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Impacts of cooperative membership on banana yield and risk exposure: Insights from China

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Abstract

The yield-increasing effects of agricultural cooperative membership have been widely examined in the literature. However, so far, little is known about whether cooperative membership has the potential to reduce farmers' exposure to production risk. We address this gap by estimating the impacts of cooperative membership on expected yield, yield variance (variability), and yield skewness (exposure to downside risk), using data collected from a survey of 626 banana farmers in China. We employ an endogenous switching regression model to address the selectivity bias issue. The empirical results show that cooperative membership increases banana yield by 3% and reduces the variance and downside risk exposure by 60% and 114%, respectively. The results are supported by robustness check estimates, using propensity score matching and inverse probability weighted regression adjustment models. Additional analysis reveals that the treatment effects of cooperative membership vary among members with different household and farm characteristics. Our findings suggest that agricultural cooperatives can be an effective institutional arrangement for reducing production risk and crop failure and point to the need for policies and programmes in developing cooperatives and increasing membership involvements of smallholder farmers.

KEYWORDS

agricultural cooperatives, banana farmers, China, crop yield, risk exposure

JEL CLASSIFICATION

C52; D81; Q13

1 | INTRODUCTION

In many developing countries, sustainable agricultural production of smallholder farmers is continually challenged by a wide range of controllable and uncontrollable challenges. These include, for example, lack of adequate knowledge on best farm management practices, limited access to improved technologies, high transaction costs of accessing input markets, frequent occurrence of pests and diseases, and uncertainty of weather conditions (Blekking et al., 2021; Gava et al., 2021; Kumar et al., 2018; Ma et al., 2021; Manda et al., 2020; Ortega et al., 2019; Serra & Davidson, 2021; Zhang et al., 2020). These constraints expose farmers to the risks of low farm productivity and crop failure, threatening the achievement of the United Nations' sustainable development goals of no poverty (goal 1) and zero hunger (goal 2).

In practice, farmers have adopted various agricultural technologies (e.g., drought-tolerant varieties and climate-smart practices) to raise farm productivity and mitigate risk. A growing number of studies have examined the impacts of technology adoption on farm productivity (measured by yield or revenue) and production risk exposure (measured by variance and skewness) (e.g., Amondo et al., 2019; Di Falco & Chavas, 2009; Huang et al., 2015; Issahaku & Abdulai, 2020; Mukasa, 2018; Sarr et al., 2021; Shahzad & Abdulai, 2020; Vroege et al., 2021). These studies show how the adoption of new techniques and practices increases crop yield and reduces production risk. For example, for maize farmers in Zambia, Amondo et al. (2019) found that adopting drought-tolerant maize varieties increases maize yield by 15% and reduces yield variance and downside risk exposure by 38% and 36%, respectively. Issahaku and Abdulai (2020) found that the adoption of climate-smart practices (e.g., crop choice and soil and water conservation) contributes to increased crop revenue and decreased crop production risk in Ghana. Sarr et al. (2021) estimated the impacts of a rain-fed system of rice intensification (SRI). They showed that SRI adoption increases rice productivity and reduces the probability of downside risk of crop failure, but it does not affect yield variability significantly.

Agricultural cooperatives may also play a role in reducing the variance and downside risk (probability of crop failure) associated with crop production. Agricultural cooperative membership affects farm production in at least four ways. First, it facilitates smallholder farmers' adoption of improved (either single or multiple) technologies (Abebaw & Haile, 2013; Ma, Abdulai, et al., 2018; Manda et al., 2020; Wossen et al., 2017; Zhang et al., 2020). For example, Manda et al. (2020) found that cooperative membership increases the adoption of inorganic fertilisers and crop rotation among maize farmers in Zambia by 11% and 24%, respectively. Zhang et al. (2020) revealed that cooperative membership in China significantly increases the number of post-harvest technologies adopted. Second, agricultural cooperatives can improve farmers' farm management skills for appropriately combining different production technologies, improving technical efficiency (Abate et al., 2014; Ma, Renwick, et al., 2018). Notably, increased technical efficiency is a prerequisite of increased crop yield. Third, membership can improve farmers' access to input markets and increase their negotiating power when purchasing high-quality inputs, improving farmers' capability of timely application of inputs and coping with production loss. Fourth, it may help reduce production risks and uncertainties by increasing members' awareness and perceptions of weather, pest and disease-related risks and facilitating contract farming (Shi & Cao, 2021; Sokchea & Culas, 2015).

