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Does Contract Farming Enhance Farmer Welfare? Evidence from Smallholder Red Chilli Farmers

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Abstract

Red chilli (Capsicum annuum L.) plays a vital role in cuisine and rural livelihoods, yet its cultivation remains vulnerable to fluctuating prices, climate risks, and limited market access. Contract farming (CF) has emerged as a potential mechanism to connect smallholder farmers with formal value chains while reducing production and marketing uncertainties. This study investigates the impact of CF on farmer welfare and the factors influencing participation among smallholder red chilli producers in East Java. Primary data from 108 farmers were analyzed using logistic regression to identify determinants of CF participation and propensity score matching (PSM) to assess income effects. The results show that participation in CF arrangements is associated with higher annual income among sampled farmers, primarily through better access to inputs, stable prices, and technical assistance. Younger farmers and those with plots located near their homes are more likely to participate, whereas those with full land ownership tend to avoid contracts to maintain autonomy. The findings suggest that CF may help mitigate market risks and improve livelihoods under comparable production settings in high-value horticulture. However, inclusive program design is essential, particularly to address regional disparities, generational gaps, and land tenure issues. Policy recommendations emphasize standardized contracts, logistical support for remote areas, and targeted outreach to marginalized farmer groups.

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Introduction

Red chilli (Capsicum annuum L.) serves as both a culinary staple and economic lifeline for Indonesian smallholders, with the nation ranking among the world's top producers (Mariyono & Sumarno, 2015; Muflikh *et al.*, 2023; FAOSTAT, 2024). Small-scale farmers dominate this vital sector, contributing over 80% of national output (Mariyono *et al.*, 2020), yet face systemic vulnerabilities including extreme price volatility (200-300% annual fluctuations), devastating crop diseases (30-50% yield losses from anthracnose), and climate disruptions that jeopardize planting cycles (Manurung, 2024). These challenges trap many of Indonesia's 1.2 million chilli farmers in poverty cycles (Sahara *et al.*, 2015), with 62% earning below provincial minimum wages. In this precarious context, contract farming (CF) has gained policy traction as an institutional solution promising market stability through pre-negotiated terms on pricing, inputs, and technical support (G. Das *et al.*, 2023; van der Haar *et al.*, 2023.

Contract farming is increasingly promoted as a mechanism to integrate smallholders into modern value chains while mitigating production and market risks (Rondhi *et al.*, 2020). Proponents argue that such arrangements provide farmers with guaranteed markets, better prices, and access to quality inputs, thereby improving productivity and income (Meemken & Bellemare, 2020). Conversely, critics highlight potential risks such as unequal bargaining power, exploitative terms, and the exclusion of the most vulnerable smallholders (Adams *et al.*, 2019). In Indonesia, CF has been adopted in various agricultural sectors, including poultry (Aji *et al.*, 2023; Setiadi *et al.*, 2022), sugarcane (Hakim & Rifin, 2024; Rokhani *et al.*, 2021), and horticulture (Angreheni *et al.*, 2024; White & Wijaya, 2022).

Despite these developments, a major research gap remains in measuring the welfare impact of contract farming within Indonesia's horticultural sector, particularly among smallholder red chilli farmers. While numerous studies have explored adoption behavior and institutional arrangements, empirical evidence on how CF affects farmers' welfare outcomes, such as income stability, access to markets, and resource autonomy, remains scarce and fragmented. This study addresses this specific gap by providing quantitative evidence of CF's welfare effects and identifying key determinants of participation in red chilli production systems. Other related gaps, such as the environmental sustainability of CF practices or gendered access to contract schemes, are acknowledged but not the primary focus of this paper. These dimensions, though important, require different methodological frameworks (e.g., environmental life-cycle assessment or gender-sensitive qualitative inquiry) that fall beyond the present study's quantitative design. By concentrating on welfare measurement, this research provides a

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focused and policy-relevant contribution to understanding how institutional innovations like CF can serve as inclusive agribusiness models for Indonesia's smallholders.

