Impact of contract farming on income of smallholder malt barley farmers in Arsi and West Arsi zones of Oromia region, Ethiopia

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Abstract: This study examined factors that influence farmers’ participation in malt barley contract farming and West Arsi zones of Oromia region, Ethiopia. Data were collected from 384 (190 contract and 194 non-contract) randomly selected farm households. The probit model showed that age, livestock ownership, credit access, distance to the main market and cooperative membership had positive and significant effects on decision regarding contract farming participation. Propensity score matching technique was used to estimate the impact of participation in contract farming on farm households’ income. And it revealed that contract farming resulted in an increased annual gross farm income of Birr 24,302.20 for contract, which is 27.80% higher than the gross annual income of non-contract malt barley farm households. The finding of this study highlights that contract farming is viable to increase farm household’s income, which policy makers and other concerned agencies may consider as an alternative rural development approach so long as it is tailored to contexts alike.

Subjects: Development Studies; Rural Development; Economics and Development

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PUBLIC INTEREST STATEMENT

In Ethiopia, agriculture is characterized by low productivity, underperformance and slow growth. Thus, the country devised agricultural transformation schemes to raise its productivity, commercialization and link to agro-industries to effect economic growth and poverty reduction. Production aggregation models such as agricultural commercialization clusters, contract farming, and producer cooperatives are the schemes to realize agriculture-led transformation. Under this context, this study was proposed to examine impact of contract farming on income of smallholder malt barley farmers in Arsi and West Arsi zones of Oromia region, Ethiopia. Data were collected in May–June 2019 from 384 (190 contract and 194 non-contract) randomly selected farm households. The finding revealed that contract farming render an increased annual gross farm household income of Birr 24,302.20, which was 27.80% higher than the non-contract counterparts. It can be inferred that contract farming is viable to increase farm household’s income, which decision makers may consider for its scaling out to other commodities so long as it is tailored to contexts alike.
Keywords: Malt barley; contract farming; arsi; probit; PSM; oromia; Ethiopia

1. Introduction

Different forms of agrifood innovations were introduced by the upstream and downstream actors to integrate smallholder farmers into local and global agri-food value chains. Contract farming is one of these innovations being promoted to address technology constraints (Swinnen and Kuijpers, 2019), ease adoption of technology (Ragasa et al., 2018), link farmers to marketing agents (Wiggins & Keats, 2013), reduce transaction costs (Bellemare, 2012) and open access to finance (Carletto et al., 2011). Contract farming refers to an institutional arrangement under which agribusiness firms contract the production of agricultural commodities out to farmers and ensure a consistent supply of quality agricultural raw materials (Bellemare & Novak, 2017).

Several studies have been conducted on the impact of contract farming on the livelihood of smallholder farmers. Most of them found positive impacts of contract farming on welfare indicators such as household income, farm productivity and food security. For instance, Alemu et al. (2016) found that contract farming increased annual income of contract organic honey producers over non-contract counterparts. Similarly, Seba (2016) and Gemechu et al. (2017) revealed that export chickpea and vegetable contract farming increased the annual income of contract farmers than their counterparts respectively. Ton et al. (2016) in their extensive meta-analysis, indicated a 62% increase in income of contract farmers over incomes of non-contract farmers. However, few studies, point out that contract farming is a strategy for agribusiness firms to pass production risks to farmers, taking advantage of unequal bargaining relationships. In this regard, Abdulai and Alhassan (2016) and Rogasa et al. (2018) observed that contract farming showed limited potential to increase incomes of producers, which means the productivity gains from improved inputs use and recommended farm management practices were insufficient to cover the high inputs and labor costs for avocado, soybean and maize farmers in Kenya and Ghana respectively.

Recently, contract farming is unfolding in Ethiopia’s agri-food systems. For instance, Holtland (2017) lists malt barley, chickpea, seed potatoes, sesame, bamboo, green beans, passion fruits, and sugar cane contract farming arrangements being practiced in the country. Also contract farming is expanding to durum wheat (Biggeri et al., 2018), milk (Lenjiso et al., 2016), honey (Alemu et al., 2016), vegetables (Gemechu et al., 2017) in Ethiopia. Given the diversity of available contract farming practices, it seems that contract farming has gained a fertile ground in the country. Yet, some farmers participate in contract farming while others are not. Although diversified schemes of contract farming are growing and with further growth potentials in Ethiopia, only few empirical studies have been conducted to assess its welfare effects. Thus, an empirical evidence on the socioeconomic factors determining farmers’ participation in malt barley contract farming and its impact on household income in Arsi and West Arsi zones serves as a source of input for decision-making by policymakers and other value chain actors. To that end, the study aimed to identify the determinants of smallholder participation in malt barley contract farming and examine its impact on malt barley farm households’ income in Arsi and West Arsi zones of Oromia region, Ethiopia (Figure 1).

