Social Sciences & Humanities Open 8 (2023) 100614

Contents lists available at ScienceDirect

Social Sciences & Humanities Open

journal homepage: www.sciencedirect.com/journal/social-sciences-and-humanities-open

Regular Article

Impact of collective marketing participation on farmers' income: Evidence from smallholder avocado farmers of Murang'a County, Kenya

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ARTICLE INFO

Keywords:
Avocado
Collective marketing participation
Logistic regression
Propensity score matching
Farmers income

ABSTRACT

Avocado (*Persea Americana*) is a major crop in Kenya but its potential to generate income is limited by challenges associated with production and marketing. The objective of this study was to assess the impact of participation in collective marketing on the incomes of smallholder avocado farmers in Kigumo Sub-County, Murang'a County, Kenya. Data was collected from 300 randomly selected households comprising of 150 participants and 150 non-participants of collective marketing. Data collected included demographic characteristics, socio-economic and institutional factors, farmers' income, and market information. Propensity Score Matching (PSM) models were employed to estimate the impact of participation in collective marketing on incomes. Results showed that farmers who participated in collective marketing benefitted from increased production and better sales. Participation in avocado collective marketing increased farmers' incomes by an average of 32.95% during the three consecutive years considered (2018, 2019, and 2020). Participants produced significantly higher avocado fruits (1251.3 kg) compared to non-participants (889.7 kg) in 2020. Participants also fetched better prices of 7.5Ksh per fruit compared to non-participants who sold their fruits at 5Ksh. Based on our findings, we recommend that farmers should participate more in collective marketing so as to improve the incomes from their avocado production. Policymakers should also promote a collective marketing strategy through interventions such as improving access to avocado collection centers and provision of market infrastructures.

1. Introduction

Horticulture is one of the major contributors to the economies of most countries in Sub-Saharan Africa (Amao, 2020; Maertens et al., 2012). A wide variety of vegetable and fruit crops are produced and plays a critical role in supporting many livelihoods by providing food, employment, and income (Achterbosch et al., 2008; Maertens et al., 2012). In particular, avocado has emerged as one of the important horticultural crops, grown for domestic consumption, local and export markets despite the challenge of pests such as tephritid fruit flies and the false codling moth in sub-Saharan Africa (Bower & Cutting, 2011; Ngutu et al., 2018). It is referred to as a universal fruit because it grows both in subtropical and temperate climatic conditions. The fruit can do well between 45 "N and 60" S latitudinal demarcations for many varieties.

Kenya occupies the third position among the largest producers of avocados worldwide behind Mexico and Peru (Amare et al., 2019). According to FAOSTAT (2021), Kenya was the leading avocado producer in Africa in 2019, with a production of 364,935 tones followed by Ethiopia, Malawi, and South Africa. Avocado forms the pillar of the horticulture sector in Kenya and accounts for 17% of the total horticultural exports and more than 50% of the fruit sub-sector's export value (Amare et al., 2019). According to (Wasilwa et al., 2017), about 70% of avocado production is dominated by smallholder farmers of Central and Eastern Provinces. The main production regions are Murang'a, Kiambu, and Thika in Central Province; Embu and Meru in Eastern Province. The main production season is between March to September but avocadoes are always available throughout the year (Duarte et al., 2016). Avocado production in Kenya is dominated by local varieties which account for 70% of the entire production, while improved varieties such as Hass and Fuerte constitute the remaining 30%. The improved varieties are preferred for export markets due to high resistance to pests and diseases, higher oil content, and reduced bruises (Johnny et al., 2019).

Despite the importance of avocado, the ability of most farmers to generate income from its production is limited by factors such as lack of appropriate preservation means and paucity of marketing information, which reduces their bargaining power. Avocado is usually sold either to

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https://doi.org/10.1016/j.ssaho.2023.100614
Received 3 October 2022; Received in revised form 23 May 2023; Accepted 27 June 2023
Available online 3 July 2023

brokers or in unorganized and informal markets where farmers fetch low value (Faris, 2016). However, collective marketing is one of the marketing strategies that have been proposed to solve marketing challenges among smallholder avocado farmers (Faris, 2016; Johnny et al., 2019). In this arrangement, a group of farmers come together either directly or indirectly and collaborate on joint activities to accomplish common interests in marketing their produce (Meier zu Selhausen, 2016).