This research contributes novel insights into how contract farming can be optimized to support both economic and social sustainability in high-value horticulture. Using a combination of household survey data and econometric analysis, combining logistic regression and propensity score matching (PSM). The logistic regression will identify key socio-economic and institutional factors influencing farmer's decision to enter contract, while PSM will control for selection bias by comparing income outcomes between contract and non-contract farmers with similar characteristics. The analysis will generate the Average Treatment effect on the Treated (ATT), allowing for a robust and quantitative understanding of the welfare impact. Given the Indonesian government's push for agricultural modernization and inclusive agribusiness models (Prihadyanti & Aziz, 2023), this research provides timely evidence to inform policymakers and development practitioners on the effectiveness of contract farming as a pro-smallholder strategy. Furthermore, with rising food insecurity and rural poverty exacerbated by climate change (Hasegawa *et al*., 2018; Mbuli *et al*., 2021) and economic shocks (Koo *et al*., 2021; Laborde *et al*., 2019), identifying sustainable farming models is critical to safeguarding farmer livelihoods and ensuring national food security. However, the findings are expected to function as a decision-making tool for policymakers, agribusiness actors, and development practitioners to design more inclusive and beneficial contract schemes.

Materials and Method

Data Description

Research relies on primary data collected through a purposive sampling strategy from 108 smallholder red chilli farmers located in three main producing districts in East Java, namely Jember, Lumajang, and Banyuwangi, which are officially recorded as chilli production centers in the province (Badan Pusat Statistik, 2024). The use of purposive (non-probability) sampling is intentional because the study aims to compare farmers participating in contract farming (CF) and those outside CF schemes within the same production system, rather than to produce statistically representative provincial estimates (Wan, 2019). Accordingly, the findings of this study are interpreted as context-specific evidence of welfare differences associated with contract farming participation and should not be generalized to the entire population of farmers beyond similar production and institutional settings.

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At the farmer level, respondents were screened using four explicit inclusion criteria:

1. Commodity criterion: actively cultivating red chilli in the last production season (not ex-chilli farmers).
2. Experience criterion: minimum 3 years of experience in chilli cultivation, to avoid including purely experimental/one-off growers.
3. Contract status criterion: belonging to either (i) farmers who had at least one season under a contract/purchase agreement with buyers/aggregators, or (ii) comparable farmers in the same village who sold via non-contract/spot markets. This is important for constructing matched treatment–control pairs.
4. Location accessibility: farm plots located within the administrative village of the selected district to ensure comparability of agro-market conditions.

These criteria were chosen to (i) make CF and non-CF farmers comparable on basic farm characteristics, (ii) reduce recall and measurement errors, and (iii) ensure that observed income differences can credibly be analyzed using matching techniques (Mweshi & Sakyi, 2020).

Data were collected through structured face-to-face interviews using a pre-tested questionnaire administered by trained enumerators. The questionnaire covered: farmer demographics, farm assets and land tenure, chilli production practices, marketing channels (including contract terms, if any), access to inputs and extension, and income from chilli and non-chilli sources. Contract farmers were additionally asked about the type of agreement, price determination, delivery requirements, and support services received. Because the sample is purposive and relatively small (n = 108), the findings are not intended to be generalized statistically to all Indonesian red chilli farmers. Instead, the results should be interpreted as analytically transferable to contexts with similar market structures and contract arrangements.

Analytical Procedures

The data analysis for this study involves a combination of logistic regression and propensity score matching (PSM). In the first stage, a logistic regression model is used to estimate the propensity score, defined as the probability of a farmer participating in institutional agreements given a set of observable characteristics (Caliendo & Kopeinig, 2008; A. Das, 2021; Rosenbaum & Rubin, 1983, such as the participation or non-participation of farmers in institutional agreements, and various independent variables. Total of eight variables are employed as seen in Table 1. Harvest quantity was included as a proxy for farmers' baseline productivity and production capacity prior to participation in institutional agreements. As such, this

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variable reflects pre-existing differences in farming performance rather than outcomes generated by the treatment.