2. Methods and Data

2.1. Description of the Research Area

The study was conducted in Tiyyo and Limu Bilbilo districts of Arsi zone and Kofele and Shashemene districts of west Arsi zone of Oromia region, Ethiopia respectively. The two zones lie between 60 45’N to 80 58’N and 380 32’ E to 400 50’ E and 6012:29” to 7042:55” latitude and 38004:04” to 39046:08” longitude. Arsi zone is dominantly characterized by moderately cool (about 40%) followed by cool (about 34%) annual temperature. Due to variations in altitude, West Arsi zone also possesses three major agro-climatic zones highland, midland and lowland. On average, the annual mean rainfalls are 1020 mm and 1300 mm for Arsi and West Arsi zone.
respectively. The two zones have suitable climatic and edaphic factors for agricultural production. Thus, the major annual crops grown in the two zones include but not limited to wheat, barley (food and malt), bean, pea, maize, teff, sorghum, oats, chickpea, nueue, linseed millet, potato and others vegetables (Oromia Finance and Economic Development Bureau (OFEDB), 2011).

### 2.2. Features of Malt Barley contract farming

In Ethiopia, until recently, barley has been a traditional crop mainly produced for consumption. More than four million smallholder farmers earn their livelihoods from barley sub-sector that ranks fifth from grain produced in the country (CSA (Central Statistical Agency), 2015). Ethiopia is the second-largest barley producer in Africa, next to Morocco, accounting for about 25% of the total barley production in the continent (FAO (Food and Agriculture Organization), 2014). On one hand, rising per-capita incomes, population growth and urbanization increased beer consumption at an annual rate of 20% in Ethiopia led to a surge in malt barley demand (ATA (Agricultural Transformation Agency), 2016). On the other hand, trade liberalization, privatization and favorable investment policy attracted beer multinationals, including Heineken and Diageo to Ethiopia (Holtland, 2017). These multinational beer companies designed malt barley local sourcing schemes to procure desired quality and volume of malt barley from smallholder farmers through contract farming (Alemu & Berhanu, 2018; Holtland, 2017).

Despite the huge number of barley producers and the large areas dedicated to the cultivation of barley, Ethiopia remains a net importer of malt barley. For instance, in 2015, malt imports reached 66,000 ton which was 65% of the total annual demand that account for US 38 USD million Ethiopian Revenue and Customs Authority (ERCA), 2016). Data from ERCA shows further growth in import and approximately 90,000 ton processed malt was imported in 2016. Given the growth trends, malt import could exceed 400 USD million by 2025 (Ethiopian Revenue and Customs Authority (ERCA), 2016). While agro-ecological factors are favorable for malt barley production (Usman & Zeleke, 2017), institutional factors constrained smallholder farmers’ barley production and productivity. In the past, smallholders lacked a sufficiently large and reliable market outlet to incentivize increased production (Holtland, 2017). Recently, new marketing channel is unfolding, where companies regularly procure malt barley at stable prices, provide technologies including
improved varieties, technical support in exchange of consistent quality malt barley supply in Arsi and West zones and elsewhere in the country. The foci for this study were as to what determine participation in contract farming and how participation in contract farming makes differences to malt barley farming households’ income.

2.3. Sampling Procedure and Data Sources
A cross-sectional household survey data were used in this study. A structured interview schedule covering various questions was used to gather detailed household-level data including: demographic, socioeconomic and institutional factors that influence malt barley production. A multistage sampling procedure was employed in the selection of the sample malt barley farmers. In the first stage, four districts were purposively selected being the major malt barley producing districts and where malt factories, breweries and the intermediaries have been supplying malt barley on contractual basis. In the second stage, a list of major malt barley producer Kebeles were identified in respective districts and two Kebeles from each district were randomly selected making a total of eight study Kebeles. In the third and final stage, sample contract and non-contract household heads were proportionally selected by simple random sampling technique using the lists provided by the respective Kebeles and cooperative officials. To determine the sample size the formula given by Kothari (2004) was used as Equation (1).

\[
n = \frac{Z^2pqN}{e^2(N-1)+Z^2pq} \quad (1)
\]

\[
n = \frac{(1.96)^2(0.5)(0.5)(92,286)}{(0.05)^2(92,286) + (1.96)^2(0.5)(0.5)} \approx 384
\]

