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Research Article

Impact of Contract Farming Scheme on Smallholder Farmers' Income: The Case of Coffee Farming System of Shebe Sombo, South West Ethiopia

Meditu Debela Hordofa[1,*], Jema Haji Mohammed[2], Ermias Melaku Addis[3], Yonas Muleta Gejea[4]

[1]Agri and Cooperative Business Development, Cooperative Bank of Oromia, Addis Ababa, Ethiopia
[2]School of Agricultural Economics and Agribusiness, Haramaya University, Dire Dawa, Ethiopia
[3]Agricultural Economics and Agribusiness Management, Jimma University, Jimma, Ethiopia
[4]Agri and Cooperative Business Development, Cooperative Bank of Oromia, Addis Ababa, Ethiopia

Abstract

This research investigated the impact of contract farming on the livelihoods of smallholder coffee producers in the Shebe Sombo district of Ethiopia. Specifically, the study aimed to understand factors influencing farmer participation in contract coffee production, evaluate the impact of contract farming on household income, and analyze the structure of existing contract farming arrangements. Employing a two-stage sampling method, the study collected data from 71 contract farming participants and 63 non-participant households through structured interviews. Data analysis involved descriptive statistics, inferential statistics, and an econometric model utilizing propensity score matching to estimate the causal impact of contract farming on household income. The findings revealed a significant positive impact of contract farming on the annual income of participating households. Notably, frequent interaction with agricultural extension services and livestock ownership emerged as key factors positively influencing both farmer participation in contract farming and subsequent income from coffee production. Conversely, larger household sizes and reliance on credit were found to negatively influence both participation in contract farming and overall household income. The study's analysis, utilizing propensity score matching, demonstrated that, on average, involvement in contract farming led to an increase of 8252.21 Ethiopian Birr in household income. These findings strongly suggest that, compared to traditional marketing channels, contract farming offers a more profitable avenue for smallholder coffee farmers to enhance their livelihoods.

Keywords

Coffee, Contract Farming, Impact, Propensity Score Matching, ATT

[*]Corresponding author: meditu5454@gmail.com (Meditu Debela Hordofa)

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1. Introduction

Ethiopia, renowned as the birthplace of Arabica coffee plays a significant role in the global coffee market [1]. A substantial portion of Ethiopian coffee production, estimated at 95%, is organic, highlighting the country's commitment to sustainable farming practices [2].

Despite its prominent position, the Ethiopian coffee sector is facing numerous challenges. The majority of coffee farmers are smallholders who cultivate small plots of land, often less than two hectares [3]. These farmers frequently encounter obstacles, such as limited access to information, market constraints, and financial limitations due to factors such as insufficient collateral. These challenges hinder their ability to invest in improved farming techniques and consequently increase their income [4, 14, 15].

Contract farming presents a potential pathway for overcoming these challenges. This agricultural production model, characterized by agreements between farmers and buyers regarding crop production under specific conditions, has demonstrated success in enhancing farmer income in various regions. By providing access to markets, essential resources, and expert knowledge, contract farming can facilitate the integration of smallholder farmers into commercial agricultural value chains, leading to improved income and poverty reduction [5, 8, 16].

However, the success of contract farming is contingent on several critical factors, including the establishment of fair contractual agreements and the provision of adequate support from contracting firms. In some instances, as observed in Ghana, the failure of contracting firms to fulfill their commitments, such as providing necessary training and support, can have detrimental consequences for farmers [8].

This study aims to address the existing gap in research by examining the impact of contract farming on the household income of coffee farmers in the Shebe Sombo district of the Jimma Zone, Ethiopia. Through an analysis of the factors influencing farmers' participation in contract farming, this research aims to provide valuable insights that can inform the development of effective policies and strategies aimed at improving the livelihoods of Ethiopian coffee farmers.

