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The impact of contract farming on household income and poverty alleviation: Insights from smallholder poultry farmers in arid and semi-arid regions of Kenya

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Abstract: This study explores the impact of contract farming on household income and rural poverty alleviation using measures outlined by World Bank among 410 smallholder Kenyan poultry farmers. Using endogenous switching regression and propensity score matching models, we found that contract farming significantly boosts household income, with participants experiencing a 74% increase. If non-participants had engaged in contract farming, their income could have risen by 45.59%. The average treatment effect on the treated was USD 0.21 *per capita* per day, corresponding to a 9.83% reduction in extreme poverty and a 16.90% reduction in poverty severity. Written contracts proved the most effective in poverty alleviation, contributing to reduction of 12.17% and 20.93% in extreme poverty and poverty severity respectively. Spot transactions resulted in a 10.35% reduction in extreme poverty and a 17.80% reduction in poverty severity, while unwritten contracts had the least impact, with reductions of 7.92% and 13.62%, respectively. These findings demonstrate the substantial benefits of contract farming in improving household income and alleviating rural poverty. They highlight the importance of implementing and supporting written contracts to maximise poverty reduction. Targeted policy interventions and support for contract farming could further enhance its effectiveness and contribute to sustainable rural development.

Keywords: dryland agriculture; Kenya; rural development; poultry value chain; small-scale farmers

High poverty levels and extreme environmental conditions in arid and semi-arid areas (ASALs) severely limit agricultural production, necessitating innovative approaches to improve livelihoods and promote sustainable development especially in developing countries (Prasad et al. 2023). Contract farming has emerged as a fundamental strategy, facilitating agreements between agribusiness enterprises and small- to medium-scale farmers (Ncube 2020). It provides crucial resources such as inputs, technical support, and market access to smallholder farmers (Mugwagwa et al. 2020).

Despite these provisions, farmers face challenges including rising production costs, and price fluctuations, which hinder their income generation and ROI (Pham et al. 2021). In recent years, Kenya's poultry sector has grown significantly not only as a vital source of house-

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hold nutrition but also contributing approximately 4.5% of the GDP and employing over 1.5 million people (Kenya National Bureau of Statistics 2021). However, the industry faces challenges such as limited market access, low productivity, and poor value chain integration – issues that could be addressed through contract farming (CF) (Pham et al. 2021).

CF enables farmers to manage production while receiving marketing and distribution support, thereby helping widen their market access (Bellemare et al. 2021). When formal contracts are not feasible, farmers may engage in spot transactions, selling directly to buyers without prior agreements, though this comes with price volatility (Johnny et al. 2019). Both written and unwritten contracts exist, providing flexibility and opportunities for farmers to manage risks and improve profitability (Mugwagwa et al. 2020). The study identifies three main types of market contracts: spot transactions, written contracts, and unwritten contracts. Spot transactions provide immediate cash flow based on market prices but can lead to income volatility. Conversely, written contracts offer legally binding agreements with fixed prices and payment schedules, providing income security and predictability. Whereas unwritten contracts rely on verbal agreements, allowing flexibility but risking delayed or inconsistent payments due to lack of legal enforceability (Mugwagwa et al. 2020). The choice of contract type therefore influences farmers' income stability and financial well-being.

Numerous studies, such as Bidzakin et al. (2019), Mulatu et al. (2017), have highlighted the positive impacts of CF on farmers' livelihoods, including increased income and productivity. CF also facilitates risk-sharing between producers and agribusiness firms, potentially reducing price and income volatility (Ncube 2020). Studies conducted by Mugwagwa et al. (2020) and Bellemare and Bloem (2018) showed that CF helps reduce market imperfections by providing credit, inputs, technology, and information, thus reducing transaction costs. A perspective supported by Pham et al. (2021).

However, contrasting viewpoints emerge in research by Ncube (2020), portraying CF as a means for agribusiness firms to exploit farmers. Specific studies, such as those by Ragasa et al. (2018), illustrate CF's contribution to technology adoption and productivity growth. Yet, these advancements did not significantly improve profitability due to high production costs among CF-involved farmers compared to non-participating farmers. Similarly, Mwambi et al. (2016) concluded that, despite productivity gains, CF participation may not substantially increase smallholder farmers' income. Notably, none of these studies focused on farmers in ASALs, which this study explored. Previous findings on CF may not automatically apply to ASAL areas due to their unique socio-economic and environmental conditions.

This study significantly contributes to the literature by examining CF dynamics in Kenya's ASALs, uniquely shaped by socio-economic and environmental challenges. Unlike prior studies, we investigated how CF impacts household income and alleviates poverty among smallholder poultry farmers in these climate-constrained areas. Grounded in utility maximisation theory, a core principle of microeconomics that explains how individuals make optimal decisions under constraints (Aleskerov et al. 2007). The study positions CF as a tool for enhancing farmers' utility.