Where \( n \) is the sample size needed, \( Z \) is the inverse of the standard cumulative distribution that corresponds to the level of confidence, \( e \) is the desired level of precision, \( p \) is the estimated proportion of an attribute that is present in the population and \( q = 1-p \). The value of \( Z \) is found from the statistical Table which contains the area under the normal curve of 95% confidence level and \( p = 0.5 \) is as suggested by Kothari (2004). Based on this, a total of 384 households were selected for the study from the four selected districts and assuming a 95% confidence level and ± 5% precision; \( q = 1-p \); and \( N \) is the size of the total population from which the sample was drawn. Finally, a total of 384 farm household heads were selected from eight Kebeles by simple random sampling with probability proportional to size (Table 1).

| District     | Sampled Kebele | Household size | Sample household size |
|--------------|----------------|----------------|-----------------------|
|              |                |                | CF        | NCF       |
| Limu Biliblo | Chiba Micheal  | 749            | 23        | 23        |
|              | Limu Dima      | 684            | 21        | 21        |
| Tyyo         | Hara Bilala    | 656            | 19        | 19        |
|              | Dasha          | 781            | 23        | 23        |
| Kofele       | Gurmicha       | 626            | 22        | 22        |
|              | Alkaso         | 672            | 24        | 24        |
| Shashemene   | Hursa Simbo    | 1037           | 31        | 32        |
|              | Gonde Karso    | 946            | 28        | 29        |
| Total        |                | 6,151          | 190       | 194       |

CF and NCF denote contract farmers and non-contract farmers
Source: Arsi and West Arsi zones Bureau of Agriculture and Natural Resources (2019).
2.4. Methods of data analysis

Descriptive statistics and econometric method called propensity score matching (PSM) were used to analyze data. We used matching technique—the Propensity Score Matching (PSM) to estimate the causal treatment effects, which is the most widely used method in impact evaluation (Chogwiza et al., 2016; Khandker et al., 2010; Mutonyi, 2019). PSM is adequate for correcting potential sample selection bias during the analyses (Caliendo & Kopeinig, 2008; Imbens & Rubin, 2015). PSM was used to estimate if there is significant difference in the mean values of the outcome indicator (gross household annual income) between contract and non-contract malt barley farmers. The first step in PSM method is to estimate the predicted probability that a household is a participant of a contract farming, also known as the propensity score obtained through the probit or logit model. We used probit model (0 = untreated and 1 = treated) to obtain the propensity scores (Rosenbaum & Rubin, 1983) for the matching purpose. Contract malt barley farmers were taken as a treatment group while no-contract malt barley farmers were taken as a control group. Average treatment effect on the treated (ATT) estimated using propensity score matching (PSM) developed by Rosenbaum and Rubin (1983). The ATT is defined as the mean difference between expected outcome values with and without treatment for those who actually participated in the program (Caliendo & Kopeinig, 2008). More specifically, it can be assumed that there are two expected outcomes, Y₀ and Y₁. Y denotes the outcome of contract participant household and Y₀is the outcome non-contract farm household. The average effect of participation in a contract farming on contract farmers’ outcome (gross annual income) is the differences between their expected outcomes when participating and the expected outcomes if they did not participate in the contract.

Hence, ATT can be presented as:

\[
ATT = E(Y_1 - Y_0 | X, P = 1) = E(Y_1 | X, P = 1) - E(Y_0 | X, P = 1)
\] (2)

Where ATT denotes the average effect of participation in contract farming on malt barley farmers’ annual gross income. X is a vector of observed characteristics of household that may affect the decision-making to participating in the contract scheme or/and the expected outcome of farmers and used as explanatory variables. P denotes participation in a contract scheme (P = 1, if farmer participates in the contract scheme, and P = 0 otherwise).