Previous studies done on some crops such as maize and banana, have demonstrated that collective marketing reduces transaction costs, improves farmers' bargaining power leading to better prices and improved livelihoods (Barrett, 2008) (Nyikahadzoi et al., 2011). According to (Murang'a County, 2019), collective marketing also enhances access to facilities such as agricultural credit, and trainings. In Kenya many studies (Barrett, 2008; Meier zu Selhausen, 2016; Nyikahadzoi et al., 2011) have associated participation in collective initiatives with increased household incomes. Collective marketing facilitated potatoes' farmers personal savings and loans, and enabled participants to fund farmers' group activities in Uganda (Oduol et al., 2013). As demonstrated by (TIA, 2013), collective marketing improves farmers' access to high value markets, new technologies, and credit facilities which increases their economies of scale and improves the farmers' bargaining power in the value chain (Nyasulu, et al., 2019).

Since 2017, the government of Kenya has increased its attention to promoting collective marketing and has been incentivizing farmers to participate in the strategy. For example, in Murang'a County there has been training of avocado farmers on good avocado production practices and benefits of marketing the produce through the cooperatives. Farmers have also received free seedlings (Murang'a County, 2019). The goal of the government is to promote income generation from the avocado crop but participation of the farmers in collective marketing is mixed with some farmers preferring to sell using other avenues.

Past studies on collective marketing have focused on market barriers reduction, government interventions, farmers' group activities, improving smallholder farmers' access to domestic and export markets and increasing bargaining power. These studies are mainly on subsistence crops such as banana, sweet potatoes, rice, and maize. Scanty information exists on impact of participation in collective marketing on income from a tree crop such as Avocado. This study was therefore carried out to assess the impact of participation in collective marketing on incomes of smallholder avocado farmers in Kigumo Sub-County, Murang'a County, Kenya for three years (2018, 2019 and2020). The hypothesis was that participation in collective marketing increases farmers' income.

2. Collective marketing of avocado in Kenya

Within the horticultural sector, avocado production is dominated by smallholder farmers, and classified as one among the major export crops in Kenya (Ongeri, 2014). Around 31,227 metric tons of avocado were exported in 2014, which was higher than mango and passion fruit which goes up to 14,048 metric tons and 404 metric tons respectively (Johnny et al., 2019). Kenya recently experienced an uptake and upward trajectory in avocado production due to new Chinese market. This positive trend provides high potential market for Kenyan smallholder avocado farmers.

Murang'a County, one of the 47 counties in Kenya selected avocado development as their priority value chain for raising incomes among farmers. The choice was based on the suitability of the climate and the fact that majority of the farmers were already growing avocado. Major promotion activities involved development of tree nurseries through Kenya Agricultural Research and Livestock Organization (KARLO) and establishment of collective marketing centers (Karing'u et al., 2020). The collective marketing centers are owned by the county Government and their management borrow heavily from the cooperative arrangement in Kenya. Under this arrangement farmers join the cooperative on a voluntary basis.

Kenya has a long history of cooperative development in almost all sectors as a means of promoting efficiency of markets. Over the years agricultural registered cooperatives has been increasing in Kenya; since 1963 1,030 cooperatives with a membership of 335,000 to 20,901 in 2019, with around 10 million members, respectively (Miroro et al., 2023).

2.1. Conceptual framework

Our conceptual framework traces impact pathway of participating in collective marketing showing a causal chain of events from promotion of collective marketing to ultimate impact (Fig. 1). We assume that training of farmers and provision of seedlings will increase production, but decision to participate in collective marketing is influenced by farmer and institutional factors (Mugwe et al., 2019; Simon et al., 2015). The decision is either to participate or not to participate in collective marketing. Those who participate are expected to benefit from better access to markets, better prices and increased production as a result of enhanced ability to invest in avocado production. Ultimately income will be increased due to higher prices and more production compared to those that fail to participate.