Smallholder farmers in ASALs face uncertainties such as limited market access, price fluctuations, and high production costs (Bellemare et al. 2021). CF mitigates these challenges by providing stable incomes, reducing financial risks, and ensuring access to essential inputs. Consequently, farmers' decisions to engage in CF are driven by the goal of achieving financial stability and reducing economic uncertainties (Mugwagwa et al. 2020). Each contract type offers varying levels of security and risk. Written contracts provide predictability through fixed pricing, which minimises income volatility. Unwritten agreements, though flexible, lack legal enforceability and pose risks. Spot transactions, while immediate, expose farmers to market price fluctuations. These variations influence farmers' choices and their ability to enhance economic welfare. Based on these, we hypothesise as follows:

H_1: CF participation is associated with increased household incomes for smallholder farmers.

H_2: CF participation reduces poverty among smallholder poultry farmers by fostering financial security and resilience.

By conducting this study, we show the interconnectedness of poverty alleviation and agricultural practices through farmers' income enhancement, aligning with SDGs 1 and 8 focus on poverty alleviation decent work and economic growth, contributing to sustainable development goals.

MATERIAL AND METHODS

Data

The study used cross-sectional design with data collected between October and December 2023 in Baringo, Nakuru, and Elgeiyo Marakwet counties of Kenya (presented by Figure 1), categorised as arid and semi-ar-

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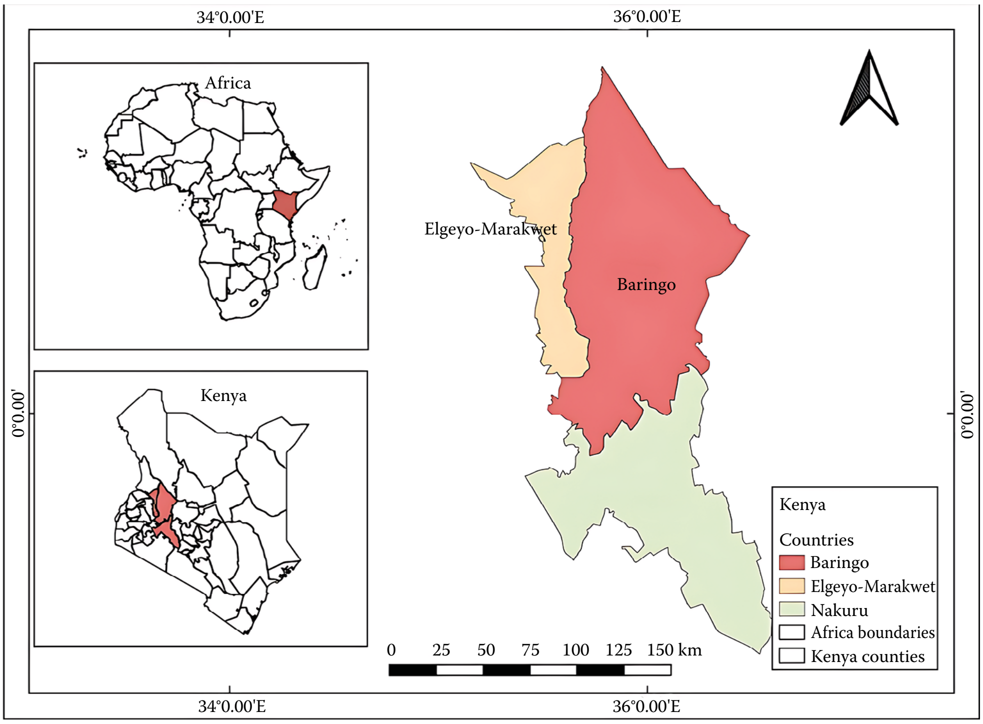

Figure 1. Map of the study area

Source: Government of Kenya, 2023

id areas (Government of Kenya 2023). These regions face limited rainfall, making crop farming challenging. Alternative livelihood strategies are therefore essential for the communities' sustenance. Poultry, a reliable source of income despite unpredictable weather patterns, demonstrates resilience to climate variability, making it a crucial resource for such regions.

Multistage sampling procedure was used to select farming households. Initially, purposive sampling was adopted to cluster farmers in 21 sub-counties, followed by random sampling to select households from the overall size of the poultry population of 6 000 (County livestock records). Subgroups were chosen using stratified sampling, and respondents were selected through random sampling. A sample of 479 smallholder poultry farmers was interviewed, selected from the population using Yamane (1967) sampling formula as presented in Equation (1).

$$n\frac{N}{1+Ne^2} \tag{1}$$

where: n– the sample size; N – a representation of the population (1 + 1 200); e^2– the precision level (0.05^2).

Farmers managing flocks ranging from semi-commercial operations (minimum 20 birds) to large-scale producers (up to 500 birds) contributed to this research. This threshold of 20 birds was chosen to exclude purely subsistence-oriented households and focus on farmers with market engagement potential and large-scale producers, ensuring representation across poultry farming scales. This stratification captures distinct challenges, such as resource access for smallholders and economies of scale for larger producers, offering insights applicable to diverse poultry systems. After data cleaning, a sample size of 410 smallholder farmers was adopted, indicating 85.56% response rate. A pilot study test had been conducted to assess the clarity, adequacy, and validity of data collection instruments.

