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Has contract farming improved the green technology efficiency of vegetable growers? Empirical evidence from rural areas in Shandong Province, China

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Abstract: Contract farming is regarded as an effective strategy for smallholder farmers in developing countries to enhance their agricultural competitiveness. However, limited research exists on its potential to promote green, sustainable development. This paper investigates the impact of contract farming participation on farmers' green technology efficiency using data from a sample of 627 vegetable growers in Shandong, China and employs the propensity score matching method. Our findings are as follows: *i*) Under the counterfactual assumption, participation in contract farming increases green technology efficiency from 0.560 to 0.614. The efficiency of contract production bases, ranked from highest to lowest, is as follows: self-owned base, stock-sharing base, and contractual base. *ii*) The provision of productive services serves as a significant mediating factor in enhancing green technology efficiency, with a more substantial impact than issuing planned instructions. *iii*) Increasing purchase prices, as an effective means of providing motivational incentives, significantly amplifies the effect of contract farming on green technology efficiency in self-owned and stock-sharing bases. As organisational models evolve toward greater integration, the enhancing effect of price incentives on green technology efficiency strengthens. This study concludes with several public policy and agricultural management recommendations.

Keywords: contract farming; green technology efficiency; productive services; propensity score matching model; purchase prices

Contract farming is regarded as an effective strategy for enhancing the productivity of smallholder farmers in developing countries (Minot and Sawyer 2016; Adam and Alelegn 2023). As a common institutional arrangement for agricultural industrialisation, it serves as an intermediary form of vertical coordination (Patel 2022; Kollenda et al. 2024). Leading enterprises initiate contract farming by establishing agreements that specify prices, quantities, timing, and product attributes, thereby purchasing agricultural products from contract farmers (Chen and Chen 2021). Farmers produce according to these contract requirements, ensuring a consistent supply of high-quality raw materials for agribusinesses (Bellemare and Novak 2017). Enterprises typically provide seeds, fertilisers, and technical assistance – along with guaranteed prices at harvest – addressing various productivity constraints faced by smallholders (Swinnen and Maertens 2007). Consequently, contract farming is widely regarded as a key tool for strengthening global food security and improv-

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ing farmers' income in developing countries (Abebe et al. 2013; Ton et al. 2018).

The existing empirical literature has primarily focused on two dimensions of contract farming. First, it examines the impact of contract farming on household welfare, particularly in terms of economic performance. Research consistently shows that contract farming positively influences farm income (Bezabeh et al. 2020; Wu et al. 2020; Selorm et al. 2023) and reduces production risks (Kumar and Kumar 2008; Abadi et al. 2024). Second, studies assess the effect of contract farming on production performance, especially technical efficiency. Some studies indicate that participating in contract farming can enhance technological efficiency (Alulu et al. 2021; Rabia et al. 2023; Hailu and Mezgebo 2024), while others find that non-contract farmers may be more efficient (Dube and Mugwagwa 2017; Kaur and Singla 2024). Additionally, some studies report no significant difference in technical efficiency between contract farmers and nonparticipants (Mishra et al. 2018).

These insights lead to two conclusions. First, while the literature on contract farming's economic impacts is extensive, limited research has focused on its environmental effects and its role in sustainable agricultural practices. A few studies suggest that contract farming can help some farmers adopt sustainable technologies (Ren et al. 2021; Weituschat et al. 2023; Zhang et al. 2023). Second, the extent to which contract participation improves agricultural efficiency remains unclear, with mixed results in the literature. Thus, the impact of contract farming on green technology efficiency is a largely unexplored area, as the environmental attributes of agricultural products are more challenging to assess than their income effects. Understanding this relationship is essential for optimising contract schemes that benefit both parties and promote sustainable practices.

In China, vegetable production is a significant rural economic industry, facing challenges which undermine its competitiveness, such as excessive fertiliser and pesticide use. As market demand for high-quality agricultural products rises, it is crucial to shift vegetable production from quantity-oriented to quality- and benefit-oriented. Given this context, this study develops a framework to analyse the impact of contract farming on green technology efficiency and employs micro-level data from 627 vegetable farmers in Shandong's vegetable industry to investigate the effects of various contract production bases on green technology efficiency.

The study presents several innovations: it explores the often-overlooked role of contract farming in enhancing green technology efficiency and clarifies its influence through both farmers' internal capabilities and external incentives. Additionally, it categorises contract farming into three types of production bases for comparative analysis, highlighting the evolution of organisational models in promoting green practices. The significance of this study lies in identifying effective pathways for improving green technology efficiency, reducing unnecessary fertiliser use, and protecting farmland environments. Furthermore, the comparative analysis of different organisational models provides guidance for agricultural enterprises in designing effective contract farming frameworks. Finally, this case study of smallholder vegetable farmers in Shandong offers valuable insights for similar agricultural producers.

Theoretical framework and hypotheses

Contract farming production bases. Contract farming in the vegetable industry is defined as an agricultural industrialisation model where farmers and enterprises sign pre-production purchase contracts. Farmers organise their production according to the contracts, while enterprises or intermediaries purchase the products. In Shandong, contract farming primarily occurs through the establishment of production bases, which can be categorised into three types (Figure 1).

First, the contractual base model, which involves long-term, fixed-contract collaborations between farmers and enterprises. The contracts specify vegetable prices, quantities, quality standards, and delivery schedules, outlining the rights and obligations of both parties (Prowse 2012; Chen and Chen 2021). Enterprises secure stable access to raw materials while providing some pre-production and in-production services to farmers. Farmers in the base fulfil the enterprise's orders and produce according to specified standards. However, this model's inherent independence and flexibility create weaknesses in contract enforcement, leading to a significant 'public domain' for opportunistic behaviour and higher transaction costs related to mutual monitoring.