Table 1 - Description of logistic regression variable on farmer decision to participate in contract farming in Indonesia, 2024

Factors	Variables	Description	Unit	Measure
Contract farming (CF)	Y	Farmer' decision to participate in contract farming (1 = participated; 0 = not participated)	–	Nominal
Age	X_1	Farmers age in the year when the research was conducted	Year	Scale
Education	X_2	Farmer's formal education from not going to school to master/doctor graduate	Year	Scale
Household size	X_3	The total of farmers' family members in each household	Person	Scale
Experience	X_4	Farmer's experience on red chilli farming	Year	Scale
Land ownership	X_5	Farmer's land ownership to cultivate red chilli (1 = owned; 0 = rented)	–	Nominal
Harvest quantity	X_6	Farmer's red chilli harvest result per years	Kg	Scale
Side occupation	X_7	Farmer has activities to generate income other than farmig (1 = Yes; 0 = No)	–	Nominal
Distance	X_8	Distance of farmer's farm to the nearest market	Km	Scale
Profit	z	Red chilli farmer income within a year	Rp	Scale

The used logistic regression model is as follow:

$$\ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} + \beta_6 X_{6i} + \beta_7 X_{7i} + \beta_8 X_{8i} \quad (1)$$

Where Y_i is the farmers decision to participate in contract farming, $X_{1\text{-}8}$ are the independent variables (refers to Table 1), P_i is the probability of farmer

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who participate in contract farming (Behera, 2019), b_0 is the constant, and b_1-b_8 are logistic regression coefficient for each variables include.

In the second stage, farmers participating in institutional agreements (treated group) are matched with non-participating farmers (control group) with similar propensity scores. Propensity Score Matching is a method for estimating causal treatment effects in observational studies by matching treated and control units with similar estimated probabilities of receiving treatment (propensity scores), thereby reducing selection bias due to observed covariates (Rosenbaum & Rubin, 2006). Since then, this analysis is widely used in many areas including agricultural policy, agricultural contract (Maertens & Vande Velde, 2017; Suwandari *et al.*, 2020; Yanuarti *et al.*, 2019a).

The identification strategy relies on the Propensity Score Matching framework, which assumes Conditional Independence and common support. The Conditional Independence Assumption (CIA) states that, conditional on observable covariates, the treatment assignment is independent of potential outcomes. In this study, farmers' participation in institutional agreements is assumed to depend on observable characteristics such as age, education, farming experience, farm size, and household characteristics. By conditioning on these variables, the selection bias due to observable factors can be reduced. In addition, the common support assumption requires that farmers in both treatment and control groups share comparable propensity scores. This condition ensures that meaningful matches can be constructed between participating and non-participating farmers.

The propensity score is the conditional probability of being treated; in our case, participating in CF. Specifically:

$$p(X) = \Pr(Y = 1 \mid X) = E(Y \mid X) \tag{2}$$

where Y is a binary variable indicating whether a farmer participates in CF (1 = Yes; or 0 = No), X is the multidimensional vector of pre-treatment characteristics of a farmer, Pr is the probability of being treated, E is the mean outcome and $p(X)$ is the propensity score. Standard logit regression models are commonly deployed to estimate $p(X)$. Following the estimation of the propensity score, one must estimate the average effect of treatment.

Estimation of the treatment effect is done using matching methods. The difference between groups of treated farmers and selected control group farmers is used to estimate the effect of treatment. Common methods include Nearest Neighborhood Matching (NNM), Kernel Matching (KM) and Radius Matching (RM) (Becker & Ichino, 2002). These alternative matching algorithms were applied to examine the robustness of the estimated treatment effects. Standard errors of the estimated Average Treatment Effect

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on the Treated (ATT) were obtained using bootstrap procedures. The quality of the matching was assessed using balance diagnostics by comparing the distribution of covariates between treated and control farmers before and after matching. In addition, the number of observations within the common support region before and after matching was reported to ensure transparency and replicability of the matching process.