Estimation strategies

Assessment of the impacts of participating in contract farming. This study utilised an endogenous switching regression (ESR) model to investigate the impact of CF participation on household income. The ESR model was selected for its ability to address biases and reveal income disparities between participants and non-participants. Using STATA 18.0 and the 'movestay' command, selection bias was mitigated by modelling separate regression equations for participants and non-participants.

The probability of CF participation was modelled using a selection equation with various covariates, while outcome equations estimated income impacts separately for participants and non-participants. The

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Average Treatment Effect on the Treated (ATT) and the Average Treatment Effect on the Untreated (ATU) quantified CF's influence on income. Propensity Score Matching (PSM) was used as a robustness check to validate the findings. This comprehensive approach ensured a rigorous analysis of CF participation's direct effects while addressing confounding variables. Lee (1982) introduced the ESR model in 1982 as an extension of Heckman's selection correction method. The model comprises two stages. Initially, a Probit model was employed to identify the factors determining household decision to participate in CF. The selection equation was estimated as given by Equation (2).

$$Z_i^* = \alpha + \gamma Q_i + \varepsilon_i \tag{2}$$

where: Z_i^* – a binary variable (value of 1 indicating household engagement in CF, and 0 otherwise); α – the intercept; Q_{i} – the set of exogenous variables influencing participation decisions; γ – the coefficient vector; ε_i – the disturbance term, characterised by a constant variance and a mean of zero.

In the second stage of the ESR model, a Full Information Maximum Likelihood (FIML) model was employed to address potential selection bias. The binary outcomes, specifically the incomes for participants, were delineated as switching regimes, outlined by Equations (3 and 4).

$$\text{Regime 1: if } Y_{1i} = X_{1i}\beta_1 + \sigma_{1\varepsilon}\lambda_{1i} + \mu_{1i} \tag{3}$$
Ai = 1 for CF participants

$$\text{Regime 2: if } Y_{2i} = X_{2i}\beta_2 + \sigma_{2\varepsilon}\lambda_{2i} + \mu_{2i} \tag{4}$$
Ai = 0 for non CF participants

where: Y_{1i} and Y_{2i} – incomes corresponding to CF participants and non-participants, respectively; β_1 and β_2 – vectors of parameters being estimated; X_{1i} and X_{2i} – vectors of determinants incomes for the i^{th} household; μ_{1i} and μ_{2i} – error terms.

While some variables in vectors X in Equation (3 and 4) may overlap with Q in Equation (2), the methodology necessitates the presence of at least one variable in Q that does not appear in X. Parameters to estimate include β and σ, while μ_{1i} and μ_{2i} are independently and identically distributed error terms in the income estimation equation.

The Inverse Mills Ratio (IMR) computed from the participation selection Equation (2) is included in Equations (3 and 4) to rectify selection bias within the ESR two-step estimation procedure given as:

$$\lambda_{1i} = \frac{\oint(Z_i\alpha)}{\varnothing(Z_i\alpha)} \quad \text{and} \quad \lambda_{2i} = \frac{\oint(Z_i\alpha)}{1-\varnothing(Z_i\alpha)}$$

where: $\oint(\bullet)$ and $\varnothing(\bullet)$ – the standard normal probability density function and normal cumulative density function, respectively; λ_{1i} and λ_{2i} – IMR evaluated at $Z_i\alpha$ used in Equations (3 and 4) to correct for selection in the two-stage estimation.

Notably, selection bias is evident when there is a non-zero correlation between error components in the selection equation and the result equation, thus rejecting the null hypothesis of its absence. Assuming a tri-variate normal distribution, the three error terms ε, μ_{1i}, and μ_{2i} are presumed to follow such a distribution, characterised by a zero mean vector and a covariance matrix as defined by Equation (5) below.

$$\Omega = \begin{bmatrix} \sigma_1^2 & \sigma_1\sigma_2 & \rho_{1e}\sigma_1 \\ \sigma_1\sigma_2 & \sigma_2^2 & \rho_{2e}\sigma_1 \\ \rho_{1e}\sigma_1 & \rho_{2e}\sigma_2 & \sigma_e^2 \end{bmatrix} \tag{5}$$

The covariance between the error terms of the selection and outcome equations is denoted as $\operatorname{cov}(\varepsilon,\mu) = \rho$. Here, ρ_{1e} and ρ_{2e} represent correlation coefficients between μ_{1i} and ε_{1i}, and μ_{2i} and ε_{2i}, respectively. If either ρ_{1e} or ρ_{2e} significantly deviates from zero, selection bias is present. A positive correlation ($\rho > 0$) indicates that lower-income households are more likely to participate in CF, while a negative correlation ($\rho < 0$) suggests that higher-income households are less inclined to engage.

To ensure identification and meet the exclusion restriction, access to extension services from the Kenya Climate-Smart Agriculture Project (KCSAP) is used as an instrumental variable (IV). Supported by the Government of Kenya and the World Bank, KCSAP provides training, technical support, and market linkages to enhance smallholder farmers' productivity and resilience, promoting CF participation. These services, accessed voluntarily, influence CF participation without directly affecting income, making the instrument relevant.