The yield-enhancing effects of cooperative members have been well examined in the literature (e.g., Kumar et al., 2018; Ma & Abdulai, 2016; Minah, 2021; Ortega et al., 2019; Priscilla & Chauhan, 2019; Shumeta & D'Haese, 2016). Using data from 1,024 coffee-producing households in Rwanda, Ortega et al. (2019) found that cooperative membership significantly increases coffee productivity. Available literature has also shown that membership in agricultural cooperatives alleviates rural poverty (Gava et al., 2021; Zeweld et al., 2015), increases consumption expenditure and food security (Ahmed & Mesfin, 2017), and boosts women's employment (Dohmwirth & Liu, 2020; Tesfay & Tadele, 2013). Gava et al. (2021) found that cooperative membership in Konjic improves berry farmers' working conditions and market access, contributing to rural poverty alleviation.

To date, little is known about whether cooperative membership has the potential to reduce farmers' exposure to production risk, despite the well-established literature on agricultural cooperative membership. Exploring the association between cooperative membership and production risk exposure can provide valuable insights for policy-makers in developing policy instruments that improve farm performance, boost sustainable rural development, and ensure food security.

We investigate the effects of agricultural cooperative membership on crop yields and risk exposure using data collected from 626 banana farmers in China. We make three contributions that help enrich the literature on agricultural cooperatives in developing countries. First, we analyse cooperative membership effects on banana yield, measured by expected yield, yield variance (variability), and yield skewness (exposure to downside risk). We rely on a moment-based specification of the production function to compute these three central moments (Amondo et al., 2019; Di Falco & Chavas, 2009; Shahzad & Abdulai, 2020; Vroege et al., 2021). Second, we apply an endogenous switching regression (ESR) model to address the selection bias issue. Since farmers voluntarily join cooperatives, the selection bias issue must be considered when quantifying the effects of cooperative membership. The ESR model addresses the selectivity bias due to both observables (e.g., age, gender, education, and family size) and unobservables (e.g., farmers' innate abilities and motivations). We also estimate the treatment effects of cooperative membership using propensity score matching model and inverse probability weighted regression adjustment estimator as robustness checks. Finally, we contribute to the literature by investigating whether the estimated treatment effects of cooperative membership are heterogeneous among members endowed with different household and farm-level characteristics. This issue has largely been neglected in the literature.

The promotion and development of agricultural cooperatives in China are long-standing. Agricultural cooperatives in China emerged as mutual-aid groups incorporating almost all rural households in the 1950s. They were gradually developed into collective farms, named the people's community system (PCS) in 1958 (Ito et al., 2012). During the PCS period, the ownership of land, labour, animals, and basic farming implements was vested at the team level. In the early 1980s, the PCS was broken up to improve productivity and production, and agricultural cooperatives in the new period gradually emerged. The promulgation of the Law of Farmers' Professional Cooperatives in China in 2007 has promoted the sustainable development of agricultural cooperatives.

The rest of the paper is structured as follows. Section 2 introduces banana production in China. This is followed by a presentation of estimation strategies in Section 3. Section 4 provides data and descriptive statistics. Section 5 presents and discusses the empirical results. The final section concludes the paper and discusses the policy implications.

2 | BANANA PRODUCTION IN CHINA

Banana is an important cash crop in China, playing a significant role in improving the livelihoods of smallholder farmers. Banana is mainly cultivated in eight provinces of China: Guangdong, Yunnan, Guangxi, Hainan, Fujian, Guizhou, Sichuan, and Chongqing (see Figure 1). Guangdong, Yunnan, Guangxi, and Hainan are the major banana-producing provinces with more favourable climate conditions. Together they cultivated 307,600 ha in 2019, accounting for 93.1% of the country's total (CRSY, 2020).