Before estimating the welfare effects of CF, the study verified the comparability between treatment (CF participants) and control (non-CF) groups through overlap assessment, common support identification, and balance testing (Pan & Bai, 2015; Rosenbaum & Rubin, 1983). The distribution of propensity scores was first examined to ensure sufficient overlap between groups, and observations with extreme values outside the common support region were excluded to improve matching quality. After matching, balance tests were conducted to confirm that the mean values of key covariates were statistically similar across both groups, indicating that differences in outcomes could be attributed mainly to CF participation. Matching quality was further assessed through the pseudo-R^2 statistic, where lower values after matching suggest adequate covariate balance and reduced selection bias.

In the final stage, the Average Treatment Effect on the Treated (ATT) is estimated to evaluate the impact of institutional agreements on farmers' welfare outcomes (Yanuarti *et al.*, 2019b). ATT is estimated as follows:

$$ATT = E[E\{Y_{1i} \mid D_i = 1, p(X_i)\} - E\{Y_{0i} \mid D_i = 0, p(X_i)\} \mid D_i = 1] \quad (3)$$

where the expectation is over the distribution of $(X_i)|D_i = 1$; i denotes the household, with 1_i and 0_i as the potential outcomes in the two counterfactual situations of treatment and non-treatment respectively and D is the treatment group indicator. The hypothesis is as follow:

H_0: Participation in CF does not affect farmers' income.

H_1: Participation in CF affect farmers' income.

Statistical inference is conducted using the standard errors associated with the ATT estimates. The null hypothesis is rejected if the estimated ATT is statistically significant at conventional significance levels ($p < 0.10$, $p < 0.05$, or $p < 0.01$).

Results

Table 2 presents comparative statistics between chilli farmers participating in contract farming (CF) and non-participants across eight

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key variables. Notably, CF participants tend to be younger (mean age = 46.87 vs 54.44 years) with marginally higher education levels (9.12 vs 8.17 years of schooling), suggesting possible age and human capital biases in CF enrollment (Meemken & Bellemare, 2020). The substantial difference in harvest quantities (12,223.21 kg vs 3,086.67 kg) likely reflects both the productivity-enhancing effects of CF and self-selection of more commercially-oriented farmers into contracts (Rondhi *et al*., 2020). Farm characteristics reveal important patterns, where CF participants operate closer to market centers (mean distance = 0.82 km vs 1.29 km), consistent with transaction cost theory predicting closer proximity reduces contract enforcement costs (Dubbert, 2019).

While land ownership is nearly balanced between groups (57 CF vs 51 non-CF), the younger average age and greater farming experience (12.97 vs 15.11 years) of CF participants may indicate generational shifts in market engagement strategies. The similar household sizes (4.01 vs 4.50 members) and side occupation prevalence (55 vs 53 households) suggest these factors are not primary determinants of CF participation in this sample.

Table 2 - Descriptive statistic of variables of farmer's decision to participate in Contract Farming (CF) in Jember, Lumajang, Banyuwangi, 2024

Variable		Participate in Contract Farming			Not Participate in Contract Farming		
		Mean	Standard Deviation	Freq.	Mean	Standard Deviation	Freq.
X_1	Age (years)	46.87	9.86		54.44	13.02	
X_2	Education (years)	9.12	2.98		8.17	2.47	
X_3	Household size (person)	4.01	1.37		4.5	1.29	
X_4	Experience (years)	12.97	8.75		15.11	8.98	
X_5	Land ownership (1 = owned; 0 = rented)			57			51
X_6	Harvest quantity (kg)	12223.21	12970.24		3086.67	2254.33	
X_7	Side occupation (1 = Yes; 0 = No)			55			53
X_8	Distance (km)	0.82	0.76		1.29	0.95	

Source: Own elaboration, 2024.

The logistic regression estimation produces a robust result, and four of six of the input variables have a statistically significant effect at the 90% confidence level.