Incorporating this instrument into the ESR model addresses biases from unobservable factors and selection biases, improving the accuracy and reliability of the analysis. The IV's validity was rigorously confirmed. The LM statistic (123.108, P-value 0.000)

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strongly supports proper identification, while the Wald F-statistic (167.781) significantly exceeds the critical value, rejecting concerns of a weak IV. Since only one IV was used, the over-identification test was not applicable. These results validate the selected IV as reasonable, robust, and effective for the study.

This paper primarily focuses on estimating the *ATT*, specifically the shift in outcomes due to engagement in CF, calculating the disparity between participating and non-participating households. The average treatment effect, denoted by Y_i, was delineated in Equations (6–9). The equations present the anticipated conditional and *ATT* for both groups. The equation characterising participation income in CF expressed as by Equation (6).

$$E\left[Y_{1i} / X, A_i = 1\right] = \alpha_1 + X_{1i}\beta_1 + \rho_{1i}\sigma_{1\varepsilon}\lambda_{1i} \quad (6)$$

The equation for CF participants income, had they decided not to get into CF is as presented by Equation (7) below.

$$E\left[Y_{2i} / X, A_i = 1\right] = \alpha_2 + X_{2i}\beta_2 + \rho_{2i}\sigma_{2\varepsilon}\lambda_{2i} \quad (7)$$

The equation for non-participants income had they decided to participate in poultry farming CF is as presented by Equation (8).

$$E\left[Y_{1i} / X, A_i = 0\right] = \alpha_1 + X_{1i}\beta_1 + \rho_{1i}\sigma_{1\varepsilon}\lambda_{1i} \quad (8)$$

The equation for non-participants income who did not participate in CF is as presented by Equation (9).

$$E\left[Y_{2i} / X, A_i = 0\right] = \alpha_2 + X_{2i}\beta_2 + \rho_{2i}\sigma_{2\varepsilon}\lambda_{2i} \quad (9)$$

Similarly, we calculated the anticipated change in non-engaged households as the Average Treatment Effect on the Untreated households (*ATU*), expressed by Equations (10 and 11).

$$ATU = E\left[Y_{1i} \ / X, A_i = 0\right] - E\left[Y_{2i} \ / X, A_i = 0\right] \quad (10)$$

$$ATU = X_{2i}(\beta_1 - \beta_2) + \lambda_{2i}(\sigma_{1\varepsilon} - \sigma_{2\varepsilon}) \quad (11)$$

Robustness tests

To validate our findings, we employed Propensity Score Matching (PSM) as a supplementary robustness check. While PSM Rosenbaum and Rubin (1985) mitigate selection bias through kernel, nearest neighbour, and radius matching algorithms, its reliance on observable factors necessitates cautious interpretation, as unobserved heterogeneity remains a limitation. Results were cross-verified with t-tests to confirm statistical significance of income differences between participants and non-participants. Since we only use PSM to measure the robustness of ESR findings, minimal space is allocated to its formal explanation. The classic discussion by Rosenbaum and Rubin (1985) serves as a foundational reference.

In addition to the statistical analysis, a poverty impact assessment was conducted using World Bank (2023) established measures (poverty severity and extreme poverty). The World Bank's definition of extreme poverty, set at living below USD 2.15 per day and USD 1.25 for poverty severity, guided the assessment. The assessment was done by calculating it from the *ATT*. The *ATT* was converted to *per capita* values per month and per day by dividing by the average household size of 5 (as described in Table 1) and the average number of days in a month (30). The potential contribution to reduction in extreme poverty and poverty severity was calculated by comparing the *ATT per capita* per day to the World Bank's poverty thresholds.

RESULTS AND DISCUSSION

The variables included in the investigation are described in Table 1. The study reveals that CF participation is prevalent among women and young farmers. Participants were found to be more educated and had more farming experience compared to non-participants. Participants also had better credit access, suggesting that access to credit resources is key in their decision to participate in CF. Additionally, the findings report that participants lived further from markets as compared to non-participants and had a lower mean price of poultry compared to non-participants, indicating that CF may have different pricing dynamics. Participants had lower access to processing facilities but larger land holdings for poultry farming compared to non-participants. They also had higher numbers of reared chickens, access to extension services, and slightly lower mean labour costs.