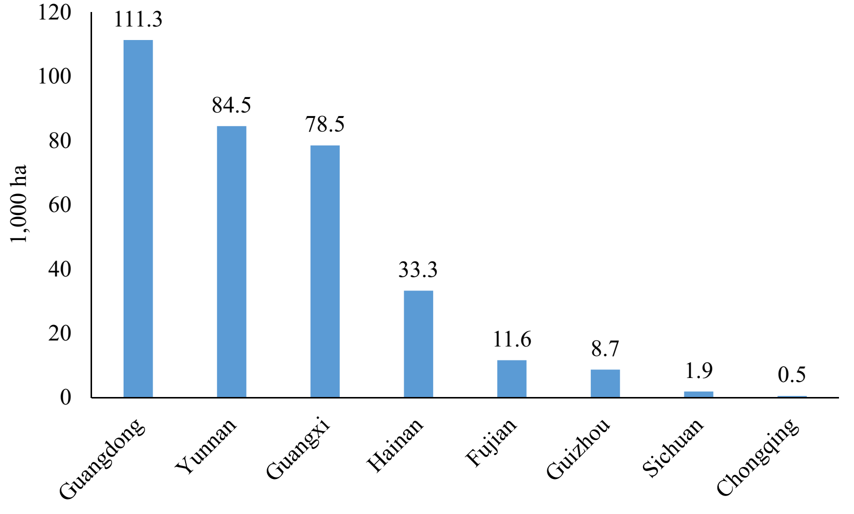

FIGURE 1 Cultivated areas of banana across the top eight provinces in China in 2019

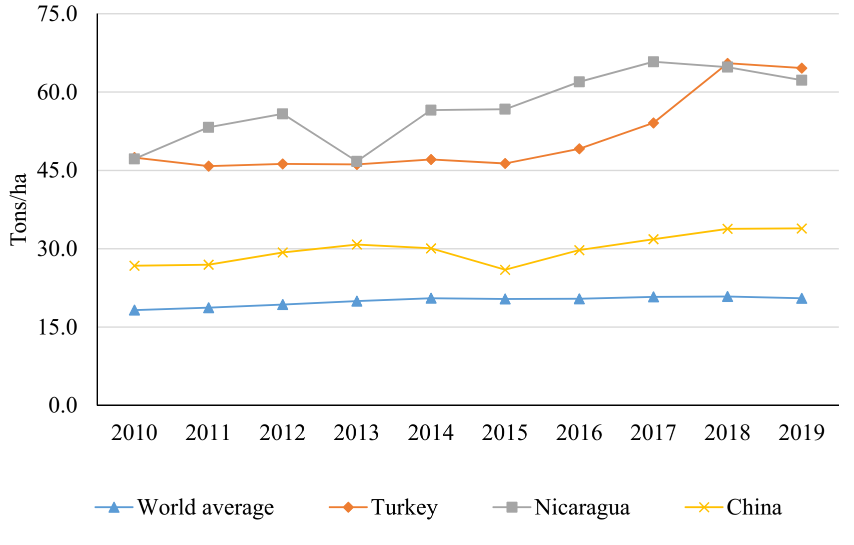

FIGURE 2 Banana yield of high-productive countries, China and world average

China is one of the largest banana producers in the world,[1] cultivating 344,000 ha and harvesting 11,656,000 tons in 2019, ranking the third (after India and Brazil) and second (after India) globally, respectively (FAOSTAT). However, yields in China are relatively low, ranked 26th globally in 2019. Figure 2 shows banana yields in the two most productive countries (Turkey and Nicaragua), compared with China and the world average from 2010 to 2019. Although banana yields in China are higher than the world average, they are significantly lower than those in Turkey and Nicaragua.

[1]Other major banana producing countries include India, Brazil, Tanzania, Rwanda, Congo, Philippines, Ecuador, Angola, Burundi and Vietnam.

Increasing banana yield is essential for boosting sustainable agricultural development and alleviating rural poverty. However, the improvement of banana yield in developing countries like China has been historically challenged by a range of factors such as pests and diseases, poor orchard management, inadequate technologies and adverse weather conditions (Dadrasnia et al., 2020; Panigrahi et al., 2021; Varma & Bebber, 2019). In China, like other developing countries such as Zambia, Nigeria, India and Ethiopia (Kumar et al., 2018; Manda et al., 2020; Sebhatu et al., 2021; Wossen et al., 2017), agricultural cooperatives have been established and promoted to help improve farm performance. Using data collected from banana farmers in China, Ma et al. (2021) found that cooperative membership positively impacts financial performance by increasing net returns, return on investment and profit margins. Here, we focus on the role of agricultural cooperative membership in mitigating risk exposure of smallholder banana farmers.

3 | ESTIMATION STRATEGIES

We evaluate the treatment effects of cooperative membership on the three moments of banana yield, measured by the expected yield, yield variance and yield skewness. To achieve this goal, we first compute the outcome variables using a moment-based production function approach. Then, we employ an endogenous switching regression model to estimate the treatment effects.

3.1 | Estimating the moments of the production function

Following previous studies (Huang et al., 2015; Mukasa, 2018; Sarr et al., 2021; Vroege et al., 2021), we specify the banana production function as follows:

$$O_i = f(I_i;\theta_i) + \varepsilon_i \tag{1}$$

where O_i refers to banana yield, measured at kg/mu (1 mu = 1/15 ha); $\boldsymbol{I_i}$ refers to a vector of production inputs (e.g., land, labour, pesticides and fertilisers); $\boldsymbol{\theta_i}$ represents a vector of parameters to be estimated, capturing how (positively or negatively) and the magnitudes regarding the effects of production inputs on banana yield; and ε_i is an error term.