Second, the stock-sharing base model, which typically involves cooperation between enterprises and cooperatives. Farmers form cooperatives by investing in land, and these cooperatives, along with enterprises, build production bases. Cooperatives manage production and negotiate with enterprises,

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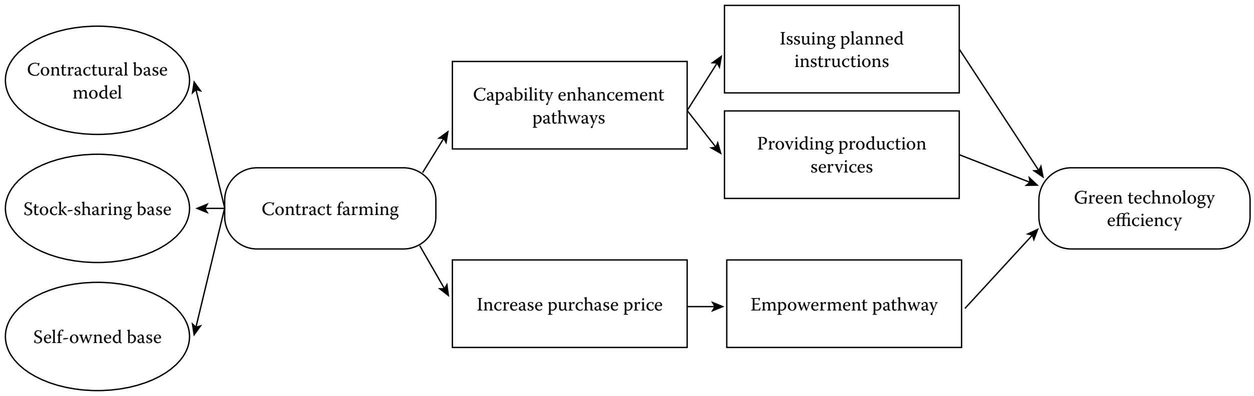

Figure 1. Research conceptual framework

Source: Authors' own elaboration

while farmers share profits based on their land investments. This model fosters closer cooperation and mutual interests, forming a hybrid contract that combines commodity and factor contracts. By integrating market incentives with reduced transaction costs, it motivates farmers to meet enterprise requirements (Geng et al. 2023).

Third, the self-owned base model, in which the enterprise leases land from farmers, obtaining operational rights to establish a high-quality vegetable production base. The enterprise then subleases the land to multiple farming households for cultivation, providing uniform production materials and technical standards throughout the farming process. In this model, farmers become production inputs, with their income tied to the yield and quality of contracted vegetables rather than market prices. This model integrates different links in the industrial chain – extending the industrial chain's reach – making the self-owned base the most integrated base model (Jin et al. 2024).

Promoting green technology efficiency in contract farming. Producing green vegetables involves various modern elements, including technology, machinery, skilled labour, and information, making it a technology-intensive production process. This raises production thresholds and market risks, limiting individual farmers' capacity for independent green production (Adnan et al. 2020). Farmers face constraints such as economic status, lack of knowledge, and limited risk management capabilities, which hinder their ability to enhance green technology efficiency (Li et al. 2021). Additionally, without adequate sales channels, farmers cannot secure reasonable returns on high-quality production (Staatz 1987), reducing their motivation to improve efficiency. Thus, this study examines the impact of contract farming on green technology efficiency from the dual perspectives of capability and motivation.

Capability enhancement pathways. In contract farming, enterprises enhance farmers' green technology efficiency through two primary methods.

First, issuing planned instructions. Enterprises provide scientific and standardised vegetable planting plans and clarify production requirements based on local conditions, optimising workflows (Némethová et al. 2017; Liu et al. 2019). These plans include planting varieties, material specifications, dosage, field management schedules, technical requirements, and yield expectations. Planned instructions serve as the foundation of contract management, directly determining green technology efficiency.

Second, providing production services. Enterprises or cooperatives exert partial control over the production process by offering socialised services for critical stages. They introduce green production elements and capital into farmers' processes (Xu et al. 2022), facilitating effective management and quality control, thus ensuring product quality. Technical personnel provide advanced production technology support and real-time agricultural advice, lowering barriers to green production (Ruml and Qaim 2021). Additionally, field management services, such as soil testing and pest control, directly influence fertiliser and pesticide use, impacting overall output levels (Cheng et al. 2022). Therefore, we propose the following hypothesis:

> H_1: Both the issuance of planned instructions and the provision of production services by the enterprises effectively improve green technology efficiency in contract farming.

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Empowerment pathways. Farmers are driven to maximise economic benefits, making price incentives crucial for transitioning to green production. Contracts often include premium prices for high-quality products, motivating farmers to adjust their production behaviours and enhance green technology efficiency (Jin et al. 2024). However, chemicals are trust-based products, and contracts involving these elements can lead to opportunistic behaviour. Farmers may believe that higher chemical application rates yield better results, leading them to engage in speculative practices when faced with price incentives, potentially undermining production standards. Thus, if economic incentives exist without adequate production supervision, they may exacerbate opportunistic tendencies.

Therefore, we propose the following hypothesis:

H_2: Purchase prices play a positive moderating role in enhancing green technology efficiency in contract farming, but the moderating effect varies among different production bases.

MATERIAL AND METHODS

Data collection and analysis

The data for this study were collected through a micro-level survey conducted by the research team in Shandong in 2022. This coastal province in East China borders the Bohai Sea and the Yellow Sea (34°22.9'–38°24.01'N, 114°47.5'–122°42.3'E) and is a major vegetable-producing area. Shandong actively implements various forms of contract farming to enhance the vegetable industry, providing empirical support for our study and favourable conditions for data collection. The selected sample areas are based on the distribution of major vegetable cultivation regions in Shandong, including Jiaozhou in Qingdao, Zhucheng in Shouguang, and Jiaxiang in Weifang, as well as Jiaxiang County in Jining. We employed a stratified sampling method, categorising the sample counties (districts) into high, medium, and low production volume groups to ensure representation from areas with varying levels of vegetable cultivation and environmental characteristics. From each group, two townships (or towns) were randomly selected, and within each township (or town), 20–30 vegetable-growing households were randomly chosen for household surveys. Vegetable-growing households were selected as the research subjects because they represent the main actors in contract farming while retaining characteristics of traditional farming. Questionnaires were administered through oral interviews with farmers and filled out by surveyors. A total of 666 questionnaires were collected, of which 627 were valid.

Based on the descriptive analysis (Table 1 and Table 2), the household heads of the sample farms exhibited characteristics of ageing, low education, risk aversion, and significant differences in agricultural production scale. Among all the samples, a total of 399 households participated in contract farming,

Table 1. Basic characteristics of sample farm households (continuous variable)

Variable name	Variable definition	Mean	SD	Min.	Max.
Head of household endowment age	age of the head of household (years)	50.08	8.14	20.00	72.00
Participation in technical training	annual average number of agricultural technical training sessions attended	3.72	1.75	1.00	8.00
Share of agricultural income	proportion of agricultural income to total family income (%)	87.35	0.17	0.05	1.00
Social network size	number of relatives and friends who maintained in contact with the family	26.84	12.84	2.00	55.00
Production scale	vegetable cultivation area (ha)	12.56	54.24	1.13	80.04
Degree of land fragmentation	average size of contiguous plots (ha)	0.59	0.17	0.20	1.00
Higher purchase price	percentage of the purchase price higher than the local vegetable average selling price last year (%)	12.85	11.94	–43.00	80.00

SD – standard deviation

Source: Author's own elaboration

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Table 2. Basic characteristics of sample farm households (categorical variable)

Variable name	Variable category	Percentage (%)
Head of household education	elementary school or below	21.89
	junior high school	46.81
	high school	23.80
	above high school	7.51
Soil quality	good	55.34
	not good	44.66
Participation in contractual base	yes	29.51
	no	70.49
Participation in self-owned base	yes	9.09
	no	90.91
Weifang sample	yes	49.44
	no	50.56
Previous administrative position	yes	19.62
	no	80.38
Risk attitude	risk preference	34.29
	risk neutral and aversion	65.71
Participation in contract farming	yes	63.64
	no	36.36
Participation in stock-sharing base	yes	25.04
	no	74.96
Qingdao sample	yes	24.40
	no	75.60
Jining sample	yes	26.16
	no	73.84

Source: Authors' own elaboration

accounting for 63.63% of the sample. Among them, 185 households (29.51%) are involved in the contractual base, 157 households (25.04%) are engaged in the stock-sharing base, and 57 households (9.09%) are engaged in the self-owned base.