2. Methodology

2.1. Description of the Study Area

The study took place in Shebe Sombo district, Jimma zone, and located 395 km southwest of Addis Ababa. The district has a population of 141,037 and an area of 1,191 km², comprising of 20 rural and two urban kebeles. Shebe Sombo features 29,668 ha of cultivable land, including 17,346 ha for coffee, alongside forests and grasslands. The altitude ranges from 1,000 m to 2,240 m, with annual temperatures between 16℃ and 30℃, and rainfall of 1,420 mm to 2,200 mm, primarily during the rainy season from February to August [9]. The local economy is based on subsistence mixed farming with key crops, such as coffee, maize, teff, and sorghum. Livestock, including cattle and poultry, play a vital role. The average crop yields were as follows: rice 45 Q/ha, teff 8 Q/ha, wheat 26 Q/ha, maize 28 Q/ha, barley 23 Q/ha and sorghum 22 Q/ha. While traditional farming methods dominate, there is a trend toward modernization with improved varieties and fertilizers. The economy is primarily agricultural and is supported by small-scale trade and off-farm activities.

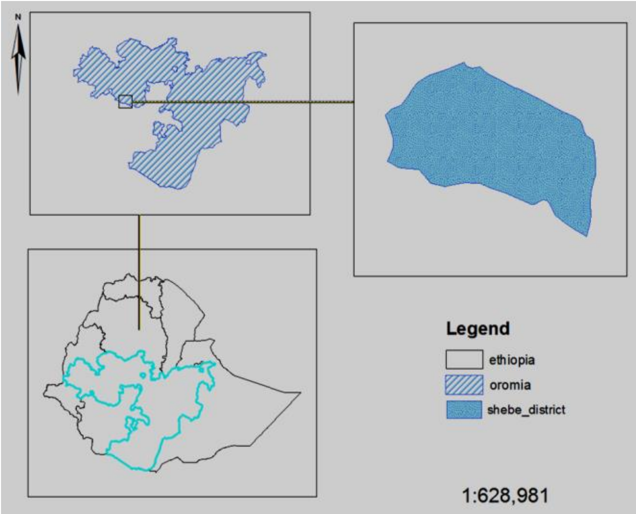

Figure 1. *Map of the study area Source: own computation.*

2.2. Types and Sources of Data

This study used both primary and secondary data sources. Primary data were gathered from randomly selected contract and non-contract coffee farmers using a pre-tested structured questionnaire, focusing on the characteristics of contractual coffee production, its impact on household income, and the factors influencing smallholder farmers' benefits from contract farming. Secondary data included published and unpublished documents from the district agricultural office as well as information obtained through rapid market appraisals, observations, and group discussions.

2.3. Sampling and Data Collection Methods

Primary survey data for the coffee production year 2017/18 were collected using a structured questionnaire that included both closed- and open-ended questions with secondary data from the Ethiopian Statistical Office. A two-stage random sampling method was applied, selecting three kebeles—Sebaka Dabiye, Shabe Daso, and Yanga Dogma—based on their coffee production potential and accessibility.

To ensure homogeneity, households were stratified into contracted and non-contracted coffee producers. There were 210 households in Sebaka Dabiye, with 21% participating in contract farming and 7% not participating, resulting in 28 participants and 10 non-participants. Shabe Daso had 101 households, with 10% participating and 20% non-participating, leading to 14 participants and 27 non-participants. Yanga Dogma included 217 households, with 22% participating and 19% non-participating, yielding 29 participants and 26 non-participants. Overall, the three kebeles had 528 households, with 71 participants and 63 nonparticipants. The sample size for coffee contract participants and non-participants was determined using Yemane's formula (1967), with a 92% confidence interval and an 8% error margin [6]. The total number of coffee producers in the selected kebeles was 989, resulting in a final sample size of 134 respondents.

$$n = \frac{N}{1+N(e^2)} = \frac{989}{1+989(0.08^2)} = 134$$

Where
n = sample size
N = total population of selected kebeles
e = error term which is 8%

2.4. Methods of Data Analysis

The data were analyzed using descriptive statistics and econometric models, as detailed in the following subsections.

2.5. Descriptive and Inferential Analysis

Descriptive statistics, including mean, standard deviation, maximum, minimum, and percentage, were used to summarize the data. Chi-square tests and t-tests served as inferential statistical tools to compare the treatment and control groups across various explanatory variables.