We employed the likelihood ratio (LR) test and Akaike Information Criterion (AIC) value to identify the most appropriate functional form. The production functions estimated by the translog specification and Cobb–Douglas specification are shown in Table S1. The results indicate that the translog specification is preferred.

Econometrically, the translog production function is specified as follows:

$$\ln(O_i) = \theta_0 + \sum_{m=1}^{6} \theta_1 \ln(I_{im}) + 0.5 \sum_{m=1}^{6} \theta_2 \ln(I_{im})^2 + \sum_{m=1}^{6} \sum_{k=1}^{6} \theta_3 \ln(I_{im}) \ln(I_{ik}) + \varepsilon_i \tag{2}$$

where $\ln(O_i)$is the logarithm of the banana yield for farmer i; $\ln(I_{im})$ is the logarithm of m input for farmer i; and $\ln(I_{im})^2$ is its squared term; $\ln(I_{im})\ \ln(I_{ik})$ captures the interaction between inputs m and k, $m \neq k$. The inputs include land, seedlings, fertilisers, pesticides, labour and other inputs (e.g., irrigation and machinery), following the relevant literature (Bai et al., 2019; Ma, Renwick, et al., 2018; Villano et al., 2015; Zheng et al., 2021). Because some farmers in our sample did not purchase seedlings and other inputs in the 2019 survey year, the two input variables have zero-value observations. We follow Villano et al. (2015) and Zheng et al. (2021) by replacing zero values with one and creating two dummy variables for seedlings and other inputs variables to deal with zero values.

Equation (2) is estimated by an ordinary least squares (OLS) regression model to calculate the first three moments (i.e., expected yield, variance and skewness) of banana yield (Huang et al., 2015; Issahaku & Abdulai, 2020).[2] Specifically, the expected banana yield is predicted as $E[\ln(Y_i)]$. The second moment represents the variance of yield, which is measured by the squared term of the error term, that is, $E[(\varepsilon_i)^2]$. The third moment represents the downside risk (skewness) of yield, which is measured by the third power of the error term, that is, $E[(\varepsilon_i)^3]$.

3.2 | Selection bias in estimating treatment effects

The propensity score matching (PSM) model and inverse-probability-weighted regression adjustment (IPWRA) estimator have been widely applied to estimate the treatment effects in the literature (Blekking et al., 2021; Manda et al., 2018; Minah, 2021; Takam-Fongang et al., 2019; Wen et al., 2021; Zheng & Ma, 2021). However, the two approaches can only address the selection bias originating from observed factors. Unlike the PSM and IPWRA methods, the endogenous switching regression (ESR) model addresses the selection bias arising from both observed and unobserved factors (Li et al., 2020; M. Liu et al., 2021; Ma & Abdulai, 2016; Takam-Fongang et al., 2019; Zheng et al., 2021). The ESR model estimates one treatment equation (i.e., cooperative membership equation) and two outcome equations (one for cooperative members and another for non-members), and then uses the estimated coefficients to calculate the average treatment effects on the treated (ATT).

For the treatment equation, we model farmers' decisions to belong to an agricultural cooperative as a random utility function, where farmers' decisions to be cooperative members are affected by a set of variables (e.g., age, gender, education, household size, and farm size). We assume that a risk-neutral and utility-maximising banana farmer i chooses to join an agricultural cooperative if the utility derived from having cooperative membership exceeds that of otherwise. Let M_i^* be the utility difference between two choices, the latent variable function for cooperative membership can be illustrated as follows:

$$M_i^* = \gamma Z_i + \varpi IV_i + \xi_i, \text{ where } M_i = \begin{cases} 1 & \text{if } M_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

where M_i is a binary decision variable that equals one if a banana farmer chooses to join an agricultural cooperative and equals zero otherwise; $\boldsymbol{Z_i}$ is a vector of variables, representing household and farm-level characteristics and social-economic characteristics, that are expected to affect cooperative membership; IV_i is an instrumental variable for ESR model identification; γ and ϖ are parameters to be estimated; and ξ_i is a random error term. We use farmer's relatives' cooperative membership as our instrumental variable. The falsification test was used to check the IV's validity (Li et al., 2020; Pizer, 2016), showing that this IV is significantly associated with farmers' cooperative membership status but is insignificantly associated with the three outcomes (banana yield, yield variance, yield skewness).