Effects of contract farming on household income

Table 2 presents the regressors of effects of CF participation and farmers' incomes. The models demonstrated a strong goodness-of-fit, as evidenced by the significant Wald chi-square value and a reasonable log likelihood. They reveal substantial income variability within both participants and non-participants, with significant coefficients for /*lns*1 and /*lns*2 highlighting these differences. Additionally, unobserved factors significantly impact

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Table 1. Definition of variables used in the study

Variable	Description	Participants		Non-participants		*t*-test
		mean	SD	mean	SD	
Gender	gender of the household head: 1 if male, 0 if female	0.511	0.501	0.477	0.511	0.337
Age	age of the household head (years)	40.049	11.825	46.660	16.804	0.999
Education	education level of the household head (years)	6.003	1.356	5.477	1.649	0.009
Farming experience	farmers' farming experience (years)	2.645	1.113	1.977	1.067	0.000
Market access	1 if farmers have access to poultry markets, 0 if otherwise	0.702	0.458	0.750	0.438	0.744
Market distance	distance to nearest poultry market (walking minutes)	53.497	70.945	36.591	27.487	0.059
Price of poultry	price per chicken (USD)	4.52	3.01	5.03	2.81	0.856
Access to processing facilities	1 if farmers have access to poultry processing facilities yes, 0 if otherwise	0.347	0.477	0.409	0.497	0.791
Size of land used for poultry	total land size used in poultry (ha)	1.281	1.093	0.606	0.670	0.000
No. of kept chickens	total number of chickens kept by a farmer	137.344	65.267	123.523	76.404	0.097
Access to extension service	1 if the household had access to extension services, 0 if otherwise	0.978	0.146	0.523	0.505	0.000
Monthly off-farm income	total off-farm income (USD)	48.70	4.07	60.68	9.26	0.876
On-farm income	total income from farming activities (USD)	50.74	58.79	23.25	48.84	0.003
Household size	total number of members of the household	5.156	0.101	5.386	0.307	0.459
Group membership	1 if the farmer is a member of a farmers group, 0 if otherwise	0.874	0.017	0.886	0.048	0.820
Total land size	total size of land owned by the household (ha)	2.259	0.079	1.400	0.191	0.000
Road accessibility	1 if all-weather road used during all weather; 2 if dry-weather roads used only during dry seasons	1.839	0.019	1.818182	0.059	0.728
Marital status	marital status of the household head. 0 if married, 1 if otherwise	1.951	0.011	1.909091	0.044	0.247
Credit Access	1 if a farmer has access to formal credit, 0 if otherwise	0.284	0.024	0.091	0.044	0.006

Source: Survey 2023

non-participants' income, as shown by the significance of r^2 coefficient. This shows that the models effectively captured income variation and the influence of both observed and unobserved factors in CF.

The significant negative relationship between age and CF participation indicates that older farmers are less likely to participate, attributed to increased risk aversion and reduced flexibility (Pham et al. 2021). Farming experience positively correlates with CF participation, as farmers use prior experiences to make informed decisions, establishing predetermined production and pricing terms, mitigating market price risks (Meemken and Bellemare 2020).

The study finds that limited access to poultry processing facilities hinders CF adoption, as distant facilities create logistical challenges and higher costs, discouraging farmer participation (Mugwagwa et al. 2020). Larger poultry farming households are less likely to participate in CF. A factor attributed to their greater labour flexibility, preference for traditional methods, and financial pressures, making CF less feasible (Meemken and Bellemare 2020). We found a positive correlation between location variable 'county' and CF participation, indicating that, farmers in Baringo, Nakuru, and Elgeiyo Marakwet counties are more likely to engage in contract farming

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due to targeted support programs, high market demand, and improved infrastructure.

Extension services significantly and positively influence CF participation. This is possible through providing knowledge, skills, and strengthening connections with market opportunities, aligning production with market demands (Mugwagwa et al. 2020).

Table 2 reveals that off-farm income and marital status positively impact household income for both groups, highlighting the role of income diversification and social settings in enhancing financial stability (Khan et al. 2019). However, market distance negatively affects CF participants' incomes due to higher transaction costs and logistical challenges. For CF par-

Table 2. Determinants of CF participation and impact on household income results

Variables	CF Participation		Income			
			participants		non-participants	
	coefficient	SE	coefficient	SE	coefficient	SE
Constant	–1.753	1.562	–7.551	5.565	0.943	7.923
Age	–0.018*	0.011	0.101	0.064	–0.026	0.024
Education	–0.127	0.132	0.782*	0.466	–1.089**	0.506
Income from crop farming	0.076	0.138	–0.269	0.299	–1.082	0.722
Off–farm income	–0.045	0.050	4.949***	0.870	4.184***	0.193
Credit access	1.169	0.852	–3.884**	1.648	–3.580	2.649
Road access	–0.108	0.305	–3.550	2.200	–0.049	0.947
Market distance	0.005	0.006	–0.009**	0.004	0.052	0.032
Access poultry processing facilities	–0.759**	0.252	–0.778	1.042	1.219	0.775
Farming experience	0.362**	0.129	0.275	0.368	0.332	0.346
Group membership	–0.159	0.324	1.099	0.880	–1.342*	0.803
County	0.603*	0.330	0.652	0.927	–1.503	1.295
Motorcycle ownership	–0.004	0.026	0.073	0.084	–0.035	0.192
Poultry farming land size	0.287	0.206	–0.381	1.031	1.491***	0.489
Household size	–0.509**	0.250	0.463	1.074	0.216	0.921
Marital status	0.304	0.456	2.715*	1.633	2.492**	1.247
Risk attitude	–0.088	0.249	0.906	1.338	1.064*	0.610
Total land size	0.078	0.145	1.200*	0.703	–0.350	0.464
Extension service	3.665***	0.846	–	–	–	–
/lns1	2.300***	0.014	–	–	–	–
/lns2	0.716***	0.088	–	–	–	–
/r1	–0.080*	0.048	–	–	–	–
/r2	–0.459	0.385	–	–	–	–
σ1	9.973	0.143	–	–	–	–
σ2	2.046	0.180	–	–	–	–
ρ1	–0.080	0.048	–	–	–	–
ρ2	–0.429	0.314	–	–	–	–
Log likelihood	–1 516.647	–	–	–	–	–
Number of obs.	410					
Wald $chi^2(13)$	80.21					
Prob > chi^2	0.000					