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Table 3 - Logistics regression output of factors that influence farmer decision whether to participate in Contract Farming or not

Variable	B	S.E.	Sig.	Exp(B) Odds Ratio
Age (years)	–0.052	0.034	0.127	0.949
Education (years)	0.111	0.118	0.344	1.118
Household size (person)	–0.415	0.220	0.060*	0.661
Experience (years)	–0.005	0.030	0.879	0.995
Land ownership	–1.655	0.672	0.014**	0.191
Harvest quantity (kg)	0.00045	0.000	0.012**	1.000
Side occupation	1.1225	0.856	0.190	3.073
Distance (km)	–0.7663	2.647	0.051*	0.465
Constant	5.783	2.289	0.012	324.66
Omnimbus Test of Model Coefficient	0.000**			
Nagelkerke R Square	0.393			
–2 Log Likelihood (step 0)	105.968			
–2 Log Likelihood (step 1)	75.654			
Classification table (overall)	85%			

* Significant at 90% confidence level.
** Significant at 95% confidence level.

Source: Own elaboration.

In Table 3, logistic regression results reveal several key factors influencing farmers' decisions to participate in contract farming (CF). Household size, land ownership, harvest quantity, and distance to market emerge as statistically significant predictors of participation. Specifically, land ownership shows a strong negative association with CF participation (B = –1.655, $p < 0.05$), with landowning farmers being 80.9% less likely to join CF schemes (Exp(B) = 0.191). This suggests that farmers with secure land tenure may prefer independent production over contractual agreements. Conversely, harvest quantity exhibits a positive and significant relationship (B = 0.00045, $p < 0.05$), indicating that more productive farmers are marginally more likely to engage in CF, likely due to their capacity to meet volume commitments.

The model also identifies household size as marginally significant (B = -0.415, $p < 0.10$), where each additional household member reduces the odds of CF participation by 33.9% (Exp(B) = 0.661). This may reflect labor allocation trade-offs, as larger households might prioritize diversified income

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sources over contractual obligations. Similarly, distance to market approaches significance (B = –0.766, p < 0.10), implying that farmers located farther from market centers are less likely to participate, possibly due to higher transaction costs.

Notably, age, education, farming experience, and side occupations do not significantly influence participation decisions in this sample. The model's robustness is supported by a significant Omnibus Test (p < 0.01) and a Nagelkerke R^2 of 0.393, explaining approximately 39.3% of the variance in CF participation. The classification accuracy of 85% further validates the model's predictive power (Ntshangase *et al.*, 2018). These findings highlight the importance of production capacity, land tenure, and market proximity in shaping smallholders' engagement with CF, providing a foundation for subsequent discussion on policy and institutional implications.

Table 4 - Balance Test Results for Propensity Score

Bias Reduction (%)	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
NNM	4.8	95.3	143.2	1.0	43.6	11.0	21.1	93.2
KM	12.6	97.8	158.4	8.9	61.7	29.4	48.6	96.5
RM	9.3	96.4	151.2	5.7	54.2	21.8	36.9	94.8

* Nearest Neighbourhood Matching (NNM), Kernel Matching (KM), Radius Matching (RM).

Table 4 reports bias reduction performance across alternative matching algorithms and shows clear improvements in covariate balance after matching. Overall, kernel matching (KM) achieves the highest bias reduction across most covariates, followed by radius matching (RM), while nearest neighbourhood matching (NNM) yields more variable performance. Substantial bias reductions are observed for key covariates such as education (X2) and market distance (X8) under all methods, indicating effective balancing of factors strongly associated with contract farming participation. KM and RM consistently improve balance for variables that remain weakly adjusted under NNM, including household size (X3), land ownership (X5), and side occupations (X7), suggesting that weighted and caliper-based approaches provide more stable matching outcomes. Although some covariates exhibit limited bias reduction under NNM, the overall pattern across matching specifications confirms that observable differences between treatment and control groups are substantially reduced, supporting the robustness of the subsequent treatment effect estimates.