We model participation in an agricultural intervention program as a situation that happens over a particular time, in a particular region; farmers would make an initial decision to adopt or not to adopt an intervention program depending on their different perceptions and experiences. Those who decide to adopt or not may change their decision over time. The decision of a smallholder farmer i to participate in avocado collective marketing t depends on the expected utility such as increasing income $U_{i\ t}$ compared to the expected utility of not participating in collective marketing $U_{i\ t}$, given a set of challenges faced by the farmer related to income and information about avocado collective marketing.

Suppose that $U_{i\ t} - U_{i\ t} = V_{i\ t} > 0$ and the challenges are not binding, then the farmer i will participate in collective marketing t. The value of $V_{i\ t}$ depends on the benefits of collective marketing such as high price, high bargaining power, access to market infrastructures, reduced distance to collection centers, access to accurate information about markets, and high-yielding avocado varieties. And also, smallholder avocado farmers gain opportunity costs of gathering information about collective marketing participation and benefit from the County government promotions.

3. Methodology

3.1. Study area

The study was conducted in Kigumo Sub-County of Murang'a County. This Sub- County has an area of 293.0 km^2 and lies on the eastern slopes of the Aberdare Ranges (Muriuki & Macharia, 2015). Kigumo Sub-County is estimated to have a population of 136,827 inhabitants distributed in five wards: Kangari, Kigumo, Muthithi, Kahumbu, and Kinyona (KNBS, 2019). Agriculture is the dominant economy activity in the area and employs about 80% of the residents (Murang'a County, 2019). The major crops grown in this Sub-County include avocado, coffee, tea, mango and macadamia.

The sub-county has the highest concentration of identifiable avocado farmers and is also the largest supplier of avocado for export and local market both in Murang'a and in the rest of Kenya (Kirui & Njiraini, 2013; Markelova & Mwangi, 2010).

3.2. Sample size and sampling procedure

The sample size for this study was 300 avocado farmers. This comprised 150 who had participated in collective marketing (participants) and 150 who had not participated in collective marketing (non-participants). The sample size was determined based on the precision

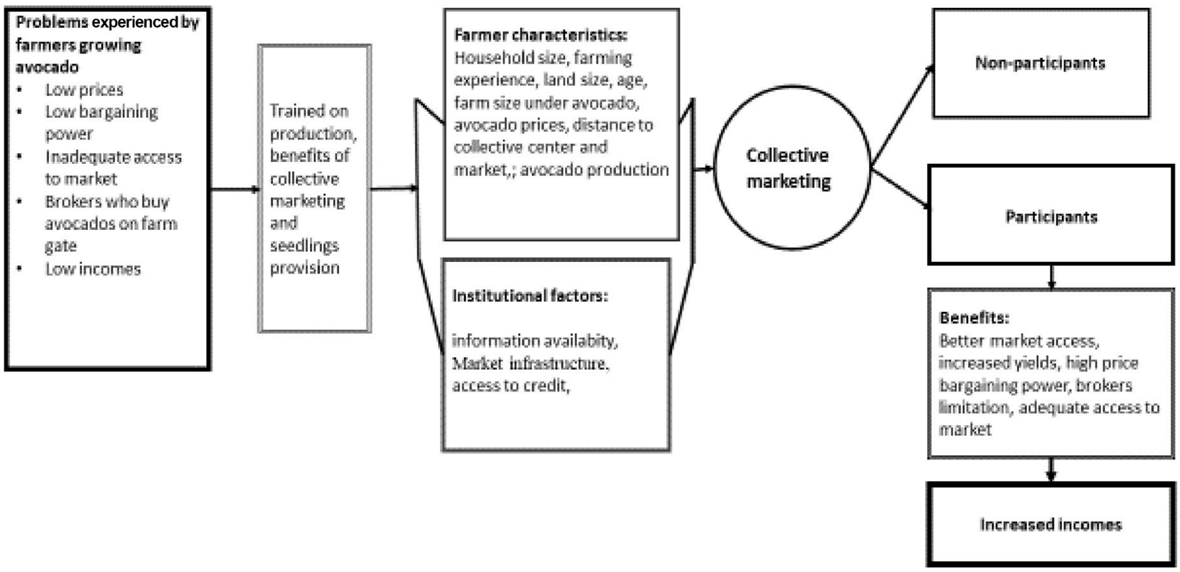


Fig. 1. Conceptual framework of the impact pathway of participating in collective marketing on income (authors construction).

and confidence level desired. The computation of the sample size followed the formula of (COCHRAN, 1977):

$$S = \frac{Z^2 \times P \times (1 - P)}{C^2}$$

Where:

S = represents a sample size, Z = Z value or score, it is the critical value of the normal distribution at the required confidence level. It can take different significance levels. The critical value at 95% confidence level is 1.96, at 90% is 1.28, at 99% is 2.58. This study used 95% confidence.