The primary vegetable varieties cultivated include field tomatoes, field cucumbers, field eggplants, field radishes, and field string beans, totalling five varieties. Key input factors for production are seeds, fertilisers, pesticides, machinery, labour (both hired and family), and plastic film. The average vegetable yield for sample households is 4 207.14 kg/mu (Table 3). Average inputs include USD 401.85 per ha for seeds, 1 862.55 kg/ha for fertilisers, USD 190.50 per ha for pesticides, USD 281.25 per ha for machinery, 396.15 person-days/ha for labour, and 28.05 kg/ha for plastic film. Due to significant differences in the input–output performance across the five types of vegetable varieties, the standard error of the input–output ratios are relatively large.

Calculation of green technology efficiency

In this study, agricultural green technology efficiency refers to the calculation of production efficiency, considering factors contributing to environmental pollution. Improving agricultural green technology efficiency involves minimising resource consumption and environmental pollution while maximising beneficial output under a given combination of input factors (Yang et al. 2022). Green technology efficiency values range between 0 and 1, with values closer to 1 indicating that a production unit is nearer to the environmental production frontier. This study employs the non-radial and non-angular slacks-based measure (SBM) data envelopment analysis (DEA) model to measure green technology efficiency, effectively addressing the limitations of the radial DEA model, which cannot measure inefficiency without slack variables and may introduce biases from radial and angular selections (Tone 2021).

The SBM-DEA model comprises both expected output and unexpected output components. Expected output is measured using vegetable yield, while unexpected output is assessed using agricultural nonpoint source pollution and CO_2 emissions. Agricultural nonpoint source pollution primarily includes the improper use and residual contamination of fertilisers, pesticides, and plastic film (Ma and Tan 2021; Bao et al. 2022; Qin et al. 2024). Carbon emissions mainly result from the use of agricultural fertilisers, pesticides, and plastic films, as well as the direct or indirect consumption of fossil fuels (primarily agricultural diesel and electricity) by agricultural machinery. However, during the research, plastic film use by farmers in vegetable production is found to be low (3.3%), and the diversity of pesticide types requiring dilution results in inaccurate pesticide usage and runoff data. Additionally, farmers' reliance on mechanised agricultural services rather than directly operating agricultural machinery made it difficult to collect data on fossil fuel usage. Therefore, this study primar-

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Table 3. Input–output descriptive statistics

Variable		Variable definition	Mean	SD	Min.	Max.
Expected output	output	yield (kg/ha)	63 107.10	32 952.75	23 775.00	139 500.00
Unexpected output	nitrogen emissions	total agricultural nonpoint source nitrogen pollution emissions (kg/ha)	147.75	62.55	70.05	269.85
	phosphorus emissions	total agricultural nonpoint source phosphorus pollution emissions (kg/ha)	17.85	6.45	8.40	29.10
	CO_2 emissions	fertiliser carbon emissions (kg/ha)	1 668.00	754.20	829.50	3 145.50
Input factors	seed input	cost of seed input (USD/ha)	401.85	393.90	151.05	1 473.90
	fertiliser input	equivalent amount of fertiliser input (kg/ha)	1 862.55	842.10	926.25	3 512.10
	pesticide input	cost of pesticide input (USD/ha)	190.50	51.75	37.20	294.00
	machinery input	total cost of own and hired machinery input (USD/ha)	281.25	63.45	165.60	455.40
	labour input	labour input from hired workers and family members (person-days/ha)	396.15	112.65	150.00	630.00
	plastic film input	plastic film input amount (kg/ha)	28.05	12.90	0.00	79.50

SD – standard deviation
Source: Authors' own elaboration

ily measures agricultural nonpoint source pollution and CO_2 emissions based on fertiliser use. Fertilisers mainly contribute to water pollution through nitrogen and phosphorus emissions. In 2017, nitrogen and phosphorus fertiliser applications in China accounted for 27.39% and 27.53% of the global total, respectively. The utilisation rates of nitrogen and phosphorus on Chinese farmland were only 30% to 35% and 10% to 20%, respectively (Yu et al. 2019), making them significant contributors to agricultural nonpoint source pollution. Nitrogen emissions primarily originate from urea, ammonium bicarbonate, and other nitrogen fertilisers, as well as diammonium phosphate (containing 18% nitrogen and 46% phosphorus) and triple-element compound fertilisers (containing 15% nitrogen and 15% phosphorus). Phosphorus-nitrogen emissions mainly come from calcium superphosphate, diammonium phosphate, and triple-element compound fertiliser. The runoff amount is calculated based on specific usage, pure quantity, and the loss coefficient. Nitrogen loss coefficient is 0.655, while the phosphorus loss coefficient is 0.326 × 43.66%. Since the effective phosphorus content in fertilisers refers to the amount of phosphorus pentoxide (P_2O_5), the phosphorus loss amount must be multiplied by the coefficient of 43.66% to calculate the effective phosphorus loss. The calculations indicate that nitrogen runoff is 147.75 kg/ha, while phosphorus runoff is 17.85 kg ha. Carbon emissions from fertilisers are calculated by multiplying the effective nutrient content of the fertilisers by the emission factor. Carbon emission factor for fertilisers is 0.896 kg CO_2 per kg of fertiliser, as reported by the

Table 4. Distribution of green technology efficiency among sample households

Green technology efficiency	(0, 0.2)	(0.2, 0.4)	(0.4, 0.6)	(0.6, 0.8)	(0.8, 1.0)
Frequency	23	171	143	159	131
Relative frequency	0.037	0.273	0.228	0.254	0.209

Source: Authors' own elaboration

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Carbon Dioxide Information Analysis Centre (CDIAC). The results indicate that carbon emissions from fertilisers amount to 1 668.00 kg/ha.