***,**, and *significance at 1%, 5% and 10%, respectively; CF – contract farming

Source: Author's compilation

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ticipants, education (secondary education or higher) and land sizes (above the mean of 2.166 ha) positively influence CF participants, potentially enhancing understand and benefit from CF opportunities, as larger landholdings may facilitate more efficient resource use and higher economic returns (Meemken and Bellemare 2020). Conversely, for non-participants, education above secondary education and group membership show a negative relationship with household income, possibly due to a mismatch between skills and local needs. Nonetheless, off-farm income, land size, and risk attitude positively influence non-participants' incomes, suggesting that financial stability, resource availability, and risk-taking foster greater participation in non-contract farming.

Treatment effects of CF participation on household income and poverty alleviation

The main estimates from the ESR as presented in Table 3 suggest a noticeable impact of CF participation on income.

Participants in CF exhibited a higher mean income compared to non-participants. The analysis showed a 74% increase in the income of CF participant farmers as compared to non-participants. Additionally, the *ATU* showed a 45.59% increase in income for non-participants if they were to engage in CF suggesting that non-participants could also benefit from CF. However, these estimates are hypothetical and based on the assumption that non-participants would achieve similar outcomes if they were to participate.

Robustness test

Using PSM (Table 4), various matching techniques – nearest neighbour, kernel, and radius – consistently showed higher incomes for participants. Nearest neighbour matching had the highest *ATT*, indicating an 82.73% income increase for farmers in CF.

Beyond the main estimates the study demonstrates the impact of CF participation on household income through the visualisation of propensity score distributions for both treated and untreated groups. The successful alignment of these distributions is shown in Figure 2, showcasing enhanced comparability between the two groups after reducing biases, highlighting the importance of CF participation in household income.

Effect of contract farming arrangements on household incomes

The study reveals that CF arrangements effectively boost household income in ASAL areas as presented by Table 5. Spot transactions significantly increase income by 69.69%, crucial for in arid regions where immediate cash is vital for managing farming risks owing to unpredictable climatic conditions (Prasad et al. 2023).

Non-participating farmers could see a 51.04% income increase if they adopted spot transactions. Written contracts provide the highest income increase at 95.71%, but their ATU was not statistically significant, suggesting enforcement challenges (Mugwagwa et al. 2020). Unwritten contracts boost income by 65.50%, highlighting the importance of trust-based relationships in regions with less effective formal legal mechanisms (Khan et al. 2019). However, the ATU for unwritten contracts was not statistically significant, indicating they work best within established community networks.

Table 3. Main estimates of treatment effects of CF participation on household income

Estimation outcome	Income		*ATT*		% *ATT*/ *ATU*
	CF participants	CF non–participants			
	Mean	Mean	Coefficient	SE	
ATT	9.835	5.653	4.183***	0.2040	74.00
ATU	11.206	7.697	3.509***	0.0611	45.59

***, **, *significance at 1%, 5% and 10%, respectively; CF – contract farming; ATU – average treatment effect on the untreated; *ATT* – average treatment effect on the treated

Source: Author's compilation

Table 4. Estimates of treatment effects of contract farming participation on household income

Estimation technique	Incomes		*ATT*		% *ATT*
	participants	non–participants			
	mean	mean	coefficient	SE	
Nearest neighbor	12.546	6.866	5.680**	3.329	82.73
Kernel–matching	12.352	7.371	4.980	3.368	67.56
Radius matching	12.546	7.683	4.863**	2.245	63.23