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Table 5 - Summary of Statistical Analysis Result for Testing Matching Quality

Matching Algorithm	Pseudo-R^2		P > Chi^2		Mean Bias		Median Bias	
	Before	After	Before	After	Before	After	Before	After
NNM*	0.612	0.431	0.00	0.28	56.8	50.4	53.50	44.30
KM*	0.612	0.430	0.00	0.37	56.8	52.3	53.50	34.23
RM*	0.612	0.441	0.00	0.25	56.8	55.1	53.50	40.62

* Nearest Neighbourhood Matching (NNM), Kernel Matching (KM), Radius Matching (RM).

Matching quality indicators indicate a consistent improvement in covariate balance across all matching algorithms after implementation (Table 5). For NNM, KM, and RM, the pseudo-R^2 values decline substantially from 0.612 to around 0.43-0.44, suggesting a marked reduction in systematic differences between contract farming participants and non-participants. Similarly, the likelihood ratio test becomes statistically insignificant after matching (P > Chi^2 ranging from 0.25 to 0.37), indicating that observable covariates no longer jointly explain treatment assignment. Mean and median bias measures also decrease across all methods, with kernel matching (KM) achieving the largest reduction in median bias, followed by radius matching (RM) and nearest neighbourhood matching (NNM). Although some residual imbalance remains, the overall pattern confirms that the matching procedures substantially improve covariate balance and provide an adequate basis for estimating treatment effects.

Table 6 - Impact of Contract Farming Participation on Red Chilli Farmers' Income

Matching Algorithm	Variable Outcome: Farmer's Income		
	ATT	Error Standard	t-value
NNM	105,760,863	53,485,129.4	1.98
KM	112,430,517	46,210,884.6	2.43
RM	108,975,342	49,876,510.2	2.18

* Nearest Neighbourhood Matching (NNM), Kernel Matching (KM), Radius Matching (RM).

Participation in contract farming cross alternative matching algorithms is consistently associated with higher farmer income (Table 6). The estimated average treatment effect on the treated (ATT) ranges from IDR 105.76

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million under nearest neighbourhood matching (NNM) to IDR 112.43 million under kernel matching (KM), with radius matching (RM) yielding an intermediate estimate of IDR 108.98 million. All estimates are statistically significant at the 5% level (t-values between 1.98 and 2.43), indicating that the positive income effect of contract farming is robust to different matching specifications. The relatively lower standard errors observed under KM and RM suggest improved estimation efficiency compared with NNM, reinforcing the stability of the estimated welfare gains. These findings provide robust empirical evidence that contract farming can serve as an effective mechanism for income enhancement among Indonesian chilli farmers, though the wide confidence interval suggests the actual benefits may range considerably depending on farmer-specific characteristics and implementation conditions. The positive ATT aligns with theoretical expectations about contract farming's potential to improve market access and price stability for smallholders.

Discussion

Factors affecting farmer decision to participate in contract farming (CF)

Farmer age has a negative influence on farmer decision to participate in CF. Odds ratio value (Exp (B)) of age is 0.949 means that older farmer have a lower tendency to participate in CF by 0.949 times compared to younger farmer, assuming other variables are constant. Younger farmers are more inclined towards engaging in contract farming (CF). The rationale behind this trend is that younger individuals in the farming sector are generally more receptive to new advancements, particularly innovative farming models like CF. Conversely, their older counterparts often show resistance and hesitancy towards embracing such modern concepts. According to Vassalos and Li (2016), there's a noticeable reluctance among older farmers to participate in CF. This reluctance can be attributed to several factors; as farmers age, they may find it challenging to enter into long-term contracts or commitments. Additionally, there is a tendency among the older farming population to exhibit a lower level of trust in entrusting their farming operations to others, further contributing to their reluctance to adopt CF (Hota *et al.*, 2019).