Using Max-DEA software, we determine that the average green technology efficiency of vegetable-growing households in the sample areas is 0.560 (Table 4). This indicates that green technology efficiency in these areas is generally low, suggesting significant potential for improvement.

Propensity score matching model

Given that the key variable, 'participation in contract farming', is subject to self-selection bias, we employed the propensity score matching (PSM) model for analysis. Compared to the endogenous switching model (ESM) and other alternatives, PSM is widely used to mitigate selection bias caused by observable variables, achieving a balance between the treated and control groups by matching them based on similar characteristics. We posit that smallholder farmers' participation in contract farming is closely related to their production endowments. Farmers with greater resource endowments, larger production scales, and more technological reserves are more likely to engage in contract farming. For instance, previous research indicates that farmers with ample labour resources and larger operational scales are more inclined to cooperate with enterprises (Singh 2002; Miyata and Minot 2009). Since these participation decision factors primarily involve observable variables, PSM provides better control over these biases compared to the endogenous switching model (Crown 2014; Umberto et al. 2018).

Moreover, our research aims to compare the effects of different categories of contract farming on green technology efficiency. By calculating the average treatment effect on the treated (ATT) between the treatment and control groups, the PSM model offers a clear and intuitive approach to comparing outcomes across different groups, aligning closely with the objectives of our study (Adjin et al. 2020).

Individuals in the treatment group are matched with individuals in the control group based on the principle of 'closeness' concerning several characteristics, ensuring that matched households have no significant differences other than their participation in contract farming. The individual propensity score (i.e. conditional probability fitting value) of farmers can be expressed as follows:

$$P(L_i) = P_r[D = 1 \mid L_i] = \frac{\exp(\eta L_i)}{1 + \exp(\eta L_i)} \tag{1}$$

where: P – estimated propensity score, denoting the probability of a farmer participating in contract farming; $P_r(.)$ – probability cumulative density function; L_i – covariate(s); η – parameters to be estimated; $D = 1$ – participation in contract farming; $D = 0$ – nonparticipation.

The ATT, weighted by propensity scores, can be expressed as follows:

$$\begin{aligned} ATT &= E[(Y_{1i} - Y_{0i}) \mid D_i = 1] = \\ &= E\left\{E[(Y_{1i} - Y_{0i}) \mid D_i = 1], P(L_i)\right\} = \\ &= E\left\{E[Y_{1i} \mid D_i = 1, P(L_i)] - E[Y_{0i} \mid D_i = 0, P(L_i)]\right\} \end{aligned} \tag{2}$$

where: ATT – average treatment effect on the treated; E – expectation operator, average over the distribution of covarities; Y_{1i} – green technology efficiency of farmers participating in contract farming; Y_{0i} – green technology efficiency of nonparticipating farmers.

After establishing the theoretical model, farmers participating in contract farming were designated as the treatment group, while those not participating formed the control group. In the model, we included the following covariates: age of the household head, education level, previous administrative positions, risk attitudes, participation in technical training, proportion of agricultural income to family endowment, social network size, production scale, soil quality, and degree of land fragmentation. We then employed the logit model in Stata 15.0 to calculate propensity scores for individual farmers, after which the ATT was calculated based on these scores.

Before analysing the ATT results, common support and balance tests were performed. Using the most commonly used nearest neighbour matching method (1–4 matching) as an example, we identified 610 observations within the common range of values, with

Table 5. Number of lost samples in the common support domain of the propensity score matching method

Group	Common support		Total
	outside common range	inside common range	
Treatment group	10	222	232
Control group	7	388	395
Total	17	610	627

Source: Authors' own elaboration

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Table 6. Balance test results of the propensity score matching method

Matching method	Pseudo R^2	LR value	P-value	Mean variance	Median variance
Before matching	0.103	84.95	0.000	26.6	26.1
Nearest neighbour matching	0.014	15.27	0.123	6.4	4.0
Radius matching	0.013	14.72	0.143	6.7	6.0
Kernel matching	0.014	15.43	0.117	6.8	6.0
Local linear regression matching	0.012	13.52	0.196	6.6	6.5

LR – likelihood ratio test statistic
Source: Authors' own elaboration

only 17 samples excluded (Table 5). This meets the common support condition. Four matching methods – nearest neighbour matching, radius matching, kernel matching, and local linear regression matching – were employed for balance tests. The results (Table 6) indicate that the pseudo-R^2 values are all close to 0, and the likelihood ratio test statistic (LR) values are not rejected after matching. This suggests that PSM significantly reduces differences between the treatment and control groups, indicating that the two sample groups are generally similar across various feature dimensions and pass the balance test.

RESULTS AND DISCUSSION

Average treatment effect of participating in contract farming

The estimated results across the four matching methods are consistent (Table 7). Using the nearest neighbour matching method as an example, and based on the counterfactual hypothesis, we find that if farmers participating in contract farming did not participate, their green technology efficiency would increase from 0.560 to 0.614 – an increase of 0.055, or 9.643%. The *ATT* value is statistically significant at the 5% level, indicating that participation in contract farming has a significant positive effect on green technology efficiency.

The results indicate that farmers' participation in contract farming can increase their potential output by 9.643%. For farmers, this translates to higher marginal returns, which is a key concern for them. At the same time, for the government, this implies that the same level of output can be achieved with lower fertiliser inputs, thereby reducing nonpoint source pollution. This aligns with the current national policy direction toward green agricultural development.

We divide the samples into three categories based on production bases and calculate the average treatment effects using the most commonly used nearest neighbour matching method (1 : 4 matching). According to the *ATT* values for sub-samples 1–3 (Table 8), for farmers who do not participate in contract farming, joining contractual bases increases green technology efficiency increases by 0.044, though this increase is only statistically significant at the 10% level. Participation in stock-sharing bases leads to a green technology efficiency increase of 0.075, which is significant at the 5% level. Meanwhile, participation in self-owned bases leads to a green technology efficiency increase of 0.096, which is significant at the 1% level.