The two outcome equations, depending on cooperative membership status, are specified as follows:

$$\text{Regime 1:}\quad Y_{1i} = \beta_1 X_i + \mu_{1i} \text{ if } M_i = 1 \tag{4a}$$

$$\text{Regime 2:}\quad Y_{0i} = \beta_0 X_i + \mu_{0i} \text{ if } M_i = 0 \tag{4b}$$

[2]It is worth mentioning here that moment-based estimation relies on OLS regression. This is different from analysing technical efficiency of crop production, which is based on an estimation of a stochastic frontier model.

where Y_{1i} and Y_{0i} are outcome measures (the expected yield, variance or skewness) for cooperative members and non-members, respectively. The vector $\boldsymbol{X_i}$ consists of exogenous variables, excluding the instrumental variable. The error terms (ξ_i, μ_{1i} and μ_{0i}) in Equations (3), (4a) and (4b) are assumed to have a tri-variate normal distribution, with zero means and constant variance (Liu et al., 2020; Lokshin & Sajaia, 2004). To correct potential selection bias due to omitted unobserved variables, the Inverse Mills Ratios (IMRs) λ_{1i} and λ_{0i} for cooperative members and non-members, respectively, from Equation (3), are included in the outcome equations. Therefore, Equations (4a) and (4b) can be rewritten as follows:

$$\text{Regime 1: } Y_{1i} = \beta_1 X_i + \delta_1 \lambda_{1i} + \mu_{1i} \text{ if } M_i = 1 \tag{5a}$$

$$\text{Regime 2: } Y_{0i} = \beta_0 X_i + \delta_0 \lambda_{0i} + \mu_{0i} \text{ if } M_i = 0 \tag{5b}$$

where δ_1 and δ_0 are the parameters of the IMRs (λ_{1i} and λ_{0i}). Within the ESR framework, the selection equation and the two outcome equations are estimated simultaneously by a full information maximum likelihood estimator (Lokshin & Sajaia, 2004). Then, the expected outcome in an observed context and the expected outcome in a counterfactual scenario (i.e., the expected outcome for members had they not participated in any cooperatives) are predicted as follows, respectively:

$$E(Y_{1i}|M_i = 1) = \beta_1 X_i + \delta_1 \lambda_{1i} \tag{6a}$$

$$E(Y_{0i}|M_i = 1) = \beta_0 X_i + \delta_0 \lambda_{1i} \tag{6b}$$

The unbiased ATT is finally derived as the difference between Equations (6a) and (6b):

$$ATT = E(Y_{1i}|M = 1) - E(Y_{0i}|M = 1) \tag{7}$$

For robustness check, we also estimate the treatment effects of cooperative membership on the expected yield, variance and skewness using the PSM model and IPWRA estimator.

4 | DATA AND DESCRIPTIVE STATISTICS

4.1 | Data

The data used in this study are obtained from a survey conducted from July to October 2019 in three major banana-producing provinces (Hainan, Yunnan and Guangzhou) in China. A multistage sampling procedure was employed to purposively select the survey provinces based on banana outputs in China and randomly select the cities, towns, villages and then rural households. First, Hainan, Yunnan and Guangzhou provinces were purposively selected as the major banana-producing provinces in China. Second, we randomly selected three to five counties from each province. Third, we randomly selected two towns from each county and then one to two villages from each town. Finally, we randomly chose between 10 and 20 households (including both cooperative members and non-members) from each village, contributing to a total of 626 households. The final sample is comprised of 138 cooperative members and 488 non-members.

The output variable used in the production function refers to banana yield. The inputs include land, seedlings, fertilisers, pesticides, labour and other inputs. The dependent variables include the expected yield of bananas, variance and skewness, calculated after estimating the

TABLE 1 Variable measurements and mean differences of selected variables between cooperative members and non-members