2.6. Propensity Score Matching (PSM) Method

This study used propensity score matching to evaluate the impact of contract farming on household income from coffee production. Given that households cannot be observed in either participant or non-participant states, this method addresses the problem of missing data inherent in such evaluations. PSM allows the matching of non-participating households to those involved in contract farming based on similar characteristics, minimizing selection bias.

The analysis aims to estimate the impact of contract participation on household income, where "treatment" refers to involvement in coffee contracts and "impact" denotes the resulting income changes. "Control" refers to households not involved in coffee contracts.

2.7. Variables Definition and Hypothesis

Dependent Variable:

Coffee Product Contract Participation Decision: A dummy variable indicating the probability of a household participating in contract coffee production, where 1 represents participation and 0 represents nonparticipation.

Outcome Variable:

Income from Coffee: Measured in Ethiopian Birr.

Independent Variables:

Various factors are expected to influence the contract involvement and income.

Age of Household Head (agehh): A continuous variable measured in years. It is hypothesized that younger household heads are more likely to participate in contracts, whereas older heads may resist change.

Gender of Household Head (sex): A dummy variable with 1 for male heads and 0 for females. Male-led households are expected to be more likely to participate, as women’s incomes can have significant developmental impacts.

Family Size (Famsize): A continuous variable representing the number of household members. Larger families may reduce marketing risks, leading to increased contract participation, but they are hypothesized to negatively affect income.

Education Level of Household Head (edustat): continuous variable indicating years of formal schooling. Higher education is expected to positively influence contract participation and income because of better adoption of innovations.

Frequency of extension agents (nofextnsn): A continuous variable indicating how often farmers are visited by extension agents. Increased contact is hypothesized to improve participation in contracts and enhance income.

Credit Use (Crdtus): A dummy variable where 1 indicates credit usage. Access to credit is expected to alleviate liquidity issues, thereby increasing participation in contracts.

Membership in Cooperatives (coopmembr): A dummy variable indicating cooperative membership. Membership is expected to influence contract participation positively by providing access to essential services and markets.

Distance to Cooperative (Distocoop): A continuous variable measured in minutes to reach the cooperative. Closer proximity is expected to reduce transportation costs and improve market access, thus negatively affecting participation.

Livestock holding (totlivestc): A continuous variable representing the number of livestock owned. Households with livestock are hypothesized to have better financial stability and to positively influence contract participation.

Experience in Coffee Production (experience): A continuous variable representing years of coffee farming experience. Greater experience is expected to positively impact contract participation due to enhanced skills and knowledge.

3. Results and Discussion

This chapter presents the study's results and discussions, organized into three main sections: the demographic and socioeconomic characteristics of sampled households, the econometric analysis of factors affecting participation in contract farming, and the impact of contractual coffee production on household income.

3.1. Descriptive Analysis of Sampled Households' Characteristics

Descriptive statistics in this study utilized the mean, percentage, standard deviation, and frequency distribution to analyze the data. Additionally, t-tests and chi-square tests were used to compare contract participants and non-participants in terms of various explanatory variables. The analysis incorporates both continuous and discrete variables to describe a sample of 134 households.

3.2. Demographic, Socioeconomic and Institutional Characteristics of Households

The total mean age of the sampled household heads was 35.95 years, with minimum and maximum ages of 26 and 60 years, respectively. The mean ages for contract farming participants and non-participants were 37.21 and 34.54 years, respectively, with a significant difference at the 1% level, indicating that participants are generally older. The average family sizes was 5.81 for participants and 6.41 for non-participants, showing no significant difference between the two groups.

The average years of education for participants and non-participants were 3.48 and 2.89, respectively, with no significant difference in education levels. Participants owned more livestock, averaging 11.63 tropical livestock units (TLU) compared to 8.08 TLU for non-participants, with this difference significant at the 1% level, suggesting better financial capital for participants. Additionally, participants had an average experience of 12.54 years, whereas non-participants had 10.21 years, with a significant difference at the 5% level. Extension contacts averaged 2.85 for participants and 1.52 for non-participants, with this difference significant at the 1% level. Lastly, participants traveled an average of 131.54 minutes to reach the cooperative, while non-participants traveled approximately 136.98 minutes, a difference that was not statistically significant (Table 1).