Table 7. Average treatment effect on green technology efficiency of sample farmers

Matching method	Treatment group	Control group	*ATT*	T-value	Matching method	Treatment group	Control group	*ATT*	T-Value
Nearest neighbour matching	0.614	0.560	0.055**	2.380	Kernel matching	0.618	0.555	0.063***	3.040
Radius matching	0.618	0.555	0.063***	3.060	local linear regression matching	0.619	0.560	0.059**	2.050

**, ***significance at 5 and 1% level, respectively; *ATT* – average treatment effect on the treated
Source: Authors' own elaboration

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Table 8. Average treatment effects of different bases on sample farmers' green technology efficiency

Sample group (sample size)		Treatment feature	Mean	*ATT*	*T*-value
Subsample 1	treatment group (185)	contractual base	0.606	0.044*	1.780
	control group (228)	nonparticipation in contract farming	0.562		
Subsample 2	treatment group (157)	stock-sharing base	0.700	0.075**	2.400
	control group (226)	nonparticipation in contract farming	0.625		
Subsample 3	treatment group (56)	self-owned base	0.635	0.096***	5.710
	control group (183)	nonparticipation in contract farming	0.539		

*, **, ***significance at 10, 5, and 1% level, respectively; *ATT* – average treatment effect on the treated
Source: Authors' own elaboration

The above results indicate the following. First, overall, participation in contract farming has a significantly positive effect on the green technology efficiency of vegetable farmers. Second, the improvement effects vary across production base models, ranked from highest to lowest as follows: self-owned base, stock-sharing base, and contractual base. The improvement in green technology efficiency is most pronounced in the self-owned base model, approximately 2.2× greater than in the contractual base model and approximately 1.3× greater than in the stock-sharing base model. This suggests that loose commodity contract relationships fail to provide farmers with sufficient incentives and constraints for green production, whereas more tightly integrated organisational forms play a more significant role in regulating farmers' green production practices.

Robustness test

Discussion based on Instrumental variable Tobit regression model (IV-Tobit). The IV-Tobit regression model is employed to assess the robustness of the impact of farmer participation in contract farming on green technology efficiency, as farmer efficiency values strictly fall between 0 and 1. To address the endogeneity issue associated with participation in contract farming, we select 'village contract farming participation' (the participation rate of other farmers in the same village in contract farming) as an instrumental variable. This instrumental variable is relevant, as farmers' decision-making is closely related to the participation of local farmers in contract farming. Additionally, the instrumental variable is exogenous, meaning it does not influence a specific household's decision to participate in contract farming once individual-specific factors are controlled for.

We conducted several tests to validate the instrumental variables. The Wald values for the weak instrumental variable tests in the four IV-Tobit models are 21.42, 7.15, 21.46, and 6.04, all exceeding the critical threshold for rejecting the weak instrumental variable hypothesis at the 5% significance level. All instrumental variables in the first-stage regressions are significant at the 1% level. The *F*-values in the first stage of the four IV-Tobit models are 30.08, 30.64, 23.81, and 27.85, respectively, all surpassing the commonly used thresholds proposed by Staiger and Stock (1997) and Stock and Yogo (2002). Lastly, the Hansen *J*-test results for over-identification indicate that the coefficients of the residuals are not significant (*P*-values of 0.475, 0.178, 0.101, and 0.379, respectively), meaning we cannot reject the null hypothesis, thereby suggesting the validity of the instrumental variables.

The IV-Tobit regression results (Table 9) show that the impact of participation in contract farming, as well as participation in self-owned base and stock-sharing base models, is positive and significant at the 1% level, whereas participation in the contractual base model variable is not significant. These results closely align with the conclusions obtained using the PSM method.

Discussion based on farmer scale classification. To further investigate the robustness of the impact of contract farming, we examine its effects on subsamples with different land sizes. Land size, an important input in farmers' production, influences both production patterns and the supervision exercised by enterprises. According to the 'Third National Agricultural Census of China', we categorise the sample farmers into two groups: the large-scale group (with a production scale greater than or equal to 6.67 ha and the small-scale group (with a production scale less than 6.67 ha). We then explore the impact of participation in different categories of contract farming on green technology efficiency within each group. According

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Table 9. IV-Tobit model estimation results of the impact of farmer participation in contract farming on green technology efficiency

Variable	First-stage regression					Second-stage regression				
	coefficient	SE	95% confficient interval		*P*-value	coefficient	SE	95% confficient interval		*P*-value
Participation in contract farming	–	–	–	–	–	0.146***	0.026	0.096	0.197	0.000
Village contract farming participation	0.850***	0.557	0.741	0.959	0.000	–	–	–	–	–
Control variables	controlled	–	–	–	–	controlled	–	–	–	–
Contractual base	–	–	–	–	–	0.362*	0.191	–0.011	0.936	0.057
Village contractual base participation	0.111***	0.042	0.028	0.193	0.008	–	–	–	–	–
Control variables	controlled	–	–	–	–	controlled	–	–	–	–
Stock-sharing base	–	–	–	–	–	0.382***	0.054	0.277	0.488	0.000
Village stock-sharing base participation	0.326***	0.066	0.195	0.456	0.000	–	–	–	–	–
Control variables	controlled	–	–	–	–	controlled	–	–	–	–
Self-owned base	–	–	–	–	–	0.242***	0.052	0.139	0.344	0.000
Village self-owned base participation	0.818***	0.052	0.716	0.920	0.000	–	–	–	–	–
Control variables	controlled	–	–	–	–	controlled	–	–	–	–

*, ***significance at 10 and 1% level, respectively; SE – standard error
Source: Authors' own elaboration

Table 10. Average treatment effects of different bases on green technology efficiency of sample farmers

Sample group (sample size)			Treatment feature	Mean	*ATT*	*T*-Value
Small-scale group	subsample 4	treatment group (172)	contract farming	0.682	0.049	1.840*
		control group (122)	nonparticipation in contract farming	0.633		
	subsample 5	treatment group (84)	contractual base	0.662	0.043	1.350
		control group (120)	nonparticipation in contract farming	0.620		
	subsample 6	treatment group (60)	stock-sharing base	0.756	0.076	2.490**
		control group (121)	nonparticipation in contract farming	0.679		
	subsample 7	treatment group (28)	self-owned base	0.697	0.084	1.940*
		control group (96)	nonparticipation in contract farming	0.613		
Large-scale group	subsample 8	treatment group (226)	contract farming	0.676	0.058	2.010**
		control group (106)	nonparticipation in contract farming	0.618		
	subsample 9	treatment group (99)	contractual base	0.649	0.050	1.550
		control group (106)	nonparticipation in contract farming	0.599		
	subsample 10	treatment group (96)	stock-sharing base	0.666	0.062	2.150**
		control group p (106)	nonparticipation in contract farming	0.603		
	subsample 11	treatment group (29)	self-owned base	0.727	0.129	2.070**
		control group (106)	nonparticipation in contract farming	0.599		

*, **significance level at 10 and 5% level, respectively; *ATT* – average treatment effect on the treated
Source: Authors' own elaboration

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to the *ATT* values for sub-samples 4–11 (Table 10), the effects of self-owned bases, stock-sharing bases, and contractual bases display a consistent pattern from small to large across both small-scale and large-scale farmers, mirroring the results from the full sample. Furthermore, a comparison of the two groups reveals that the impact and significance of contract farming are greater for large-scale farmers than for small-scale farmers. The larger the scale of the farmers, the more pronounced the effect of contract farming on improving their green technology efficiency.