Education positively impacts farmers' decisions to participate in contract farming because it equips them with essential knowledge and skills (Hoang, 2021; Olounlade *et al.*, 2020). Educated farmers are more aware of the latest agricultural practices and the benefits of contract farming, such as better access to markets and advanced technologies (Bellemare & Bloem,

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2018). They also possess superior risk management and negotiation skills, making them more capable of securing favorable contract terms. Additionally, education fosters a willingness to embrace new innovations and improves their ability to understand the legal and financial aspects of contracts (Power & Goodnough, 2019). This combination of factors makes educated farmers more open and better prepared to engage in contract farming, recognizing it as an opportunity to enhance their productivity and income.

Household size, experience, land ownership, and distance from home to farming area can negatively impact farmers' decisions to participate in contract farming (CF) for various interconnected reasons. Larger household sizes may increase the need for immediate and stable income, leading farmers to prefer traditional farming methods perceived as less risky than CF (Ali, 2021), which often involves specific production standards and market uncertainties. Experienced farmers might be more set in their ways and skeptical of the benefits of CF (Poulsen *et al.*, 2018), preferring to rely on traditional farming practices that have served them well in the past. Additionally, they may prefer to maintain complete control over their farming practices rather than adhering to the requirements set by CF agreements.

Farmers who own their land outright may be less inclined to participate in CF due to a desire to maintain autonomy over their land use and skepticism about the long-term benefits of CF arrangements (Djurfeldt *et al.*, 2018), fearing potential loss of control over their most valuable asset. Together, these factors create a situation where farmers with larger households, more experience and have land ownership are less likely to see the benefits of participating in CF, opting instead for traditional farming methods that offer them more perceived control and stability. However, the positive but statistically weak association between side occupations and CF participation ($p = 0.190$) presents an interesting paradox – while supplemental income could theoretically enable farmers to absorb CF risks (Buitenhuis *et al.*, 2022), it also divert labor away from contracted production (Vicol *et al.*, 2022).

Meanwhile, distance between farmers' homes and their cultivated areas significantly affects their decision to participate in contract farming (CF), with a negative and marginally significant coefficient ($p = 0.051$). This suggests that farmers whose fields are located farther from their residences are less likely to engage in CF arrangements. This finding aligns with farm management theory, which posits that greater distances between homesteads and fields increase transportation costs, time constraints, and monitoring difficulties (Deininger *et al.*, 2017; Shuhao *et al.*, 2008). For CF schemes requiring strict adherence to production protocols (e.g., scheduled inputs, quality control), remote plots may be less attractive to both farmers and agribusiness firms due to higher supervision costs and lower compliance

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likelihood. In Indonesia, where many chilli farmers maintain multiple small plots, this distance factor may explain why CF adoption remains limited despite its potential benefits.

Enhancing farmer participation in contract farming for red chilli commodities is essential to consider and address the identified factors that influence their decisions. Firstly, recognizing the negative influence of farmer age on participation implies that targeted efforts should be made to educate and engage older farmers in the benefits of contract farming (Vabi Vamuloh *et al*., 2019). Initiatives such as workshops, training programs, and knowledge-sharing platforms can be implemented to bridge the generation gap and showcase the advantages of adopting innovative farming models like contract farming. Additionally, creating mentorship programs where younger farmers can share their positive experiences and outcomes in contract farming may help dispel the resistance among older farmers (Penniman, 2018).

Moreover, the impact of education on farmer participation suggests a need for widespread education initiatives within the farming community. Investments in educational programs that focus on the benefits, legal aspects, and risk management strategies associated with contract farming can empower farmers with the knowledge and skills necessary for successful participation (Amanah *et al*., 2021; Davis *et al*., 2021). Collaborations between agricultural institutions, government bodies, and NGOs can facilitate the dissemination of relevant information and ensure that farmers are well-informed about the advantages of contract farming.

Furthermore, considering the negative impact of factors such as household size, experience, land ownership, tailored strategies are needed to address the concerns of farmers with these characteristics. Implementing flexible contract terms, addressing concerns related to income stability, and customizing agreements based on the specific needs of larger households or experienced farmers could make contract farming more appealing to a broader demographic. Additionally, emphasizing the scalability of contract farming and showcasing success stories from farmers with extensive landholdings can dispel misconceptions and highlight the potential benefits of participation (Wanjira *et al*., 2020).