Table 1. Description of outcome, treatment and household characteristics (for continuous variables).

Variables	Total N=134		Participants N=73		Non-participants N=61		t-test
	Mean	Std.dev.	Mean	Std.dev.	Mean	Std.dev	
Average income	19585.37	6952.65	23375.55	6798.33	15313.91	4065.01	8.29***
Age	35.96	7.71	37.21	8.20	34.54	6.92	2.02***
Education	3.20	2.92	3.48	3.00	2.89	2.81	1.17
Family size	6.10	2.47	5.81	2.18	6.41	2.74	1.43
Total livestock	9.96	5.01	11.63	5.08	8.08	4.23	4.37***
Experience	11.44	7.39	12.54	8.19	10.21	6.21	1.84**
Distance to cooperative	134.10	42.62	131.54	41.46	136.98	44.05	0.74
Extension contact	2.22	1.76	2.85	1.90	1.52	1.27	4.67***

Source: Own field survey data, 2018
Note: *** and ** means significant at 1% and 5% probability level respectively.

The gender of the respondent farmers was analyzed as a discrete variable hypothesized to influence participation in contract farming. The results showed that 4.8% of both contract participants and non-participants were female-headed households, with no significant differences between the groups. Among the contract participants, 43% were cooperative members, compared to 28% who were not; for non-participants, 31% were cooperative members and 32% were not. The chi-square test indicated no significant differences between the groups. Regarding access to credit, 27% of contract participants had access, 44% did not, 31% had access, and 32% did not, again showing no statistically significant differences between the two groups (Table 2).

Table 2. Descriptive and inferential statistics of sampled HHs (for dummy variables).

Variables		Total N=134		Participants N=71		Non-participants N=63		χ^2-Value
		N	%	N	%	N	%	
Gender	Male	122	91.04	65	48.51	57	42.54	0.05
	Female	12	8.96	6	4.48	6	4.48	
Credit use	Yes	58	43.28	27	20.15	31	23.13	1.79
	No	76	56.72	44	32.84	32	23.88	
Cooperative membership	Member	74	55.22	43	32.09	31	23.13	1.74
	Non-member	60	44.78	28	20.90	32	23.88	

3.3. Results of Econometric Estimation

3.3.1. Factors Affecting Participation in Contract Farming

If all farmers are eligible to participate in contract farming, why does one participate? This study employed a probit model to analyze the socioeconomic characteristics influencing contract farming participation among sampled households. The model demonstrated statistical significance at the 1% level, indicating good fit for the hypothesized relationships. The coefficient of multiple determinations (R^2) revealed that 29% of the variation in coffee contract participation can be explained by the included explanatory variables.

Table 3. Determinants of coffee contract participation.

Variables	Coefficients	Std. Err.	P>Z	Marginal effects
Gender	-0.246	0.471	0.602	-0.095
Age	0.081	0.051	0.116	0.032
Education	0.042	0.047	0.374	0.017
Family size	-0.161***	0.055	0.004	-0.064
Livestock	0.136***	0.034	0.000	0.054
Experience	-0.060	0.055	0.273	-0.024
Distance to cooperative	0.001	0.004	0.752	0.0005
Extension contact	0.330***	0.082	0.000	0.131
Credit use	-0.575***	0.271	0.034	-0.225
Cooperative membership	-0.013	0.285	0.963	-0.005

Source: Survey result, 2018
Number of observation = 134, Pseudo-R^2 = 0.29, Prob> chi2 = 0.0000***
Note: Dependent variable is coffee contract participation
***, ** and * significant at 1, 5, and 10 probability levels respectively.

The probit model estimation yielded a Pseudo-R^2 of approximately 0.29, indicating that the included variables explained approximately 29% of the probability of farm households participating in coffee contracts. Chi-square tests confirmed that the overall goodness of fit for the model was statistically significant at less than 1%, demonstrating that the independent variables collectively influenced coffee producer participation.