Capacity enhancement pathway of participation in contract farming on green technology efficiency

Our theoretical analysis indicates that the planned instructions and production services provided by contract providers serve as intermediary pathways through which contract farming enhances green technology efficiency. We represent issuing planned instructions using the variables 'whether the enterprise issues planned instructions' (coded as 1 for 'yes' and 0 for 'no') and 'whether the enterprise provides technical guidance' (coded as 1 for 'yes' and 0 for 'no'). Additionally, we represent the provision of production services using the variable 'whether they obtain soil testing and integrated pest management services' (assigned as 1 for 'yes' and 0 for 'no'). Given that these three intermediary variables coexist, we construct a parallel multiple-mediation model. Unlike a single-mediation model, a multiple-mediation model corrects parameter estimation biases caused by the simultaneous presence of multiple variables, enabling the comparison of multiple mediation effects to obtain the total mediation effect. For all self-owned base samples, production is uniformly arranged by the enterprise, with production plans, technical support, and socialised services provided to every contracted household. Since this does not meet the conditions for mediation analysis, we only test the contract-based and stock-sharing base models.

We employ Preacher and Hayes' bootstrapping method (Preacher and Hayes 2008) to test the mediation effects (5 000 iterations). For the contractual bases (Table 11), the mediation effect of issuing planned instructions is 0.028, but this effect is not significant; the mediation effect of providing technical guidance is 0.034 and is significant at the 5% level; and the mediation effect of providing soil testing and integrated pest management services is 0.044, also significant at the 5% level. These results indicate that both providing technical guidance and production services are potential pathways to enhancing farmer green technology efficiency, thereby confirming H_1. However, the issuance of planned instructions is not always effectively conveyed to farmers, resulting in a lack of significant mediation effect.

For the stock-sharing base (Table 11), the mediation effect of issuing planned instructions is 0.033, significant at the 5% level, while the mediation effect of providing technical guidance is 0.041, also significant at the 5% level. The mediation effect of providing soil testing and integrated pest management services is 0.068 and is significant at the 5% level. By comparing the mediation effect values for the contract-based and stock-sharing base models, we find that the mediation effect of production services surpasses that of planned instructions, indicating that enterprise-provided socialised services have a more substantial impact on enhancing farmers' green technology efficiency.

Table 11. Multiple-mediation model results for contractual bases and stock-sharing bases

Mediation effect coefficient		Contractual bases			Stock-sharing bases		
		coefficient	95% confidence interval		coefficient	95% confidence interval	
Direct effect		0.037	0.0004	0.069	0.020	–0.015	0.050
Parallel indirect effects	issuing planned instructions	0.028	–0.001	0.065	0.033	0.002	0.053
	providing technical guidance	0.034	0.011	0.047	0.041	0.027	0.072
	soil testing and integrated pest management services	0.044	0.021	0.068	0.068	0.040	0.093
Total effect		0.143	0.110	0.171	0.151	0.117	0.176

Source: Authors' own elaboration

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Empowerment pathway of participation in contract farming on green technology efficiency

To measure the impact of procurement prices on enhancing green technology efficiency in contract farming, we use 'higher purchase price', defined as the 'percentage of purchase price higher than local vegetable average selling price last year', as a moderating variable. This variable interacts with participation in contract farming for moderation-effect analysis. Given the endogeneity issues affecting the participation variable, we use 'village contract farming participation' as an instrumental variable. The two-stage least squares (2SLS) method with instrumental variables is employed for this analysis.

The unidentifiable test results yield an LM value of 26.37, strongly rejecting the null hypothesis at the 1% significance level. The weak instrumental variable test, indicated by a Cragg–Donald Wald *F*-statistic of 13.46, exceeds the critical value for 10% bias, signifying no weak instrumental variable problem. The results (Table 12) reveal that the interaction term is positive and highly significant (at the 1% level), indicating that higher procurement prices significantly enhance the positive effect of contract farming on green technology efficiency.

To further differentiate the incentive effects of procurement prices across different types of contract organisations, we conduct a heterogeneity analysis for the three model types. These three models also underwent over-identification tests and weak instrumental variable tests, all of which rejected the null hypothesis. Due to space constraints, specific test values are not provided. In the contractual base model, the interaction term is not significant, suggesting that economic incentives may not necessarily enhance the green technology efficiency of farmers within this model. Conversely, in the self-owned base and stock-sharing base models, the moderation effect is significant, indicating that increasing procurement prices can effectively motivate farmers' transformation toward green pro-

Table 12. Moderation-effect model considering endogeneity

Variable	Coefficient	SD	*P*-value
Total sample			
Participation in contract farming	0.031	0.029	1.050
Higher purchase price	0.519***	0.054	9.600
Participation in contract farming × higher purchase price	1.193**	0.506	2.360
Control variables	controlled	controlled	controlled
Contractual base model			
Contractual base model	0.073	0.088	0.406
Higher purchase price	0.537***	0.126	4.260
Contractual base × higher purchase price	0.426	0.722	0.555
Control variables	controlled	controlled	controlled
Self-owned base model			
Self-owned base model	0.127***	0.027	4.610
Higher purchase price	0.602***	0.066	9.710
Self-owned base × higher purchase price	0.815***	0.217	3.760
Control variables	controlled	controlled	controlled
Stock-sharing base			
Stock-sharing base	0.190	0.294	0.650
Higher purchase price	6.379***	1.736	3.670
Stock-sharing base × higher purchase price	0.506***	0.094	5.370
Control variables	controlled	controlled	controlled

**, ***significance at 5 and 1% level, respectively; SD – standard deviation

Source: Authors' own elaboration

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Table 13. Threshold model regression results

Model	Threshold value	Coefficient 1	SE	Coefficient 2	SE
Contractual base	0.062	−0. 079***	−4.150	0.118***	7.900
Self-owned base	0.066	−0. 030***	−1.420	0.143***	7.790
Stock-sharing base	0.062	−0.046	−1.540	0.185***	6.230

***significance at 1% level; SE – standard error
Source: Authors' own elaboration

duction in these models. This result validates H_2 and highlights shortcomings in the contractual base model regarding its ability to incentivise farmers' green production transformation.

To clarify the impact of procurement prices on farmers' green technology efficiency, we employ a single-threshold model to compare the incentive effects of procurement prices across the three base models. By comparing the model results of the three types of bases (Table 13), we find a distinct nonlinear threshold relationship between contract farming participation and green technology efficiency. The positive effect of participating in contract farming on green technology efficiency is influenced by the procurement price. At the same procurement prices, as the organisational production of the base becomes more integrated, the enhancing effect of price incentives on green technology efficiency becomes significantly stronger.