P = the estimated sample proportion of the study population. This study used 50% as a conservative approach to get the largest possible sample size.

C = is the margin of error. It is the range where the expected true population lies. The precision depends on the margin error and is expressed as a decimal (0.0565).

Then, $S = (1.96)^2 \times 0.5 \times (1 - 0.5) / (0.0565)^2 = 300$.

The sampling was conducted across all the 5 wards constituting the Kigumo sub-county. First, 150 participants in avocado collective marketing were randomly selected from the list presented by the chief representative of registered avocado farmers' groups in each of the 5 wards (Kamau et al., 2018). Secondly, the non-participants were identified, and categorized into 5 strata. A simple random procedure was used to select 30 non-participants from each stratum giving a total of 150 non-participants.

3.3. Data collection

A household survey was conducted in the selected 300 households during August 2020. Data were collected using a standard questionnaire that was administered to the farmers in a face-to-face interview. The main data collected included farmers' socio-economics, demographic characteristics, and collective marketing activities. Additionally, during the interviews farmers were asked to recall and provide information on production and incomes for three consecutive years (2018, 2019, and 2020).

The questionnaire was pretested before the data collection. To pretest the questionnaire, data from ten percent (10%) of respondents (15 participants in avocado collective marketing and 15 non-participants) were collected and analyzed to verify if the questionnaire responds to the objective of the study.

3.3.1. Data analysis

Descriptive statistics (mean and standard deviation) were used to summarize the data on socio-economic, demographic and institutional characteristics while *t*-test was used to assess the significance of differences in observations between participants and non-participants in avocado collective marketing. To analyze factors influencing farmers' income, logistic regression model was used, not for inferential purposes but simply for the purpose of creating propensity scores (Harris & Horst, 2016). A set of few covariates were selected from the data set to get blocks or regions of common support where different matching algorithms were applied.

3.3.2. Model specification for assessing impact

The study adopted the approach applied by (Rosenbaum & Rubin, 1984) based on impact assessment which aimed to determine and compare the impact of participation in collective marketing on income among avocado farmers. A Propensity Score Matching (PSM) approach was adopted and data analyzed using STATA version 15. The propensity score matching model used three principal steps as explained by (Harris & Horst, 2016): the first step estimated the propensity scores created from covariates related to participants' self-selection into a program or intervention; the second step choose the matching algorithms using a common approach to create balanced intervention and comparison groups.; the third step measured the impact after the creation of matches and the assessment of the quality of the matches. In addition to the three main steps, sensitivity analysis was done to check for hidden biases that may arise and affect the matching estimators which reduce the robustness of the analysis due to unobserved variable that affect assignment into treatment and the outcome variable (Becker & Caliendo, 2007).

To estimate the propensity scores, logistic regression model was used. This fundamental approach is included to express the dummy variable that explain the probability of participation in collective marketing or otherwise. It is simply used when computing the probability that the person received the intervention (0/1) given a set of covariates included in the model.

$$Y_i = \alpha\, X_{i+}\, \beta\, D_{i+}\, \mu_i \qquad \text{Equation 1}$$

Where *Yi* is the mean outcome of the target variable *i*; D_i is a dummy variable, $D_i = 1$ for participation in collective marketing and $D_i = 0$ otherwise; μi the normal stochastic term expressing unobserved characteristics that can affect the outcome variable (Ogutu et al., 2014).

X_i is a vector of socio-economic and demographic factors including gender, household education level, distance to the nearest avocado collection center and market, avocado harvested in 2018, 2019, 2020, avocado selling price among others.

The approach expressed in equation (1) is mostly used when evaluating impact in which direct effect is measured from the program D based on outcomes Y. The approach is likely to create biased estimates due to the assumption that participation in collective marketing is exogenously determined while it is potentially endogenous.