Among the ten hypothesized explanatory variables, four were found to be statistically significant. Family size (famsize) and credit use (crdtus) were positively associated with participation, while livestock ownership (totlivestc) and frequency of extension contact (nofextnsn) had negative impacts on participation. The findings, detailed in Table 3, support the reliability and appropriateness of the probit model used in this study. The effects of the model estimates were interpreted in relation to the significant explanatory variables in the model, as follows:

Family size: Family size negatively and significantly affects the likelihood of participation in coffee contracts. Specifically, a one-unit increase in family size led to a 6.37% decrease in participation. This finding suggests that larger families do not necessarily yield higher incomes in coffee contracts.

Livestock ownership: Livestock ownership significantly and positively influences coffee contract participation, with an increase in livestock correlating to a 5.399% increase in household income. This effect is likely due to livestock providing additional income, thereby enhancing the financial stability of farmers.

Frequency of extension contact in a year: The frequency of contact with extension agents positively and significantly affects coffee contract participation, with each additional contact increasing participation by 13.054%. Regular interactions with extension agents enhance farmers' awareness and likelihood of increasing income through contracts.

Credit use: Unexpectedly, credit use negatively and significantly affects coffee contract participation, with non-user farmers being 22.534% more likely to participate than those who use credit, at a 1% significance level. This suggests that if non-user farmers have equal access to contracts, resources, and information, they could achieve higher participation rates. This finding is in line with who reported credit access for coffee productions significantly influence household participation in contract farming [13, 14].

3.3.2. Econometric Analysis of the Impact of Coffee Contract Participation

(i). Choice of Matching Algorithm

Various commonly used matching estimators, such as Nearest Neighbor (NN), Kernel Matching (KM), Caliper Matching (CM), and Radius Matching, were applied to match treatment and control households within the common support region (Table 4). However, the selection of an appropriate method remains challenging.

There is no one-size-fits-all answer; the choice of the matching estimator depends on a specific dataset [10]. The effectiveness of each method varied based on the overlap between the treatment and comparison groups in their propensity scores. When there is a significant overlap, most matching algorithms tend to produce similar results (Visconti and Zubizarreta 2018). Thus, specific context and data characteristics are crucial for determining the best matching estimator.

Table 4. *Performance of matching estimators.*

Matching estimators	**Balancing test***	**Pseudo-R^2 after matching**	**Matched sample size**
Nearest Neighbor (NN)			
NN (1)	10	0.054	116
NN (2)	9	0.059	116
NN (3)	10	0.037	116
NN (4)	10	0.043	116
NN (5)	10	0.041	116
Caliper Matching (CM)			
0.01	10	0.040	92
0.1	10	0.054	116
0.25	10	0.054	116
0.5	10	0.054	116
Kernel Matching (KM)			
With band width of (0.01)	10	0.046	92
With band width of (0.1)	10	0.027	116

Matching estimators	Balancing test*	Pseudo-R^2 after matching	Matched sample size
With band width of (0.25)	10	0.028	116
With band width of (0.5)	10	0.089	116
Radius Matching			
With band width of (0.01)	10	0.209	116
With band width of (0.1)	10	0.209	116
With band width of (0.25)	10	0.209	116
With band width of (0.5)	10	0.209	116

Source: Authors compilation, 2018

* Number of explanatory variables with no statistically significant mean differences between the matched groups of participant and non-participant households after matching

As shown in Table 4, after evaluating the results and considering relevant indicators, kernel matching with a bandwidth of 0.1 was identified as the best estimator for the dataset. Consequently, the following estimation results and discussions directly reflect the outcomes derived from this kernel-matching algorithm:

(ii). Verifying the Common Support Condition

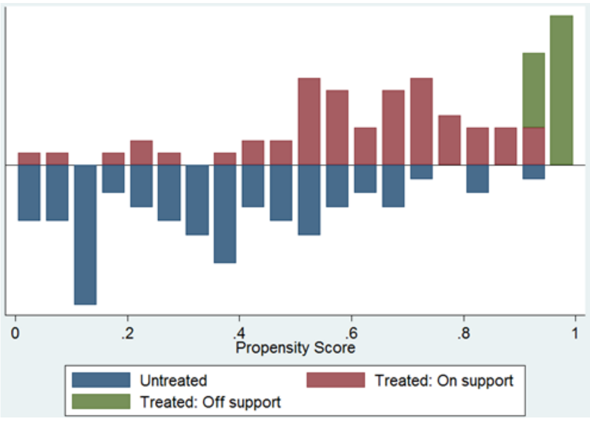

Figure 2. Distribution of propensity scores of contract participant and non-participant before common support.