CONCLUSION

To identify the significant role of contract farming in 'greening' the agricultural industry, this study constructs an analytical framework based on the dual dimensions of 'ability-motivation' to assess the impact and mechanisms of contract farming on the green technology efficiency of planting farmers across various base models. Empirical tests were conducted using sample data from 627 vegetable planting farmers in Shandong. The results are summarised as follows.

First, under the counterfactual assumption, if planting farmers participate in contract farming, green technology efficiency increases from 0.560 to 0.614. The improvement varies across different production base models: self-owned base, stock-sharing base, and contractual base. This conclusion holds even when employing the IV-Tobit model and conducting a scale heterogeneity analysis.

Second, as a pathway to improving green technology efficiency, providing productive services has a significant mediating effect in the self-owned stock-sharing base models and contractual bases, whereas issuing planned instructions fails to effectively reach farmers in the contractual base model. Significantly, the mediating effect of productive services is greater than that of planned instructions.

Lastly, increasing procurement prices significantly enhances the effect of contract farming on green technology efficiency in the self-owned and stock-sharing base models. There exists a clear nonlinear threshold relationship between participation in contract farming and green technology efficiency, where tighter integration of organisational models amplifies the role of price incentives in enhancing efficiency.

In summary, we believe that contract farming has a 'hidden function' in enhancing the green technology efficiency of vegetable industry households, addressing gaps identified in previous studies. Importantly, the role of contract farming in promoting green transformation is largely influenced by the organisational model. Effective communication of planting instructions through integrated models and supervision mechanisms is crucial for achieving incentive effects, preventing opportunistic behaviour among farmers, and aligning with green production goals. This study confirms the necessity of upgrading contract farming organisational models to more advanced forms to facilitate green transformation: as contract organisational forms evolve toward integration, the capacity and effectiveness of contract farming to improve green technology efficiency will gradually increase. From an influencing mechanism perspective, planned instructions, productive services, and price incentives are effective pathways. However, planned instructions and price incentives often 'fail' in contractual bases, indicating that loose organisational models may not adequately motivate or constrain farmers to undergo production transformation. Conversely, the direct effect of productive services on production is more pronounced, aligning with findings from other studies (Shi et al. 2023; Yang et al. 2023).

The policy implications of this study are as follows. First, the vegetable industry contract farming model

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should be improved by promoting 'high-quality contract farming' to facilitate the industry's green production transformation. This would involve encouraging regional planting, standardised production, and large-scale operations through long-term contracts, thereby enhancing farmers' production efficiency. Second, the modes of self-owned bases for contract farming should be innovated by promoting their construction through financial support and developing win–win cooperation systems between enterprises and farmers. Lastly, the productive service mechanism within contract farming should be strengthened, as it serves as an essential pathway to standardising and scaling production. The use of green technologies, industry-specific systems, and material equipment should be leveraged to facilitate the comprehensive transformation and enhancement of farmers' production toward sustainability.

In addition to contributions to theory and practice, this study has some limitations. First, the investigation focused solely on Shandong. Future research should expand the sample area to determine whether similar conclusions can be drawn from other regions. Second, the study employs a cross-sectional design, relying on data from a single point in time. Future studies may benefit from utilising longitudinal designs to enhance the generalisability of the empirical findings.

REFERENCES

Abadi H.H., Mohamadi-Nejad A., Gilanpour O., Khaledi M. (2024): Investigating factors affecting the development of contract farming. Case study: Tomatoes in Kermanshah Province. Brazilian Journal of Biology, 84: e281760.

Abebe G.K., Bijman J., Kemp R., Omta O., Tsegaye A. (2013): Contract farming configuration: Smallholders' preferences for contract design attributes. Food Policy, 40: 14–24.

Adam A.G., Alelegn W.A. (2023): Contract farming as an alternative to large-scale land acquisition and promoting inclusive and responsible agricultural investment: Evidences from Ethiopia. Corporate Social Responsibility and Environmental Management, 30: 2840–2851.

Adjin K.C., Goundan A., Henning C.H.C.A., Sarr S. (2020): Estimating the impact of agricultural cooperatives in Senegal: Propensity score matching and endogenous switching regression analysis. Working Papers of Agricultural Policy, No. WP2020–10.

Adnan N., Nordin S.M., Anwar A. (2020): Transition pathways for Malaysian paddy farmers to sustainable agricultural practices: An integrated exhibiting tactics to adopt green fertilizer. Land Use Policy, 90: 104255.

Alulu J., Jakinda Otieno D., Oluoch-Kosura W., Ochieng J. (2021): Comparison of technical efficiency and technology gaps between contracted and non-contracted vegetable farmers in Western Kenya. Cogent Food & Agriculture, 7: 1910156.

Bao B.F., Zhang L.G., Lei X.B., Yang S., Zhao D. (2022): Analysis on the influencing factors of green grain technology efficiency under the background of new pattern economic development: Taking the Poyang Lake basin as an example. Economic Geography, 42: 185–194.

Bellemare M.F., Novak L. (2017): Contract farming and food security. American Journal of Agricultural Economics, 99: 357–378.

Bezabeh A., Beyene F., Haji J., Lemma T. (2020): Impact of contract farming on income of smallholder malt barley farmers in Arsi and West Arsi zones of Oromia region, Ethiopia. Cogent Food & Agriculture, 6: 1834662.

Chen J., Chen Y.J. (2021): The impact of contract farming on agricultural product supply in developing economies. Production and Operations Management, 30: 2395–2419.

Cheng C., Gao Q., Qiu Y. (2022): Assessing the ability of agricultural socialized services to promote the protection of cultivated land among farmers. Land, 11: 1338.

Crown W.H. (2014): Propensity-score matching in economic analyses: Comparison with regression models, instrumental variables, residual inclusion, differences-in-differences, and decomposition methods. Applied Health Economics Health Policy, 12: 7–18.

Dube L., Mugwagwa K.E. (2017): The impact of contract farming on smallholder tobacco farmers' household incomes: A case study of Makoni district, Manicaland province, Zimbabwe. Scholars Journal of Agriculture and Veterinary Sciences, 4: 79–85.

Geng L., Yan S., Lu Q., Liang X., Li Y., Xue Y. (2023): A rural land share cooperative system for alleviating the small, scattered, and weak dilemma in agricultural development: The cases of Tangyue, Zhouchong, and Chongzhou. Agriculture, 13: 1675.

Hailu H.G., Mezgebo G.K. (2024): Contract farming and sesame productivity of smallholder farmers in Western Tigray, Ethiopia. Cogent Food & Agriculture, 10: 2325093.

Jin Q., Dang H., Wang H., Zhang Z. (2024): Exploring cooperative mechanisms in the Chinese agricultural value chain: A game model analysis based on leading enterprises and small farmers. Agriculture, 14: 437.