Using the PSM technique attempts to reveal or capture the effects of various observed covariates X on participation in each single propensity score. In the context of the present study, propensity score can be explained as the conditional probability that an avocado farmer will participate in collective marketing given his pre-participation characteristics. Wherefore to get the program outcomes, a comparison between participants and non-participants should be done using similar propensity scores.

A conditional independent assumption (CIA) is used to create conditions of a randomized experiment; it implies that once X is controlled for, participation adoption is random and uncorrelated with the outcome variables (Ali & Abdulai, 2010). Therefore, the propensity score under CIA is given by:

$$P(X) = Pr\ (D = 1\ /\ X) = E(D\ /\ X) \qquad \text{Equation 2}$$

Another assumption employed to create condition of a randomized experiment is common support (CSA), it assumes that every participant has a non-participant match and vice versa and ensures that each individual has a positive probability of being matched. The CSA is expressed as:

$$0 < pr(D = 1\ /\ X) < 1 \qquad \text{Equation 3}$$

Then the impact of participation in collective marketing initiatives is expressed as:

$$\tau = Y_1 - Y_0 \qquad \text{Equation 4}$$

Only participation was observed in collective marketing initiatives outcome of avocado for those who received treatment $Y1$ and $Y0$ non-participation in collective marketing outcome of avocado for those who did not participate. That led to conclude that if $\boldsymbol{\tau}$ is a dummy variable showing the effect of participation in collective marketing initiatives, for each farmer, the only observed outcome.

The parameter of interest is the average treatment effect on the treated (*ATT*). It is the outcome generated from treatment for those avocado farmers who were selected for the treatment (Kirui & Njiraini, 2013). *ATT* would give the expected treatment effect of collective marketing participation, which is the difference between the actual income and the income if a household did not participate in collective marketing. This was given by:

$$ATT = E\ (Y_1 - Y_0)\ /\ D = 1) = E\ (Y_1\ /D = 1) - E\ (Y_0\ /D = 1)\ \ldots\ \ldots \text{Equation 5}$$

Given that: $Y1$ is the income for a participant in collective marketing, $Y0$ is the income for a non-participant in collective marketing and D denotes participation of a farmer in collective marketing, where $D = 1$ if a farmer participates and 0 otherwise. $E\ (Y_1/D = 1)$ represented the observations of outcome variable for participants.

Since $E\ (Y_0/D = 1)$ expressed as a counterfactual outcome is not observed for a given avocado farmer, this should imply that although ATT may be estimated using $E\ (Y_0/D = 0)$ which is likely to be biased. This indicated that the main focus of evaluating the impact of participation in the intervention should not lie in estimating $E\ (Y_0/D = 1)$ and not even $E\ (Y_0/D = 0)$ The use of $E\ (Y0\ /D = 0)$ may cause a problem because the avocado farmers who participate and those who do not participate may not be similar before the intervention; hence, the expected difference between these two groups of avocado farmers may not be totally caused by the program intervention.

For non-participant's farmers, average treatment effect on the untreated (ATU) is the average response to treatment. Mathematically this is expressed as below:

$$ATU = E\ (Y_1 - Y_0)\ /\ D = 1) = E\ (Y_1\ /D = 1) - E\ (Y_0\ /D = 1) \qquad \text{Equation 6}$$

The average response to treatment (*ATE*) for a random sample from the population is given by:

$$ATE = E\ (Y_1 - Y_0)\ /\ D = 1) = E\ (Y_1\ /D = 1) - E\ (Y_0\ /D = 1) \qquad \text{Equation 7}$$

Before *ATT* is calculated, the balancing property is tested on $p(X)$, and the matching methods are employed. The test of the balancing property ensures that the distribution of the relevant characteristics is balanced by groups of participants.