Variables	Measurements	Overall (*n* = 626)		Members (*n* = 138)		Non-members (*n* = 488)		
		Mean	SD	Mean	SD	Mean	SD	Diff.
Output and inputs variables used in the production function								
Banana yield	Yield of banana production (1,000 kg/mu)[a]	3.18	2.83	3.45	2.92	3.10	2.80	0.34
Land	Total size of bbnbnb orchbrds (100 mu)	0.29	0.73	0.41	0.70	0.26	0.73	0.15**
Seedlings	Expenditures on seedlings (100 Yubn/mu)[b]	2.88	2.85	2.87	3.37	2.88	2.69	−0.01
Fertilisers	Expenditures on fertilisers (100 Yuan/mu)	12.42	10.55	10.89	6.89	12.86	11.34	−1.97*
Pesticides	Expenditures on pesticides (100 Yuan/mu)	5.20	10.10	4.67	7.30	5.34	10.76	−0.67
Labour	Number of family labour and hired labour (100 days/mu)	0.77	1.01	0.70	0.88	0.80	1.04	−0.10
Other inputs	Expenditures on machinery and irrigation (100 Yuan/mu)	7.69	10.33	9.04	8.41	7.30	10.79	1.74*
Outcome variables								
Expected yield	The expected value of banana yield (log), predicted after estimating the production function	7.80	0.46	7.89	0.37	7.77	0.48	0.11**
Yield variance	Variance of banana yield, measured by the square term of the error term in the production function	0.43	1.01	0.26	0.47	0.48	1.11	−0.23**
Yield skewness	Skewness of banana yield, measured by the third power of the error term in the production function	−0.23	2.64	0.10	0.77	−0.32	2.96	0.42
Independent variables								
Age	Age of household head (years)	48.20	9.90	47.15	9.09	48.50	10.10	−1.35
Gender	1 = Male; 0 = otherwise	0.83	0.37	0.95	0.22	0.80	0.40	0.15***
Education	Educational level of household head (years)	8.08	3.12	8.86	3.12	7.86	3.09	0.99***
Family size	Number of household members (persons)	5.98	2.37	6.46	2.39	5.84	2.34	0.62***
Farm size	Total farm size for banana production (mu)	29.33	72.93	41.39	70.14	25.92	73.41	15.47**

TABLE 1 (Continued)

		Overall (n = 626)		Members (n = 138)		Non-members (n = 488)		
Variables	**Measurements**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Diff.**
Land quality	1 = Good quality; 0 = otherwise	0.72	0.45	0.77	0.42	0.71	0.45	0.06
Asset ownership	1 = Air conditioner owner; 0 = otherwise	0.44	0.50	0.51	0.50	0.42	0.49	0.09*
Village cooperative	1 = There exists a cooperative in farmers' residing or neighbouring village; 0 = otherwise	0.49	0.50	0.96	0.20	0.35	0.48	0.60***
Distance to market	Distance to the nearest input market (km)	5.72	8.46	6.71	7.45	5.43	8.71	1.27
Distance to station	Distance to the nearest transport station (km)	8.00	9.13	5.88	6.31	8.60	9.70	−2.73***
Hainan	1 = Hainan province; 0 = otherwise	0.37	0.48	0.13	0.34	0.43	0.50	−0.30***
Yunnan	1 = Yunnan province; 0 = otherwise	0.29	0.46	0.43	0.50	0.26	0.44	0.17***
Guangdong	1 = Guangdong; 0 = otherwise	0.34	0.47	0.44	0.50	0.31	0.46	0.13***
IV	1 = Farmers' relatives have cooperative membership, 0 = otherwise	0.27	0.45	0.70	0.46	0.15	0.36	0.55***

*$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. SD refers to the standard deviation.

[a]1 mu = 1/15 ha.

[b]Yuan is Chinese currency (1 USD = 6.40 Yuan).

moment-based production function. The variables included in the cooperative membership equation are selected from the literature that examines the farm production effects of cooperative membership in developing countries (e.g., Abebaw & Haile, 2013; Ahmed & Mesfin, 2017; Kumar et al., 2018; Ma, Renwick, et al., 2018; Tilahun et al., 2016; Wossen et al., 2017; Zhang et al., 2020). Specifically, we include age, gender, education, family size, farm size, land quality, asset ownership, village cooperative, distance to market, distance to station and location dummies in our model.

4.2 | Descriptive statistics

Table 1 presents the variables' measurements, means and standard deviations and compares these for the cooperative members and non-members. Figure S1 depicts the banana yield distributions by cooperative membership status, showing indications of negative skewness and greater yield variance for non-members relative to cooperative members. The mean difference (last column of Table 1) indicates that cooperative members are systematically different from their non-member counterparts in terms of observed characteristics. For example, the land size cultivated by cooperative members is significantly larger than that of non-members. Cooperative members spend significantly less on fertilisers but more on other inputs than non-members. Cooperative members are more likely to be better educated, have a larger family size and farm size than their non-member counterparts. These notable differences indicate that cooperative membership would generate a selection bias issue in our estimation.