The problem arising when estimating ATT given Equation (2), is that it could not be measured \( E(Y_0 | X, P = 1) \) since this is unobserved. The fact is that it could not be observed simultaneously the outcome produced in case of non-participation for the same person who actually participated in the scheme. This problem may be solved by replacing unobserved outcome values (missing) of contract farmer \( E(Y_0 | X, P = 1) \) with the expected outcome values of matched non-contract farmer who has similar observable characteristics to the contract farmer \( E(Y_0 | X, P = 0) \) called counter factual outcome. Therefore, Equation (2) can be re-written as:

\[
ATT = E(Y_1 - Y_0 | X, P = 1) = E(Y_1 | X, P = 1) - E(Y_0 | X, P = 0)
\] (3)

To ensure the similarity of characteristics in a dimension, the vector X could be condensed as the propensity score (Ito et al., 2012), which is the individual probability of taking the participation given the observable variables. Therefore, Equation (3) was used to estimate the effect of contract farming on malt barley farmers’ gross annual income. To use PSM for estimating ATT, two important assumptions must be satisfied. The first condition is the conditional independence assumption (CIA) of expected outcomes and selection into the treatment given observable variables (Imbens & Rubin, 2015). In other words, all variables that influence treatment assignment and expected outcomes must be observed (Caliendo & Kopeinig, 2008). The second condition is the overlap or the common support condition, which ensures that for each treated subject there are control subjects with the same observable covariates (Nannicini, 2007). To measure ATT using PSM approach, a five-step procedure was adapted (Nhan, 2019), including: (1) selection of the variables that are used for matching; (2) choice of the matching algorithm; (3) estimating the propensity
scores and matching based on the estimated propensity score; (4) checking and testing the balance for covariates before and after matching; and (5) estimating the average treatment effects from the matched data.

3. Results and Discussions

3.1. Descriptive Statistics

The average age of the household heads for the entire sample is 44.49 years (Table 2). The mean ages of non-contract and contract malt barley farmers are 43.36 and 45.65 years, respectively. The t-test result shows that there is a statistically significant mean age difference between the two groups at less than 5% significance level. This indicates that as household heads get older they incline to participate in contract farming as compared to younger counterparts. The result is against our expectation and prior studies. The average family size for the whole sample household is 7.32 persons, but for contract and non-contract of contract farming they are 7.77 and 6.88 persons, respectively. The t-test result shows that there is a statistically significant mean difference between the two groups in terms of family size at <1% significance level. This indicates that households with relatively large family size participate in contract farming than others. Total cultivated farm size for the entire sample is 2.39 ha. The mean cultivated farm size of non-participants and participants of contract farming is 2.39 and 2.40 hectares, respectively. The t-test for equality of means is found to be statistically insignificant. It indicates that farm size was not a restriction for joining contract farming. Livestock ownership in TLU is 7.26 for entire sample. Average livestock holding for the non-contract and contract farm households are 6.84 and 7.69 TLU, respectively. The t-test statistic for equality of means between the groups shows that participant households own significantly higher number of livestock at <10% significance level. This indicates farm households with more livestock in TLU are able to join contract farming than others. The mean distance travelled in minutes from farm household residence to main market was 60.52 minutes for the entire sample. While contract and non-contract households on average travel 62.55 and 58.53 minutes respectively to reach the main market with no significant difference between the two groups. Off/non-farm annual income for the entire sample was 7,210.94 Birr. The mean off/non-farm annual income of non-contract and contract malt barley farmers was 6,802.63 and 7,627.84 Birr, respectively. The t-test for equality of means is found to be statistically insignificant.

Coming to categorical variables, the majority of the sampled farm households (94.79%) were male-headed. Only 24 (5.21%) of the sampled female-headed households participated in contract farming. The result indicates that there is low female participation in malt barley contract farming. Access to credit is expected to attract farmers to contract farming. From the total sample, only 24.48% had access of credit. A chi-squared test for independence indicated that there is a significant difference in the percentage of contract and non-contract malt barley farmers’ credit access: \( \chi^2(1, n = 384) = 31.09, p = 0.000 \). About 37% of the contract farmers had access of credit as compared with 12.37% non-contract farmers. Access to market information: Of the total sample households, 32.55% had access to proper market information. A chi-squared test indicated that there is a significant difference in the percentage of contract and non-contract farmers’ market information access: \( \chi^2(1, n = 384) = 5.90, p = 0.000 \). A total of 38.42% of contract farmers had access to market information as compared to 26.80% non-contract farmers. Cooperative membership: studies show cooperative membership has a positive impact on farmers’ access to information, input and output markets, technology access and put farmers in better position to influence buyers. Accordingly, 53% of respondents are cooperative members. A chi-squared test indicated significant difference in the percentage of cooperative membership between contract and non-contract farmers; \( \chi^2(1, n = 384) = 86.77, p = 0.000.76.84\% \) of contract farmers were members of cooperatives as compared to 29.38% non-contract farmers. Summary of categorical variables’ statistics presented in Table 3.
| Variable                                | Total (n = 384) | Non-contract (n = 194) | Contract (n = 190) | T-test |
|-----------------------------------------|-----------------|------------------------|--------------------|--------|
|                                         | Mean            | Std. Dev.              | Mean               | Std. Dev. |       |
| Age of household head                   | 44.49           | 11.12                  | 43.36              | 11.07    | 45.65  | 11.08  | 2.02** |
| Family size                             | 7.32            | 3.04                   | 6.88               | 3.00     | 7.77   | 3.02   | 2.90***|
| Education (schooling year)              | 6.15            | 3.44                   | 6.07               | 3.37     | 6.24   | 3.53   | 0.49   |
| Total cultivated land (ha)              | 1.66            | 1.38                   | 1.73               | 1.38     | 1.58   | 1.38   | 1.07   |
| Distance to market (Minute)             | 60.52           | 27.11                  | 58.53              | 26.69    | 62.55  | 27.45  | 1.46   |
| Livestock ownership (TLU)               | 7.26            | 4.31                   | 6.84               | 4.28     | 7.69   | 4.31   | 1.94*  |
| Off/non-farm income (Birr)              | 7,211           | 12,543                 | 6,803              | 11,485   | 7,628  | 13,557 | 0.64   |