Figure 2 presents a histogram of the estimated propensity scores for participants and non-participants in coffee contracts. A visual inspection of the density distributions revealed that the common support condition was satisfied, indicating a substantial overlap between the two groups' propensity score distributions. The lower half of the graph displays the propensity score distribution for non-participants, whereas the upper half represents the participants. The y-axis indicates the density of the scores.

The label "Treated/Untreated: On Support" indicates observations in the participation group that have suitable comparisons, while "Off Support" refers to those with no suitable comparisons.

In the figure, red represents the distribution of propensity scores for treated households, while green represents the distribution for control households. Most treated households have propensity scores of approximately 0.9, whereas a significant majority of the control households display scores of approximately 0.1.

(iii). Matching Involved and Non-involved Households

To match participants and nonparticipants based on observed covariates, three crucial tasks must be completed: first, estimate the predicted likelihood of participation for all households; second, impose a common support condition on the propensity score distributions for households with and without the program; and third, discard any observations with predicted propensity scores that fall outside the common support range. The common support criterion involves removing observations with scores lower than the minimum for the program group or higher than the maximum for the control group [11].

Table 5. Distribution of estimated propensity scores.

Group	Obs	Mean	Std.Dev	Minimum	Maximum
Total household	134	0.534	0.289	0.005	0.997
Treatment household	71	0.697	0.237	0.028	0.997

Group	Obs	Mean	Std.Dev	Minimum	Maximum
Control household	63	0.351	0.226	0.005	0.921

Source: Authors compilation, 2018

As shown in Table 5, the estimated propensity scores for treatment households ranged from 0.028 to 0.997, with a mean of 0.697, whereas control households had scores between 0.005 and 0.921, with a mean of 0.351. The common support region, therefore, lies between 0.028 and 0.921, marking the minimum and maximum values for the treated and control households, respectively, which are considered for matching. This overlap ensured that all characteristics observed in the treatment group could also be found in the control group. Without this overlap, estimating the average treatment effects on the ATT parameter would not be possible [14, 15]. Consequently, 18 participants (treated) were excluded. Fortunately, all non-participant households fell within the common support region, meaning that none needed to be excluded from the sample to compute the impact estimator.

(iv). Testing the Balance of Propensity Score and Covariates

After selecting the best-performing matching algorithm and establishing the common support condition, the next step involved checking the balance of propensity scores and covariates using various procedures. The primary goal of estimating propensity scores is to balance the distributions of relevant variables in both the treatment and control groups rather than to achieve precise predictions of treatment selection. Balancing effectiveness was assessed through different tests, including the reduction in mean standardized bias between matched and unmatched households, equality of means via t-tests, and chi-square tests for the joint significance of the variables.

Table 6. Propensity score and covariate balance.

Variables	Sample	Mean			% reduct	t-test	
		Treated	Control	%bias	Bias	t	p>t
Age	U	37.21	34.54	35.2		2.02	0.045
	M	37.377	35.963	18.6	47.1	0.89	0.378
Education	U	3.4789	2.8889	20.3		1.17	0.244
	M	3.283	2.9918	10.0	50.6	0.49	0.624
Family size	U	5.8028	6.4127	-24.6		-1.43	0.154
	M	5.792	6.2736	-19.4	21.1	-0.95	0.344
Livestock	U	11.634	8.0794	76.0		4.37	0.000
	M	10.208	9.3218	18.9	75.1	1.08	0.284
Experience	U	12.535	10.206	32.1		1.84	0.068
	M	12.755	11.462	17.8	44.5	0.83	0.406
Distance cooperative	U	131.55	136.98	-12.7		-0.74	0.463
	M	136.23	137.03	-1.9	85.1	-0.10	0.922
Extension contact	U	2.8451	1.5238	81.7		4.67	0.000
	M	2.3208	1.9598	22.3	72.7	1.17	0.244
Gender	U	.91549	.90476	3.7		0.22	0.830
	M	.92453	.89094	11.7	-213.0	0.59	0.555
Credit use	U	.38028	.49206	-22.5		-1.30	0.195