5 | EMPIRICAL RESULTS

5.1 | Moments of the production function

The results of translog production function OLS estimation (Equation 2) are shown in column 2 of Table S1. Because our estimated model has interaction terms, the estimated coefficients do not directly indicate the elasticities. To provide a better understanding, we calculate the input-output elasticities (Table S2), reflecting the percentage banana yield changes when a specific input increases by 1%.

5.2 | Determinants of cooperative membership

Table 2 presents the ESR model estimates of the selection equation (Equation 3), reporting the determinants of cooperative membership. Consistent with previous studies on cooperative membership (Blekking et al., 2021; Priscilla & Chauhan, 2019), we find that older household heads have a lower probability of being members of a cooperative. Male household heads are more likely to be cooperative members than their female counterparts. Family size increases the likelihood of belonging to a cooperative. The finding of the positive relationship between family size and cooperative membership has also been found in other studies (Manda et al., 2020; Minah, 2021; Olagunju et al., 2021; Wossen et al., 2017). The village cooperative variable has a positive and significant marginal effect, which is consistent with Ma and Zhu (2020). The marginal effect of the IV variable is positive and statistically significant, indicating that the propensity of joining cooperatives will increase by 17% if farmers' relatives are cooperative members, again in line with Ma et al. (2021), implying a positive peer effect.

TABLE 2 Determinants of cooperative membership: ESR model estimates of the selection equation

Variables	Coefficients	Marginal effects
Age	−0.02 (0.01)***	−0.00 (0.00)***
Gender	0.67 (0.26)***	0.12 (0.05)***
Education	−0.01 (0.02)	−0.00 (0.00)
Family size	0.06 (0.03)*	0.01 (0.01)*
Farm size	−0.00 (0.00)	−0.00 (0.00)
Land quality	0.20 (0.17)	0.04 (0.03)
Asset ownership	−0.04 (0.20)	−0.01 (0.04)
Village cooperative	1.49 (0.23)***	0.28 (0.04)***
Distance to market	−0.01 (0.01)	−0.00 (0.00)
Distance to station	−0.01 (0.01)	−0.00 (0.00)
Hainan	−0.35 (0.22)	−0.07 (0.04)
Yunnan	−0.10 (0.23)	−0.02 (0.04)
IV	0.90 (0.16)***	0.17 (0.03)***
Constant	−1.76 (0.57)***	
Sample size	626	

*$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. The reference province is Guangdong. Robust standard errors are presented in parentheses.

TABLE 3 Average treatment effects of cooperative membership on expected banana yield and production risk: ESR model estimates

	Mean outcomes			
Outcome	Actual	Counterfactual	ATT	Change (%)
Expected yield	7.89 (0.19)	7.69 (0.20)	0.20 (0.13)***	2.60
Yield variance	0.26 (0.17)	0.65 (0.18)	−0.39 (0.18)***	−60.00
Yield skewness	0.10 (0.31)	−0.71 (0.36)	0.81 (0.52)***	114.08

***$p < 0.01$. ATT refers to average treatment effects on the treated. Expected yield is measured at log-transformed forms. Robust standard errors are presented in parentheses.

Because we are more interested in investigating the treatment effects of cooperative membership, we present the coefficients estimates of the outcome equations in Table S3. In the next section, we discuss the treatment effects of cooperative membership.

5.3 | Treatment effects of cooperative membership

The results for the treatment effects of cooperative membership on the first three moments of banana yield (i.e., the expected yield, variance and skewness) are presented in Table 3. The results are estimated by Equation (7) within the ESR framework. Compared with the mean differences in Table 1, these ATT estimates in Table 3 correct for selection bias.

Our estimates show that cooperative membership increases banana yield by 3%, consistent with previous studies (Kumar et al., 2018; Ma & Abdulai, 2016; Ortega et al., 2019). The negative and statistically significant ATT for yield variance (–0.39) indicates that cooperative membership reduces the volatility of banana yield by about 60%. The mean skewness changes from negative (–0.71) to positive (0.10) due to cooperative membership. Thus, agricultural cooperative membership reduces downside risk by 114%. These findings clearly imply that agricultural cooperatives are effective for improving farm productivity and mitigating farmers' exposure to production risk.

5.4 | Robustness check

We also estimate the treatment effects of cooperative membership on expected banana yield, yield variance and yield skewness using the PSM and IPWRA models. Since the reliability of the PSM model depends on the quality of matching cooperative members and non-members (Wossen et al., 2017), we present the extent of overall covariates balancing. Potentially, cooperative members and non-members can be matched by different techniques such as kernel-based matching, nearest-neighbour matching (NNM), and radius matching. Kernel-based matching is used in this study because it generates better results. Table S4 presents the matching quality test results, confirming the superior performance of kernel-based matching.