Source: Survey data analysis (2019).
Table 3: Summary statistics of categorical variables

| Variable                      | Category | Total (n = 384) | Non-contract (n = 194) | Contract (n = 190) | Chi²(1) |
|-------------------------------|----------|-----------------|------------------------|-------------------|---------|
|                               |          | Freq. %         | Freq. %                | Freq. %           |         |
| Sex                           | Female   | 20 5.21%        | 12 6.23%               | 8 4.24%           | 0.93    |
|                               | Male     | 360 94.79%      | 182 93.77%             | 178 95.76%        | 0.07    |
| Age                           | Total    | 384 100%        | 194 100%               | 190 100%          |         |
|                               | Freq.    | 5.21%           | 12%                    | 4.24%             |         |
|                               | %       | 94.79%          | 93.77%                 | 95.76%            |         |
| Cooperative membership       | Yes      | 203 52.82%      | 103 53.21%             | 100 52.63%        | 0.96    |
|                               | No       | 181 47.18%      | 91 46.79%              | 90 47.37%         | 0.94    |
|                               | Total    | 384 100%        | 194 100%               | 190 100%          |         |
|                               | Freq.    | 52.82%          | 53.21%                 | 52.63%            |         |
|                               | %       | 47.18%          | 46.79%                 | 47.37%            |         |
| Access to credit             | Yes      | 24 6.22%        | 14 7.24%               | 10 5.26%          | 86.77***|
|                               | No       | 260 93.78%      | 180 92.76%             | 80 94.74%         | 0.06    |
|                               | Total    | 284 100%        | 194 100%               | 90 100%           |         |
|                               | Freq.    | 6.22%           | 7.24%                  | 5.26%             |         |
|                               | %       | 93.78%          | 92.76%                 | 94.74%            |         |
| Access to market information  | Yes      | 73 18.92%       | 38 19.68%              | 35 18.42%         | 0.31**  |
|                               | No       | 311 81.08%      | 156 80.32%             | 155 81.58%        | 0.84    |
|                               | Total    | 384 100%        | 194 100%               | 190 100%          |         |
|                               | Freq.    | 18.92%          | 19.68%                 | 18.42%            |         |
|                               | %       | 81.08%          | 80.32%                 | 81.58%            |         |

Source: Survey data analysis (2019).

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3.2. Results of Propensity Score Matching

Probit model was utilized for estimation of the propensity scores as it best fits the data compared to logit model. The Wald chi-square test was statistically significant at <1% significance level which indicates that the null hypothesis of no explanatory power of the model was strongly rejected. The pseudo-R² is 0.2650, which is moderately low, indicating that there was no systematic difference in the distribution of covariates between contract and non-contract farmers.

Table 4 presents the probit regression model output. Accordingly, discussions and implications of the significant variables follow. The age of the household head is positive and significantly influence contract farming participation. That is an additional year of age is associated with, on average, a 0.8% point increase in the probability of contract farming participation. The result is against to the expectation and what Geoffrey et al. (2013) and Olounlade et al. (2020) reported that an increase in age is associated with low risk taking and participation in contract farming.

