficients increase monotonically per quantile. The findings suggest that farmers with higher household incomes tend to benefit more from CAP adoption than their counterparts with lower household incomes. This may be because farmers with higher household incomes tend to have more knowledge, skills, and productive resources. They are more likely to adopt the best package to maximize returns.

The results also show that the CAP adoption intensity exerts a positive and statistically significant influence on net farm income across the quantiles that have been chosen for analysis. The magnitudes of the coefficients decrease consistently in a monotonous manner from the lowest 20th quantile to the highest 80th quantile. Our results support the finding of Liang et al. (2021), who noted that rice farmers with limited farm incomes tend to experience greater benefits from CAP adoption than their counterparts with high farm incomes. At the lowest 20th quantile, CAP adoption intensity demonstrates a significant and positive impact on household diversity, but its impact is not significant at the higher quantiles.

5.5 Additional estimations

To verify the robustness of our main results, we employed the Endogenous treatment regression (ETR) model to examine the influence of CAP adoption. Like the 2SRI model, the ETR model can account for the selection bias issues arising from observable and unobservable factors. Here, CAP adoption is measured as a dummy variable, which equals 1 if a farmer adopts any of those seven selected CAPs and 0 otherwise. Table 7 in the Appendix presents the results that estimate the impact of CAP adoption on household income, net farm income, and income diversity. The significance of the correlation coefficient $\rho_{\varepsilon\mu}$ indicates the existence of selection bias stemming from unobserved variables, affirming the suitability of employing the ETR model.

The results presented in Table 7 in the Appendix show that CAP adoption is positively associated with household income, net farm income, and income diversity, suggesting that CAP adoption exerts a positive and significant impact on household economic benefits (Imran et al. 2019; Issahaku and Abdulai 2020). The findings are consistent with the outcomes derived from our estimation of CAP adoption intensity, as illustrated in Table 4, thereby affirming the robustness of our estimates.

6 Conclusions and policy implications

Although previous literature has examined the role of CAP adoption, little is known about the multiple economic impacts of CAP adoption intensity. This study comprehensively examines the economic impacts of CAP adoption intensity, focusing on household income, net farm income, and income diversity. To address the endogeneity issues, we utilized the 2SRI model to estimate household data for 2020 CRRS. Besides, the IVQR model was utilized to capture the heterogeneous impacts of CAP adoption intensity.

The results obtained from the first stage estimation of the 2SRI model indicate that the education level of the household head and geographical location determine farmers' adoption intensity of CAPs. The results from the second stage of the 2SRI model reveal that higher levels of CAP adoption are positively and significantly associated with higher household income, net farm income, and income diversity. The results from the IVQR model show that CAP adoption intensity is associated with economic welfare, but the effects are not homogenous. The impacts of CAP adoption intensity are more significant for the higher quantile of the household income distribution and the lower quantile of the net farm income distribution. Low-income diversity farmers tend to benefit more from CAP adoption intensity than their high-income diversity counterparts.

Our findings have important policy implications for promoting CAP adoption and improving farmers' household welfare. First, the positive effects of CAP adoption intensity on household economic welfare underscores the pressing need to incentivize farmers to incorporate CAPs more extensively. To bolster the adoption rate, particularly for practices with currently lower adoption rates, such as water-saving irrigation and crop rotation, policymakers should pursue a multifaceted approach. This approach involves identifying the pivotal drivers that can encourage the widespread adoption of CAPs. To this end, strategies such as offering financial incentives, crafting well-supported voluntary schemes, delivering robust training programs, and facilitating the dissemination of relevant informational tools should be considered. Achieving higher adoption rates requires a comprehensive approach that synergistically combines economic, educational, and motivational factors. This integrated strategy fosters a favorable environment for farmers to effortlessly incorporate CAPs into their practices, ultimately boosting their economic prosperity and operational sustainability.

Second, the evident link between education and the intensity of CAP adoption emphasizes the critical need for targeted interventions designed to assist farmers with limited educational backgrounds. To enhance 'farmers' ability to withstand climate variability by widely adopting CAPs', it's imperative to ensure that farmers comprehend the inherent value of these practices. As such, offering comprehensive technical training with CAPs becomes a pivotal method to foster increased adoption rates among farmers.