In literature, various matching methods have been used. However in this study we used three matching algorithms; Nearest-Neighbor 1 and 5, Matching, Kernel Matching, and Caliper Matching These are the most commonly preferred and used (Ogutu et al., 2014). The use of propensity score matching requires more important and useful steps to come up with good results. Many questions may arise when a researcher prefers to use PSM model to assess the effect of an intervention program such as: how to choose the regression model used to create propensity scores; what kind of covariates are more likely to be used in the model; what does it imply and what the researcher intends to do to sort out the issue in case of unbalancing variable or a score outside the common support region; what to do in case of unobserved variables that constrains the robustness of the entire analysis due to hidden bias raised by its presence. All these questions were answered by different authors such as (Marco & Sabine, 2005).

4. Results and discussion

4.1. Characteristics of participants and non-participants

The results (Table 1) showed that the mean land area allocated to avocado cultivation by participants was (0.8 acres) while for non-participants was (0.4 acres). This implies that participants had allocated significantly more land for avocado than non-participants (P = 0.0001). Farmers with large fields produced more avocado than those with smaller fields. Therefore, the need of good market, transportation

Table 1
Characteristics (continuous variables) of participants and non-participants of avocado growing in Kigumo Sub-County.

Variables	Participants (N = 150)	Non-participants (N = 150)	T- value
Age of household head (years)	56.06 (1.14)	54.03(1.22)	−1.211
Education of household head (years)	10.05(0.25)	9.67(0.27)	−1.058
Household size	4.08(0.141)	3.82(0.141)	−1.269
Farming experience of Household head (years)	23.59(12.97)	24.25(14.27)	.479
Avocado farming experience of Household Head (years)	11.08(8.08)	12.74(9.10)	.805
Total land size (acres)	1.82(1.22)	2.06(1.36)	−1.639
Size of land under avocado trees (acres)	0.8(0.5)	0.37(.28)	−5.343 * * *
Shortest distance to the regular avocado market (km)	1.13(0.11)	0.76(0.09)	−3.322 * *
Distance to the nearest avocado collection center (km)	0.42(0.09)	0.18(0.04)	−2.153 * *
Number of active household members in avocado farming	1.80(0.64)	2.10(0.80)	3.597 * * *

Values in parenthesis are standard deviations for the respective means.
Source: Survey Data (2020) N = 300; * *, * * * denotes significant levels at 5% and 1%

facilities and fair prices may have motivated them to market collectively and increase their price bargaining power. This result was consistent with the findings of (Fred et al., 2020) in Uganda (Methamontri et al., 2022a), in northeast Thailand and (Nyambune, 2017) in Kenya. There are also similar studies about land's influence in decision making such as (Amare et al., 2019) who assessed and found that farmers with large farm size get high production and adopt participation in avocado export market for better prices (Olwande & Mathenge, 2012); indicated the role of land in increasing farmers' production and gives hope to small scale farmers to participate in markets and increase families' incomes. Also (Muhia et al., 2022) reported the influence of land size in decision making to participate in sorghum contracting farming in Laikipia County (Methamontri et al., 2022b); reported that the area allocated to paddy rice was associated with the will of participation in collective marketing.

The shortest distance to the regular avocado market was 1.13 Kilometers for participants and 0.76 Kilometers for non-participants. This means that participants had to walk for a longer distance to the avocado markets than for non-participants. This may explain their participation behavior in collective marketing in order to benefit from facilities that include distance reduction by installing avocado collection centers. This result is consistent with those of (Martey et al., 2012) who reported the influence of distance in making decisions to participate in crops marketing. On the other hand, the nearest avocado collection center was at 0.42 Km and 0.18 Km for participants and non-participants, respectively. The mean difference between the two groups was significant at 5% level (P = 0.015). This observation contradicts the logic that shorter distance encourages participation and does not agree with observations of (Musa et al., 2022a) who reported that shorter distance to collective marketing center increased probability of a farmer joining collective marketing. Explanation for the observation in our study could be that other factors besides distance could be responsible for the decision-making regarding participation. Indeed, perception may be more useful as seen in Table 2.

The mean number of active household members in avocado farming was 1.80 for participants and 2.10 for non-participants. The mean difference between the two groups was significant at 1% level (P = 0.0001). This result would suggest that the more the number of household active members the less is the need to participate in collective marketing. This result agreed with that of (Musa et al., 2022b) who reported that large families size were less likely to adopt agroforestry in Western Kenya. It may also suggest that a family with larger number of adults may consume more avocado which reduces the quantity of avocado sold, or the contribution as labor in avocado production may be less as demonstrated by a study conducted in Western Ethiopia (Gurmis & Melese, 2022).