**significance at 5%, respectively; *ATT* – average treatment effect on the treated

Source: Author's compilation

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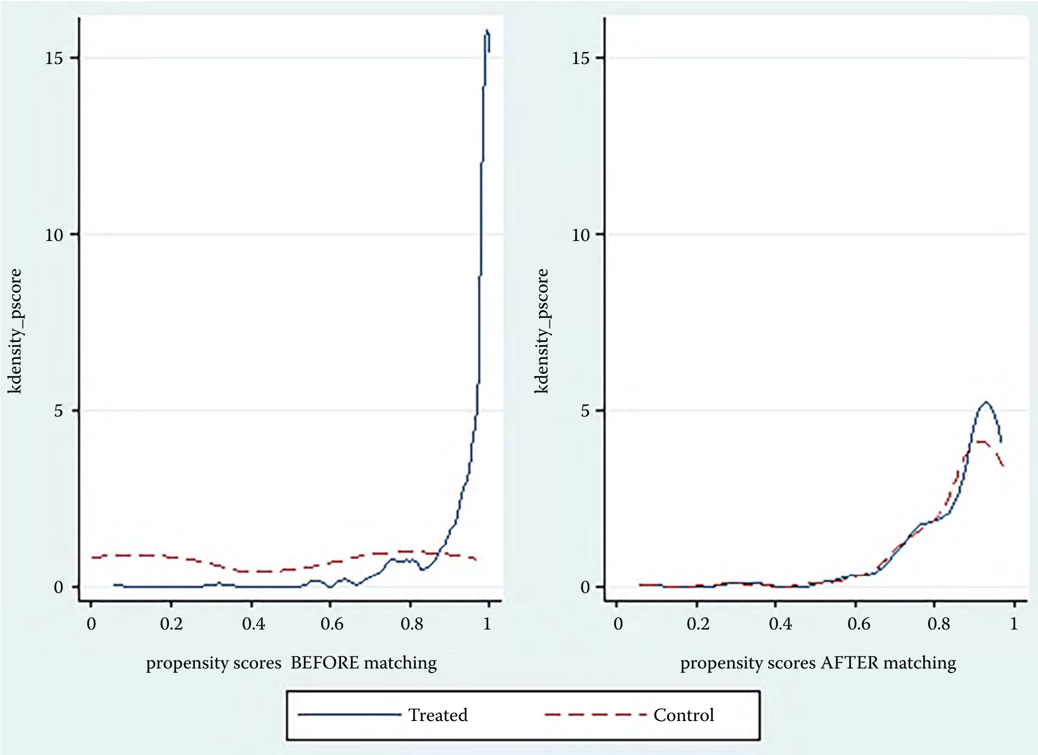

Figure 2. Kdensity_pscore plots for treated and untreated groups

Source: Author's compilation

Implication on poverty alleviation

Table 6 shows that CF participation reduces extreme poverty by 9.83% and poverty severity by 16.90%, demonstrating its role in alleviating poverty in climate constrained regions. Effectiveness varies by contract type – written contracts offer greater impact, lowering extreme poverty by 12.17% and severity by 20.93% by providing farmers security, predictability, quality inputs, technical assistance, and market access.

Spot transactions show a 10.35% reduction in extreme poverty and a 17.80% reduction in poverty severity, but are less effective compared to written contracts due to their informality and dependence on immediate market conditions. Similarly, unwritten contracts contribute the least to poverty alleviation, reducing extreme poverty by 7.92% and severity by 13.62%.

Discussion

The findings are firmly rooted in utility maximisation theory, demonstrating the rational decision-making of smallholders in ASALs who face severe constraints such as limited credit, climatic volatility, and infrastruc-

Table 5. Effect of contract farming arrangements on household incomes

Estimation outcome		Income		*ATT*		% *ATT*/*ATU*
		participants	non–participants			
		mean	mean	coefficient	SE	
Spot transactions	*ATT*	10.728	6.322	4.406***	0.993	69.69%
	ATU	8.672	5.741	2.930**	1.378	51.04%
Written contracts	*ATT*	10.593	5.413	5.181***	1.148	95.71%
	ATU	10.1495	6.776	3.373	3.495	49.78%
Unwritten contracts	*ATT*	8.438	5.068	3.370***	0.964	66.50%
	ATU	15.582	11.148	4.433	7.024	39.76%

*** and **significance at 1% and 5%, respectively; *ATU* – average treatment effect on the untreated; *ATT* – average treatment effect on the treated

Source: Author's compilation

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Table 6. Implications of contract farming participation on poverty alleviation

Aspect	Pooled	Contract farming arrangements			Comment
		spot	written	unwritten	
ATT (USD)	31.69	33.38	39.25	25.53	–
ATT per capita per month	6.34	6.68	7.85	5.11	*ATT* in USD/average household size (5) (Table 2)
ATT per capita per day	0.21	0.222525	0.26	0.17	*ATT per capita*/average days in a month (30)
Potential contribution to extreme poverty reduction	9.83%	10.35%	12.17%	7.92%	*ATT per capita* per day/extreme poverty per day (USD 2.15)
Potential contribution to poverty severity reduction	16.90%	17.80%	20.93%	13.62%	*ATT per capita* per day/poverty severity per day (USD 1.25)

The yields shown are predictions based on the coefficients estimated with the ESR model. As the dependent variables in the model are the shilling/1000 per month, the predictions are also given in this form; *ATT* – average treatment effect on the treated
Source: Author's compilation

tural deficiencies. The findings indicates a substantial 74% increase in incomes among CF participants, validating H_1: CF participants earn higher incomes than non-participants.

Contract farming mitigates price fluctuations, providing participants with greater stability in poultry pricing – an essential factor for risk-averse smallholders (Mulatu et al. 2017). These results align with similar findings in Vietnam, where fixed-price CF arrangements significantly boosted rice farmers' incomes (Pham et al. 2021). Additionally, despite longer distances to markets, CF participants benefit from contractors' collection services, which reduces transaction costs, a crucial advantage in regions with poor road infrastructure (Mugwagwa et al. 2020).