The estimated coefficient of total cultivated land size was negative and significant (p = 0.000) in influencing the farmer’s decision to participate in malt barley contract farming. This result is inconsistent with our expectations and previous studies (Bellemare, 2012; Goshu et al., 2012; Okezie et al., 2012). This could be due to the role of farm size in boosting total production level and sales of surplus produce. Moreover, farm households with large farm size could allocate their land partly for food crop production and partly for cash crop production including malt barley giving them better position to participate in contract farming. In line with this result, Minot and Ronchi (2015) could not observe farm size to determine participation in contract farming. However, Azumah et al. (2016) found a significant negative relationship between farm size and participation in rice contract farming in Northern Ghana. Despite these findings, there are evidences of bias towards the participation of relatively larger farm farmers in areas where contract farming takes place.

| Independent variables | Coef. | Std. Err. | Z     | P>|z| |
|-----------------------|-------|-----------|-------|------|
| Sex of household head (1 = Male) | 0.357 | 0.335 | 1.070 | 0.287 |
| Age of the household head (years) | 0.017** | 0.009 | 1.790 | 0.073 |
| Education level of the household head (years) | 0.013 | 0.025 | 0.520 | 0.603 |
| Household size (number) | −0.003 | 0.029 | −0.110 | 0.914 |
| Farm size (ha) | −0.191*** | 0.069 | −2.780 | 0.006 |
| Livestock ownership (TLU) | 0.065*** | 0.022 | 2.900 | 0.004 |
| Access to credit (1 = Yes) | 0.935*** | 0.184 | 5.090 | 0.000 |
| Distance to main market (walking minutes) | 0.005* | 0.003 | 1.660 | 0.097 |
| Access to market information (1 = Yes) | 0.100 | 0.181 | 0.550 | 0.580 |
| Cooperative membership (1 = Yes) | 1.339*** | 0.154 | 8.710 | 0.000 |
| Off-farm income (Birr/Year) | 0.000 | 0.000 | −0.410 | 0.683 |
| Constant | −2.676*** | 0.658 | −4.070 | 0.000 |
| Log likelihood | −195.60971 | 14.108 | | |
| LR chi2(11) | 14.108 | 0.0000 | | |
| Prob > chi2 | 0.0000 | | | |
| Pseudo-R² | 0.2650 | | | |
| Number of obs | 384 | | | |

*and *** denote significance at 10% and 1% levels, respectively.

Source: Survey data analysis (2019).
Livestock ownership (TLU) has a positive effect (at <1% level of significance) on decision-making regarding contract farming participation. Livestock has a multitude of social and economic functions that enhance farmers’ capacity to participate in new interventions including contract farming. The result is both consistent with our expectation and a recent study of Gemechu et al. (2017) who revealed that farmers with more livestock come out to participate in vegetable contract farming.

The coefficient of the variable access to credit is positive and significant, indicating that farmers getting access to credit are 40.8% more likely to participate in contract farming than others. This implies that farmers with access to credit in monetary terms or in kind as inputs are incentivized to join contract farming than others. The result is in line with findings of Mugwagwa et al. (2020).

Distance of household’s residence from main market exerts positive and significant effect on contract farming participation decision. That is as a farmers’ residence distance increase by one unit so does the probability of participation. It opposes our expectation, the possible reason could be, distance is affecting farmers’ market participation as a result they seek to benefit from closer market access contract farming alike. The implication is that presence of contract farming resolves some input and output market transaction costs, which are more noticeable as distance increases from the market place. The result is against the expectation and at odds with prior study of Gemechu et al. (2017), but in line with the finding of Ejigu et al. (2012).

The variable cooperative membership is positive and significant. That is cooperative members are more likely to participate in contract farming than their non-member counterparts. The result is consistent with findings of (Carillo et al., 2017; Biggeri et al., 2018; Mishra et al., 2018).

After estimating the propensity scores using the probit model, the next step is determining the common support region. In setting the common support conditions, the minima and maxima comparison was made. Table 5 shows the distribution of estimated propensity scores, which varies between 0.063 and 0.980 with a mean of 0.659 for contract and between 0.041 and 0.931 with a mean of 0.334 for non-contract households. Hence, the common support region would lie between 0.063 and 0.931. Due to this restriction, eight households (all from contract farmers) were dropped from the analysis in estimating the average income effect of contract farming. Having completed estimation of the propensity scores and the common support region, the next step is seeking an appropriate matching estimator (algorithm). On basis of the stated criteria, Kernel matching with bandwidth (0.1) was the best matching estimator identified since it balances all of the explanatory variables (results in insignificant mean differences between the two groups), bearing a low pseudo-R² value, and results in a large matched sample size. Table 6 shows that after matching, the differences are no longer statistically significant, suggesting that matching helps to reduce the bias associated with observable characteristics.