Contract farming impact on farmer's income

Positive and statistically significant Average Treatment Effect on the Treated (ATT) demonstrates that contract farming (CF) substantially improves red chilli farmers' income in research area. This finding aligns with the theoretical proposition that CF reduces market uncertainties and improves

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access to quality inputs (Barik *et al.*, 2024; Dubbert, 2019). The magnitude of this income effect, suggests CF can be transformative for rural livelihoods. Some mechanisms likely explain this result, first, CF's input provision (particularly improved seeds and fertilizers) appears to have boosted yields (Ncube, 2020), as evidenced by participants' significantly higher harvest quantities. Second, price stabilization clauses in contracts (Bizikova *et al.*, 2020) protected farmers from chilli's notorious price volatility. Third, technical assistance component potentially reduced production risks (Gramzow *et al.*, 2018; Meemken & Bellemare, 2020).

These findings carry important policy implications. The demonstrated income effects support Indonesia's National Agricultural Contract Farming Development Program but highlight the need for: 1) standardized contract templates ensuring fair terms, 2) targeted inclusion of smaller landholders, and 3) quality control systems maintaining chilli premium prices. Future research should explore the sustainability of these income gains and environmental impacts of intensified production. Compared to CF impacts on other Indonesian crops, red chilli shows exceptional responsiveness, likely due to its high value-per-hectare and traditional market inefficiencies. This suggests horticultural crops may benefit most from CF interventions in developing economies.

Conclusion and Suggestion

Participation in contract farming (CF) is associated with higher welfare outcomes among sampled smallholder red chilli farmers operating within comparable production and institutional settings. Specifically, CF participants earned, on average, approximately IDR 105.76 million more annually than non-participants. These welfare differences are linked to improved access to quality inputs, price stabilization mechanisms, and technical assistance, which together enhance productivity and reduce exposure to market risks. Farmer participation in CF is shaped by several socio-economic and spatial factors. Younger farmers are more likely to engage in CF schemes, while landowners and farmers with plots located farther from homesteads show lower participation probabilities. Although education and household size exhibit weaker statistical significance, their estimated effects remain consistent with broader theoretical expectations related to human capital and labor allocation decisions.

The findings highlight the conditional potential of CF as a pathway for agricultural commercialization and income enhancement among smallholder horticultural producers under similar contextual conditions. To improve

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inclusivity and equity within CF arrangements, policy interventions should focus on: (1) promoting standardized and transparent contract designs to safeguard smallholders, (2) strengthening logistical support for farmers managing spatially dispersed plots, and (3) designing targeted outreach strategies for older and landowning farmers who may face higher entry barriers or exhibit greater risk aversion toward CF participation. Future research should extend this analysis using longitudinal data to capture dynamic welfare effects, examine environmental sustainability implications, and assess the role of digital technologies in expanding CF accessibility. Such efforts would improve understanding of how CF arrangements function across diverse institutional and agroecological contexts.

Author contributions

Conceptualization was contributed by Anik Suwandari and Joni Murti Mulyo Aji. Methodology was contributed by Anik Suwandari, Joni Murti Mulyo Aji, Mohammad Rondhi, and Rizky Yanuarti. Investigation and data curation were conducted by Anik Suwandari, Ebban Bagus Kuntadi, and Rokhani. Formal analysis was performed by Anik Suwandari, Ebban Bagus Kuntadi, Mohammad Rondhi, and Rizky Yanuarti. Writing – original draft was undertaken by Anik Suwandari. Writing – review and editing was contributed by all authors. Supervision was provided by Joni Murti Mulyo Aji, Mohammad Rondhi, and Rizky Yanuarti. Project administration was handled by Anik Suwandari.

Conflict of interest

All authors declare no conflict of interest.

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