Different contract types reflect various approaches to utility maximisation. Spot markets, chosen by 41.2% of farmers, cater to those prioritising immediate liquidity to address urgent cash needs, particularly during droughts. This trend aligns with Fink et al. (2020), who examined seasonal liquidity among Zambian farmers.

Written contracts, adopted by 21.7% of farmers, appeal to risk tolerant farmers who prioritise predictable returns over short-term flexibility (Bellemare et al. 2021). Unwritten contracts, comprising 37.1% of agreements, offer a middle-ground solution, utilising social capital to minimise enforcement costs while preserving adaptability.

CF participation significantly reduces extreme poverty, with a reduction of 9.8%, and alleviates poverty severity by 16.9%, supporting the second hypothesis. The impacts vary depending on the formality of contracts. Written contracts yield the strongest effect, reducing extreme poverty by 12.2% through mechanisms such as fixed pricing that mitigate market shocks and the provision of subsidised inputs, including feed and vaccines, which enhance production stability. Participants under written contracts also demonstrated greater resilience, reflected in their larger average chicken stocks (137 birds compared to 124 among non-participants). These findings underscore the role of CF as a risk-sharing institution (Bellemare et al. 2021).

Unwritten contracts, by contrast, contributed the least to poverty alleviation, reducing extreme poverty by 7.92% and poverty severity by 13.62%. Their limited impact is attributed to a lack of legal binding and guarantees, which often result in inconsistent support and unreliable income streams. Moreover, unwritten contracts frequently fail to include provisions for essential resources, such as subsidised inputs and market access, further curtailing their benefits.

Spot markets achieved a modest poverty reduction impact, lowering extreme poverty by 10.35%. While spot markets maximise liquidity to meet immediate utility needs, they also expose farmers to price volatility, perpetuating long-term financial precarity. Non-participants faced the lowest incomes and structural barriers, such as restricted access to credit, which kept them trapped in low-utility equilibria.

The study refines classical microeconomic assumptions, highlighting distinctions in utility maximisation. Despite written contracts offering higher returns, their

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low adoption rate reflects challenges posed by weak formal systems in Kenya's ASALs, such as limited contract enforcement mechanisms. Social utility also plays a role, with unwritten contracts leveraging relational trust as an alternative to formal legal safeguards (Mugwagwa et al. 2020).

CONCLUSION

Policy recommendations

This study investigated the impact of CF on household income among smallholder poultry farmers in Kenya's arid and semi-arid regions. Utilising endogenous switching regression and propensity score matching for robustness tests to analyse the dynamics of CF in these climate constrained environments. The results show positive correlations between CF engagement and factors such as farming experience, county and extension services, while age, access to poultry processing facilities, and household size had negative relations. For participant farmers, education, off-farm income, marital status, and total land size had significant positive relationships, while credit access and market distance showed negative relations.

Beyond its significant positive effects on income, CF proves to be an important factor in poverty alleviation. Different CF arrangements influence farmers' economic outcomes, with written agreements providing the most stability and financial advantages. While spot transactions offer benefits, their dependence on fluctuating market conditions makes them less reliable. Similarly, unwritten agreements contribute to household income but lack the security and predictability of more formalised arrangements.

In light of these findings, several policy recommendations emerge to support smallholder farmers in arid and semi-arid regions. For farm managers, embedding price stability and market access guarantees into CF arrangements can enhance income stability and attract broader participation. Addressing barriers like poor infrastructure and limited credit access is crucial for expanding CF benefits. Additionally, leveraging risk-sharing mechanisms and community trust fosters resilience and inclusivity in smallholder farming systems. Tailored education and training equip poultry farmers to manage contracts effectively and boost their earnings, while improved access to credit enables investments in infrastructure and technology to enhance productivity despite limited resources.

For policy makers, strengthening extension services specifically designed for poultry farming in these regions can lead to better outcomes, as knowledgeable advisory services ensure that farmers adhere to best practices and contractual obligations. Additionally, developing policy frameworks that safeguard the rights of smallholder poultry farmers fosters inclusive economic growth and resilience in these challenging environments. Investments in infrastructure, including transportation networks and storage facilities, can alleviate logistical barriers that limit market access, thereby expanding opportunities for poultry farmers. The study highlights the need for a balanced approach to CF policies, where formalisation efforts align with the realities of smallholder farmers while optimising both legal protections and income generation. By addressing these crucial areas, policymakers can support sustainable development and contribute to poverty reduction in climate constrained regions.

Limitations

While this study provides important insights into the relationship between contract farming and household income, several aspects merit further consideration. These include aspects such as using cross-sectional data, addressing selection bias through ESR and PSM, and not fully representing all smallholder poultry farmers. The study also suggests that focusing on farmers' perspectives without considering companies' views may limit policy recommendations. Additionally, self-reported data might introduce response bias. Despite these limitations, the study provides valuable insights into contract farming's role in enhancing household income in Kenya's arid and semi-arid regions. Future research should use longitudinal data and diverse methodologies for more robust findings.

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