Having completed the estimation of propensity scores and the common support region the next step is seeking an appropriate matching estimator. The alternative matching estimators (algorithms) were searched in matching the participants and non-participants households in the common support region (Table 6). Kernel matching with bandwidth of 0.1 was chosen since it

| Groups         | Observations | Mean  | Std. Dev. | Min  | Max  |
|----------------|--------------|-------|-----------|------|------|
| All households | 384          | 0.495 | 0.287     | 0.041| 0.980|
| Contract       | 190          | 0.659 | 0.230     | 0.063| 0.980|
| Non-contract   | 194          | 0.334 | 0.243     | 0.041| 0.931|

Source: Survey data analysis (2019)
balances all of the explanatory variables (i.e. results in insignificant mean differences between the two groups), bearing a low pseudo-$R^2$ value and results in a large matched sample size and mean standard bias (Gemechu et al., 2017; Nhan, 2019).

The propensity scores estimated should balance the distributions of relevant variables in treatment and control groups. This means, by matching subjects on the propensity scores, the distribution of covariates should be similar across treatment and control groups. Table 7 shows that after matching, the differences are mostly statistically insignificant, suggesting that matching helps to reduce the bias associated with observable characteristics before matching.

The final step in conducting PSM is estimating treatment effects on the outcome variable in the matched sample through a student’s t-statistic. Table 8 shows supportive evidence of statistically significant gross household income effect of contract farming participation. After controlling for pre-participation differences, it has been observed that, on average, farmer participating in contract farming has increased the gross income by 24,302.20 Birr during the survey year. This means contract farming has increased the gross income of contract households by 27.80%. The result is consistent with the findings of Sebo (2016), Gemechu et al. (2017), Moertens and Velde (2017), and Dubbert (2019) who observed that farmers who participated in contract farming obtained significantly higher income as compared to non-contract farmers in chickpea, vegetable, rice and cashew production respectively in Ethiopia and elsewhere.

The sensitivity test is the final step used to investigate whether the causal effect estimated from the PSM is susceptible to the influence of unobserved covariates. The legitimacy of propensity score analysis is based on the assumption of strongly ignorable treatment assignment that assumes all relevant covariates are employed in the treatment assignment and the bias due to the

### Table 6. Performance of the different matching algorithms

| Matching estimator | Matching performance criteria |
|--------------------|-------------------------------|
|                    | Balancing test* | $Ps R^2$ | Mean Bias | Matched sample size |
| Nearest neighbor   | Neighbor(1) | 11 | 0.024 | 6.7 | 377 |
|                    | Neighbor(2) | 11 | 0.023 | 6.6 | 377 |
|                    | Neighbor(3) | 12 | 0.015 | 5.9 | 377 |
|                    | Neighbor(4) | 12 | 0.011 | 5.2 | 377 |
|                    | Neighbor(5) | 12 | 0.013 | 5.1 | 377 |
| Kernel             | Bwidth(0.01) | 11 | 0.015 | 6.7 | 353 |
|                    | Bwidth(0.1) | 12 | 0.012 | 4.7 | 376 |
|                    | Bwidth(0.25) | 10 | 0.041 | 9.0 | 376 |
|                    | Bwidth(0.5) | 9 | 0.069 | 13.4 | 376 |
| Caliper            | Caliper(0.01) | 11 | 0.024 | 10.3 | 280 |
|                    | Caliper(0.1) | 9 | 0.024 | 8.7 | 373 |
|                    | Caliper(0.25) | 9 | 0.024 | 8.7 | 373 |
|                    | Caliper(0.5) | 9 | 0.024 | 8.7 | 373 |
| Radius             | Bwidth(0.01) | 8 | 0.251 | 33.5 | 376 |
|                    | Bwidth(0.1) | 8 | 0.251 | 33.5 | 376 |
|                    | Bwidth(0.25) | 8 | 0.251 | 33.5 | 376 |
|                    | Bwidth(0.5) | 8 | 0.251 | 33.5 | 376 |

*Number of independent variables with no statistically significant mean difference between the matched groups of households