Variables	Sample	Mean			% reduct	t-test	
		Treated	Control	%bias	Bias	t	p>t
	M	.39623	.40484	-1.7	92.3	-0.09	0.929

Source: Authors compilation, 2018

Table 6 presents the mean standardized bias before and after matching in the fifth column, whereas the sixth column shows the total bias reduction achieved. In the current matching models, the standardized difference in Z before matching ranged from 3.7% to 81.7% in absolute terms. Post-matching, the remaining standardized differences for all covariates fell between 1.7% and 22.3%, which is below the critical threshold of 20% recommended by [7]. This indicates that the sample differences in the unmatched data significantly exceeded those in the matched samples. Overall, the matching process successfully achieved a high degree of covariate balance between the treatment and control groups, making them suitable for further estimation.

After selecting the best-performing matching algorithm and establishing the common support condition, the next step involved checking the balance of propensity scores and covariates using various procedures. The primary goal of estimating propensity scores is to balance the distributions of relevant variables in both the treatment and control groups rather than to achieve precise predictions of treatment selection. Balancing effectiveness was assessed through different tests, including the reduction in mean standardized bias between matched and unmatched households, equality of means via t-tests, and chi-square tests for the joint significance of the variables.

Table 7 below presents results from covariate balancing tests before and after matching. The standardized mean difference for overall covariates used in the propensity score (around 34.3% before matching) is reduced to about 13.6% after matching. The bias substantially reduced, in the range of 29 to 14% through matching. The p-values of the likelihood ratio tests indicate that the joint significance of covariates was always rejected after matching; whereas it was never rejected before matching. The pseudo-R2 also dropped significantly from 14.04% before matching to about 0.12% after matching. The low pseudo-R2, low mean standardized bias, high total bias reduction, and the insignificant p-values of the likelihood ratio test after matching suggest that the proposed specification of the propensity score is fairly successful in terms of balancing the distribution of covariates between the two groups.

Table 7. *Propensity score matching: quality test.*

Sample	Ps R^2	LR chi^2	p>chi^2	MeanBias	MedBias	B	R	%Var
Unmatched	0.290	53.68	0.000	34.3	24.6	140.4*	1.26	29
Matched	0.058	8.56	0.479	13.6	17.8	57.9*	1.25	14

Source: Authors compilation, 2018

(v). Treatment Effect on the Treated (ATT)

Table 8 presents the average annual income of participants and non-participants in a coffee contract along with the estimated treatment effect. Using kernel matching, we find that contract participation has a statistically significant positive impact on income [12]. On average, participants earned 8252.21 ETB more than non-participants, controlling for socioeconomic differences. This represents a 35% increase in income owing to participation, suggesting a substantial benefit for the involved households.

Table 8. *Treatment effect on the treated.*

Outcome variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Annual income (ETB)	Unmatched	23375.55	15313.91	8061.65	983.23	8.20

Outcome variable	Sample	Treated	Controls	Difference	S.E.	T-stat
	ATT	23452.15	15199.94	8252.21	1334.47	6.18***

Source: Authors compilation, 2018, Bootstrapped with 100 replications.

(vi). Sensitivity Analysis

A sensitivity analysis using a range of propensity score-matching bandwidths (gamma) indicates that our impact estimates are robust to unobserved selection bias. Even when allowing for significant differences in treatment probability between participants and non-participants, the estimated treatment effect remained statistically significant. This finding suggests that our analysis adequately controls for observable and unobservable confounders, providing a reliable estimate of the causal impact of coffee contract participation on household income.

4. Summary and Conclusions

4.1. Summary

This study aims to analyze the impact of contract farming on the income of smallholder farmers, focusing on participants and non-participants in a contract farming scheme in the Shebe Sombo district. Data were collected from 134 farm households, comprising 71 participants and 63 non-participants, using structured questionnaires and secondary sources. Households were randomly selected based on their similar farm and socioeconomic characteristics.