The results of the PSM model are presented in column 2 of Table S5, while the results of the IPWRA estimator are demonstrated in the last column of the same table. The results show that the estimated ATTs for expected yield and yield skewness are positively and statistically significant, and the estimated ATTs for yield variance are negative and statistically significant. Overall, the findings of both PSM and IPWRA model estimations (Table S5) are very similar to the results of the ESR model estimation (Table 3), verifying that our ATT estimates are robust.

5.5 | Heterogeneous effects over household and farm characteristics

The ATT estimates indicate that agricultural cooperative membership improves banana yield and reduces risk exposure. However, these results are average effects for all cooperative members in our sample. Previous studies have revealed that the effects of cooperative membership can be heterogeneous (Abebaw & Haile, 2013; Ma et al., 2021; Sebhatu et al., 2021; Verhofstadt & Maertens, 2014; Wossen et al., 2017). Exploring the differential effects of cooperative membership is therefore important for appropriate agricultural development policy design. Therefore, we estimate the heterogeneous treatment effects of cooperative membership across household and farm characteristics. Following Verhofstadt and Maertens (2014) and Wossen et al. (2017), we used ATTs of individuals in the treated group, that is, cooperative members, as dependent variables in an OLS regression.

Table 4 reports the empirical results, showing that the cooperative membership effects on banana yield, yield variance and yield skewness are significantly related to some of our household characteristics. For example, we find that the positive impacts of cooperative membership on the expected yield are stronger for households with larger farm sizes, whereas the yield variance and downside risk-reducing effects of cooperative membership increase with owned assets (i.e., air conditioner). On the other hand, increasing distance to market is associated with reduced yield and downside risk effects of cooperative membership.

6 | CONCLUSIONS AND POLICY IMPLICATIONS

We examined the effects of cooperative membership on crop yield and production risk exposure, measured by yield variance and skewness. We analysed data from 626 banana farming households collected from three major banana-producing provinces in China. The endogenous switching regression (ESR) model was utilised to address the selection bias arising from

TABLE 4 Determinants of expected yield and production risk: OLS estimations

Variables	ATT (Expected yield)	ATT (Yield variance)	ATT (Yield skewness)
Age	−0.01 (0.00)***	0.01 (0.00)***	−0.01 (0.00)*
Gender	0.04 (0.03)	−0.00 (0.06)	−1.34 (0.14)***
Family size	−0.00 (0.00)	−0.01 (0.01)	−0.04 (0.02)*
Farm size	0.00 (0.00)**	0.00 (0.00)***	−0.00 (0.00)
Asset ownership	−0.03 (0.02)	−0.06 (0.03)*	0.18 (0.09)**
Distance to market	−0.00 (0.00)**	−0.00 (0.00)	−0.01 (0.00)**
Constant	0.44 (0.07)***	−0.63 (0.12)***	2.64 (0.27)***
Sample size	138	138	138

*$p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. Robust standard errors are presented in parentheses.

observed and unobserved factors. We also estimated the PSM and IPWRA methods to check the robustness of our main results.

The results show that farmers' membership of agricultural cooperatives is positively and significantly affected by their gender, family size and the existence of village cooperatives but negatively and significantly influenced by household heads' age. The average treatment effect on the members (treated) (ATT) estimates show that cooperative membership increases the expected banana yield by 3% and reduces yield skewness by 114% and yield variance by 60%. These findings are confirmed by the PSM and IPWRA estimates. The additional analysis revealed that the treatment effects of cooperative membership on the expected yield, yield variance and yield skewness differ among members associated with farm household characteristics.

We draw some policy implications based on the findings from this study for developing the banana sector sustainably. The significant role of agricultural cooperatives in increasing banana yield and reducing exposure to downside risk suggests that policies to promote smallholder farmers' participation in cooperatives would be sensible. This is particularly important for China and other countries where production risks threaten farm production and challenge food security. Our findings also provide practical implications for alleviating farmers' constraints in participating in agricultural cooperatives. Because older and female household heads may face obstacles when making decisions to join cooperatives, the government could consider collaborating with local cooperatives to recruit more older and female members. Besides, since we found that farmers' cooperative participation decisions are positively affected by relatives' membership status, policies that encourage cooperative participation could consider providing incentives (e.g., material rewards or social recognition) to members with a strong social network in rural areas. In practice, the government could help agricultural cooperatives cultivate elite members and provide monetary support to leading members to encourage them to invite co-villagers to join agricultural cooperatives.

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