Source: Survey data analysis (2019).
Table 7. Balancing test for the impact of participation in CF on household’s income

| Variables                        | Matching sample | Mean          | %reduct     | bias | t     | p>|t| | V(\(\Gamma\))/V(\(\Gamma\)) |
|----------------------------------|-----------------|---------------|-------------|------|-------|------|-----------------|
|                                  | Treated         | Control       |             |      |       |      |                 |
| pscore                           | U               | .65842        | .33251      | 137.6| 13.48 | 0.000| 0.89            |
|                                  | M               | .64499        | .63596      | 3.8  | 97.2  | 0.38 | 0.702           |
| Sex                              | U               | 1.0632        | 1.0412      | 9.8  | 0.97  | 0.335| 1.01            |
|                                  | M               | 1.0604        | 1.0746      | −6.4 | 35.2  | −0.54| 0.590           |
| Age                              | U               | 45.647        | 43.361      | 20.6 | 2.02  | 0.044| 1.23            |
|                                  | M               | 45.242        | 44.746      | 4.5  | 78.3  | 0.45 | 0.651           |
| Education                        | U               | 6.2421        | 6.067       | 5.1  | 0.50  | 0.619| 1.1             |
|                                  | M               | 6.2967        | 6.5189      | −6.4 | −26.9 | −0.60| 0.549           |
| Family size                      | U               | 7.7684        | 6.8763      | 29.6 | 2.90  | 0.004| 1.02            |
|                                  | M               | 7.7033        | 7.89        | −6.2 | 79.1  | −0.59| 0.558           |
| Farm size                        | U               | 1.5795        | 1.7308      | −11  | −1.08 | 0.283| 1.1             |
|                                  | M               | 1.6009        | 1.7202      | −8.7 | 21.1  | −0.81| 0.419           |
| Livestock ownership (TLU)        | U               | 7.6885        | 6.8386      | 19.8 | 1.94  | 0.053| 1.02            |
|                                  | M               | 7.6571        | 7.6706      | −0.3 | 98.4  | −0.03| 0.979           |
| Credit access                    | U               | .36842        | .12371      | 59.1 | 5.80  | 0.000| 0.68*          |
|                                  | M               | .34066        | .30549      | 8.5  | 85.6  | 0.72 | 0.474           |

(Continued)
| Variables                      | Treated Mean | Control Mean | % reduction V(T)/V(Ω) | % bias bias | t-test | p>|t| | V(T)/V(Ω) |
|-------------------------------|--------------|--------------|-----------------------|-------------|--------|----------|--------------|
| Distance to market            | 62.553       | 58.531       | 14.9                  | 1.46        | 0.0146 | 1.06     | 0.146        |
| Market information            | 61.346       | 63.714       | -8.7                  | 41.1        | 0.82   | 0.412    | 0.94         |
| Coop. membership              | 1.2474       | 1.2268       | 4.8                   | 0.47        | 0.037  | 0.94     | 0.037        |
| Off/non-farm income           | 7627.8       | 6802.6       | 107.8                 | 10.56       | 0.15   | 0.920    | 1.22         |

*if variance ratio outside [0.75; 1.33] for U and [0.74; 1.34] for M sample.

Source: Survey data analysis (2019).
unmeasured covariates is ignorable. The sensitivity test helps to explore how sustainable the treatment effect is to the potential effect of unmeasured covariates. If the estimated treatment effect is sensitive to the presence of unmeasured covariates, or in other words, the estimated treatment effect is possibly washed away with the unmeasured covariates, the treatment effect may be due to the bias of unobserved covariates rather than a true effect.

Table 9 shows that the impact result estimates are insensitive to unobserved selection bias. We could not get the critical values gamma where the estimated ATT is questioned even if we have set largely up to 10. That means for all outcome variables estimated, at various levels of the critical value of gamma, the p-critical values are significant which further indicates that our impact estimates (ATT) are insensitive to unobserved selection bias and are a pure effect of participation in malt barley contract farming.

### 4. Conclusion and Recommendations

In this study, we analyzed factors that influence farmers’ participation in malt barley contract farming and the impact of contract farming on household income in Arsi and West Arsi zones of Oromia region, Ethiopia. Probit regression model indicated positive and significant effects of age of household head, livestock ownership, credit access, distance to main market and cooperative membership on farmers’ contract farming participation decisions. Moreover, the PSM test estimated the treatment effects on the outcome variable in the matched sample through a student’s t-statistic. The empirical results revealed that contract farming significantly contributes to the improvement of gross annual household income of malt barley farmers. Although spillover effects are not measured, contract farming could have triggered managerial and technological spillover
effects on other crops produced, and investment effects. Given that participation in contract farming increases farm households’ income, rural development policy makers and other concerned agencies may consider scaling contract farming, thereby improve the livelihoods of smallholder farmers in barley production potential areas in general, and in the study area in particular, so long as it is tailored to contexts alike.

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Note
1. Kebele is the lowest administrative unit in Ethiopia

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