The study employed descriptive and inferential statistics, including t-tests and chi-squared tests, to compare the two groups. A binary probit model was used to identify factors influencing contract participation, revealing that family size, livestock holdings, frequency of extension agent contact, and credit use significantly impacted participation. Additionally, a propensity score matching technique was applied to create comparable treatment and control groups, based on observable characteristics. Ultimately, 53 treatment households are matched with 63 controls, allowing for a robust analysis of the impact of contract participation on coffee income.

Controlling for socioeconomic differences, it was found that participating households earned, on average, 8,252.21 ETB more than non-participants, translating to a 35% increase in income from contract farming. This result is statistically significant at the 1% level. Sensitivity analyses confirmed the robustness of these findings, indicating a minimal hidden bias from unobservable factors. The study concludes that contract farming substantially enhances the income of participating smallholder farmers, underscoring the potential benefits of such schemes in improving their agricultural livelihoods.

4.2. Conclusions

Based on the findings of this study, it can be concluded that participation in contract farming has a significant positive impact on the income of participating households, with an average increase of 8,252.21 ETB. Conversely, households that participated experienced an income decrease of the same amount did not engage in the contract.

The analysis revealed that livestock ownership and frequency of extension contact positively and significantly influenced the likelihood of participating in contract farming. In contrast, family size and credit use have a negative and significant effect on contract participation.

Specifically, family size is found to have a negative and statistically significant relationship with contract farming at the 1% level. This aligns with the expectation that larger families will be less likely to participate in contract farming. Conversely, the number of livestock owned by farmers showed a positive and statistically significant relationship with contract participation, indicating that those with more livestock were more inclined to engage in such contracts.

Additionally, the frequency of extension services from agents is positively and significantly related to contract participation, which is also significant at the 1% level. This supports the hypothesis that households with more frequent extension contact are more likely to participate in contract farming.

Interestingly, credit use was found to negatively and significantly influence participation in contract farming. This suggests that farmers who utilize credit are less likely to engage in contracts, which may reflect the underlying financial constraints or risk perceptions related to contract farming.

5. Recommendations

Contract farming has proven to be an effective means of increasing farmers' incomes in the study area, significantly reducing vulnerability to poverty, which is an essential requirement for smallholder farmers. To maximize the benefits of contract farming, organizations facilitating these opportunities should implement policies aimed at encouraging broader participation among those currently excluded.

First, livestock production plays a crucial role in rural livelihoods by generating additional income that may reduce the demand for contract farming. Therefore, attention should be directed toward scientific livestock management practices to enhance rural households' welfare. Additionally, credit institutions should enhance training for credit providers, ensuring that borrowers are well informed about their obligations and can make sound decisions regarding credit use.

This study highlights that larger family sizes negatively impact participation in contract farming. Consequently, health extension services and relevant organizations should promote family planning awareness to help households understand how reducing family size can enhance their economic benefits from contracts.

Moreover, the frequency of extension services is vital for disseminating knowledge about improved production systems and technologies. Strengthening these services can significantly boost participation in contract farming, thereby increasing household incomes. Development agents and related bodies should maintain ongoing contact with producers to provide the necessary support and information.

Overall, continuous efforts to promote participation in contract farming are essential for increasing household incomes. Future research should explore the nature of contract farming across different contexts, focusing on its potential impact on livelihood, social dynamics, environmental practices, and technology adoption.

Abbreviations

ATT	Average Treatment Effect on the Treated
ETB	Ethiopian Birr
HHs	Households
KM	Kernel Matching
LC	Letter of Credit
NN	Nearest Neighbor
PSM	Propensity Score Matching
TLU	Tropical Livestock Units

Author Contributions

Meditu Debela Hordofa: Conceptualization, Methodology, Investigation, Formal Analysis, Data Curation, Writing – Original Draft, Writing – Review & Editing

Jema Haji Mohammed: Supervision (Major Advisor), Advising, Validation

Ermias Melaku Addis: Supervision (Co-Advisor), Advising, Validation

Yonas Muleta Gejea: Reviewing and Editing

Conflicts of Interest

The authors declare no conflicts of interest.

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