Kaur P., Singla N. (2024): Empirical gains from growing potato under contract farming in Punjab, India. Potato Research, 68: 1–16.

Kollenda P., Brals D., Kabubo-Mariara J., Oostendorp R., Pradhan M., van Rijn F. (2024): Ripe for contracts? Estimating the impact of an avocado producer

https://doi.org/10.17221/43/2024-AGRICECON

organization contract farming intervention. Agricultural Economics, 55: 758–783.

Kumar J., Kumar K.P. (2008): Contract farming: Problems, prospects and its effect on income and employment. Agricultural Economics Research Review, 21: 243–250.

Li Y., Fan Z., Jiang G., Quan Z. (2021): Addressing the differences in farmers' willingness and behavior regarding developing green agriculture – A case study in Xichuan county, China. Land, 10: 316.

Liu P., Ravenscroft N., Ding D., Li D. (2019): From pioneering to organised business: The development of ecological farming in China. Local Environment, 24: 539–553.

Ma G.Q., Tan Y.W. (2021): Impact of environmental regulation on agricultural green total factor productivity – Analysis based on the panel threshold model. Journal of Agrotechnical Economics, 313: 77–92.

Minot N., Sawyer B. (2016): Contract farming in developing countries: Theory, practice, and policy implications. In: Devaux A.T., Donovan M., Horton J., Douglas E.: Innovation for Inclusive Value-chain Development: Successes and Challenges. Washington D.C., International Food Policy Research Institute: 127–158.

Mishra A.K., Shaik S., Khanal A.R., Bairagi S. (2018): Contract farming and technical efficiency: Evidence from low-value and high-value crops in Nepal. Agribusiness, 34: 426–440.

Miyata S., Minot N. (2009): Impact of contract farming on income: Linking small farmers, packers, and supermarkets in China. World Development, 37: 1781–1790.

Némethová J., Dubcová A., Nagyová Ľ., Kramáreková H. (2017): Ecological farming in Slovakia and its regional disparities. European Countryside, 9: 746–768.

Patel S.S. (2022): Informal-contract farming in an agriculture supply chain: A game-theoretic analysis. International Journal of Operational Research, 43: 208–225.

Preacher K.J., Hayes A.F. (2008): Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40: 879–891.

Prowse M. (2012): Contract farming in developing countries: A review. A Savoir, 12: 9–87.

Qin L., Zhang Y., Wang Y., Pan X., Xu Z. (2024): Research on the impact of digital green finance on agricultural green total factor productivity: Evidence from China. Agriculture, 14: 1151.

Rabia M., Hossein A., Steven V.P., Rando V., Marcin P., Rytis S., Zou W., Bi W. H. (2023): Does contract length matter? The impact of various contract-farming regimes on land-improvement investment and the efficiency of contract farmers in Pakistan. Agriculture, 13: 1651.

Ren Y., Peng Y., Castro Campos B., Li H. (2021): The effect of contract farming on the environmentally sustainable production of rice in China. Sustainable Production and Consumption, 28: 1381–1395.

Ruml A., Qaim M. (2021): New evidence regarding the effects of contract farming on agricultural labor use. Agricultural Economics, 52: 51–66.

Selorm A., Sarpong D.B.S., Egyir I.S., Bonsu A.M., An H. (2023): Does contract farming affect technical efficiency? Evidence from soybean farmers in Northern Ghana. Agricultural and Food Economics, 11: 9.

Shi F., Cai B., Meseretchanie A., Geremew B., Huang Y. (2023): Agricultural socialized services to stimulate the green production behavior of smallholder farmers: The case of fertilization of rice production in south China. Frontiers in Environmental Science, 11: 1169753.

Singh S. (2002): Contracting out solutions: Political economy of contract farming in the Indian Punjab. World Development, 30: 1621–1638.

Staatz J.M. (1987): The structural characteristics of farmer cooperatives and their behavioral consequences. Cooperative Theory: New Approaches, 18: 33–60.

Staiger D., Stock J. (1997): Instrumental variables regression with weak instruments. Econometrica, 65: 557–586.

Stock J.H., Yogo M. (2002): Testing for weak instruments in linear IV regression. National Bureau of Economic Research: 0284. Available at https://www.nber.org/papers/t0284 (accessed Jan 5, 2024).

Swinnen J.F.M., Maertens M. (2007): Globalization, privatization, and vertical coordination in food value chains in developing and transition countries. Agricultural Economics, 37: 89–102.

Ton G., Vellema W., Desiere S., Weituschat S., D'Haese M. (2018): Contract farming for improving smallholder incomes: What can we learn from effectiveness studies? World Development, 104: 46–64.

Tone K. (2021): Dealing with desirable inputs in data envelopment analysis: A slacks-based measure approach. American Journal of Operations Management and Information Systems, 6: 67–74.

Umberto B., Stuart J.H., Gianni D.A., Eugene H.B. (2018): Statistical primer: Propensity score matching and its alternatives. European Journal of Cardio-Thoracic Surgery, 53: 1112–1117.

Weituschat C.S., Pascucci S., Materia V.C., Caracciolo F. (2023): Can contract farming support sustainable intensification in agri-food value chains? Ecological Economics, 211: 107876.

Wu W., Wu G., Yin C., Chien H. (2020): Impact of contract farming on farmers' income: A case of Wuchang rice in China. Japan Agricultural Research Quarterly, 54: 171–177.

Xu C., Wang Q., Fahad S., Kagatsume M., Yu J. (2022): Impact of off-farm employment on farmland transfer: Insight

https://doi.org/10.17221/43/2024-AGRICECON

on the mediating role of agricultural production service outsourcing. Agriculture, 12: 1617.

Yang Y., Ma H., Wu G. (2022): Agricultural green total factor productivity under the distortion of the factor market in China. Sustainability, 14: 9309.

Yang Y., Yu Y., Li R., Jiang D. (2023): Impact of pesticide outsourcing services on farmers' low-carbon production behavior. Frontiers in Environmental Science, 11: 1226039.

Yu C. Q., Huang X., Chen H. Godfray H.C.J., Wright J.S., Hall J.W., Gong P., Ni S., Qiao S., Huang G., Xiao Y., Zhang J., Feng Z., Ju X., Ciais P., Stenseth N.C., Hessen D.O., Sun Z., Yu L., Cai W., Fu H., Huang X., Zhang C., Liu H., Taylor J. (2019): Managing nitrogen to restore water quality in China. Nature, 567: 516–520.

Zhang W., Gao L., Zolghadr M., Jian D., El Hafsi M. (2023): Dynamic incentives for sustainable contract farming. Production and Operations Management, 32: 2049–2067.

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