Third, it is essential to consider regional disparities during the policy formulation process. To this end, we recommend conducting in-depth research to elucidate the specific hurdles farmers in the western region encounter when adopting CAPs. This proactive step will provide valuable insights that can guide the development of policies tailored to the unique circumstances of this region. Policymakers can craft strategies by understanding the distinct challenges and opportunities in the western region, resulting in more targeted and impactful initiatives.

Appendix

Table 6 Validity tests for the instrumental variables (Pearson correlation coefficient analysis)

Variables	Correlation coefficients	*p*-value
CAP adoption intensity	0.357***	0.000
Household income	0.023	0.338
Farm income	0.024	0.309
Income diversity	0.011	0.658

*** $p < 0.01$

Table 7 Impact of CAP adoption on household income, net farm income, and income diversity: ETR model estimations

	Model 1		Model 2		Model 3	
Variables	CAP adoption	Household income	CAP adoption	Net farm income	CAP adoption	Income diversity
CAP adoption		4.419 (2.436)*		5.641 (1.327)***		0.138 (0.075)*
Age	0.000 (0.005)	-0.147 (0.042)***	0.000 (0.005)	-0.149 (0.034)***	-0.001 (0.005)	0.002 (0.001)***
Gender	0.231 (0.181)	-2.226 (2.067)	0.227 (0.183)	0.301 (1.887)	0.252 (0.179)	0.025 (0.024)
Education	0.022 (0.014)	0.470 (0.147)***	0.021 (0.014)	-0.070 (0.104)	0.022 (0.014)*	-0.001 (0.002)
Health status	-0.024 (0.042)	1.153 (0.378)***	-0.025 (0.042)	0.358 (0.301)	-0.031 (0.042)	-0.009 (0.005)*
Household size	0.036 (0.030)	-0.898 (0.262)***	0.036 (0.030)	-0.961 (0.217)***	0.033 (0.030)	-0.009 (0.003)***
Dependency ratio	0.393 (0.195)**	-6.787 (1.431)***	0.388 (0.195)**	-2.852 (1.100)***	0.406 (0.192)**	0.059 (0.021)***
Farm size	0.000 (0.001)	0.055 (0.019)***	0.000 (0.001)	0.039 (0.017)**	0.001 (0.001)	0.000 (0.000)
Asset ownership	-0.050 (0.093)	0.085 (0.995)	-0.050 (0.093)	2.001 (0.827)**	-0.069 (0.093)	0.037 (0.011)***
Wheat	0.106 (0.146)	1.140 (1.276)	0.103 (0.146)	2.173 (1.060)**	0.119 (0.146)	0.022 (0.015)
Maize	0.139 (0.105)	0.375 (1.131)	0.134 (0.105)	0.964 (0.960)	0.120 (0.106)	0.030 (0.013)**
Eastern	0.508 (0.148)***	-1.565 (1.131)	0.505 (0.147)***	-3.685 (0.792)***	0.478 (0.148)***	-0.095 (0.017)***
Central	0.253 (0.109)**	-3.007 (1.041)***	0.255 (0.107)**	-1.495 (0.875)*	0.270 (0.108)**	-0.037 (0.013)***
IV	0.962 (0.105)***		0.967 (0.106)***		0.940 (0.114)***	
Constant	-0.810 (0.420)*	20.212 (4.027)***	-0.796 (0.418)*	12.259 (3.277)***	-0.690 (0.424)	0.151 (0.071)**
$\rho_{\varepsilon\mu}$	-0.062 (0.062)		-0.079 (0.040)*		-0.368 (0.212)*	
Ln (σ)	2.863 (0.065)***		2.654 (0.097)***		-1.560 (0.023)***	
Wald test ($\rho_{\varepsilon\mu}$=0)	1.00, with $Prob > chi^2$=0.318		3.75*, with $Prob > chi^2$=0.053		3.02*, with $Prob > chi^2$=0.082	
Observations	1,785	1,785	1,785	1,785	1,785	1,785

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Declarations

Conflict of interests There is no conflict of interest.

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