Fifty-nine percent (59.30%) of participants in avocado collective marketing agreed that roads were accessible while 40.70% disagreed. For non-participants, 21.30% agreed that roads were accessible while 78.70% disagreed. This showed that around 80% of non-participants complained about roads to market accessibility compared to almost 41% of participants. Perception regarding accessibility to road was significantly associated with participation in collective marketing (Chi-square; p = 0.001) (Table 2). This implied that positive perception regarding road accessibility may increase participation in collective marketing. The result was consistent with that of (Peng et al., 2017) who reported that road mobility is necessary for long distance travel and facilitates transportation of products and services.

Perception in regard to government support in market infrastructures was significantly different between participants and non-participants at 5% (Table 2). Around 95% of participants agreed that the government supported them with market infrastructures while 5% disagreed. For non-participants, around 99% disagreed against 1% who agreed that the government supported avocado farmers with market infrastructures. Government market infrastructure support has the potential to motivate avocado farmers to participate in collective marketing due to provision of good roads to markets and collective center. This result is consistent with those of (Arouna, 2018a; Bergaly & Tameko André, 2014) who reported that rural infrastructures, such as, road had a significant role in agricultural production and household income improvement.

Table 2
Characteristics (categorical variables) of participants and non-participants in collective marketing of avocado in Kigumo Sub-County.

Variable		Participants (N = 150)	Nonparticipants (N = 150)	χ^2
Sex of household (Male)	Yes	113(75.30)	110(73.30)	.692
	No	37(24.70)	40(26.70	
Marital status of the Household head	Single	9(6.00)	16(10.70)	.128
	Married	127(84.70)	115(76.70)	
	Divorced	0	3(2.00)	
	Widowed	14(9.30)	16(10.70)	
Labor availability	Yes	96(64.00)	103(68.70)	.392
	No	54(36.00)	47(31.30)	
General credit access	Yes	19(12.7)	15(10)	.466
	No	131(87.3)	135(90)	
Avocado credit access	Yes	10(6.7)	11(7.3)	.821
	No	140(93.3)	139(92.7)	
Perception on government support in market infrastructures	Yes	142(94.7)	1(.7)	.018 * *
	No	8(5.3))	149(99.3)	
Perception on government support in agrochemical	Yes	15(10)	19(12.7)	.466
	No	135(90)	131(87.3)	
Perception on accessibility of road to market	Yes	89(59.30)	32(21.30)	.0001 * * *
	No	61(40.70)	118(78.70)	

Source: Survey Data (2020) N = 300; * *, * * * denotes significant levels at 5% and 1%

4.2. *Production of avocado*

The results (Table 3) indicated that avocado production varied among participants and non-participants of collective marketing from 2018 to 2020 (Table 2). In 2018, the mean avocado production for participants was not significantly different from that of non-participants (P = 0.576).

In 2019, though not significantly different, participants produced more avocado compared to non-participants. This can be explained by the high motivation that participants in collective marketing have due to increased access to better markets and higher bargaining power. This result agrees with those of (Cavatassi et al., 2011) who reported that agricultural intervention programs increased production of participants in Ecuador.

The situation changed significantly in 2020, with a big difference of 361.6kgs observed between avocado produced by participants (1251.3kgs) and non-participants (889.7kgs). This may be explained by the increase in support given by the county government to farmers' groups such as trainings and provision of seedlings. In addition to this, there has been emergence of a new market (export to China) which has

Table 3
Avocado quantity of participants and non-participants farmers in collective marketing in Kigumo sub-county from 2018 to 2020.

Year	Avocado quantity in kgs		
	Participants (N = 150)	Non-participants (N = 150)	T- value
2018	506.3(336.5)	531(411.8)	.754
2019	671.4(540.7)	628.8(377)	−.678
2020	1251.3(735.2)	889.7(526.5)	−6.314 * *

Values in parenthesis are Standard deviations.
Source: Survey Data (2020) N = 300; * * denotes significant levels at 1%

boosted the price of avocado and motivated farmers to invest more in avocado farming. In support of this, Andae (2022) reported that Kenya's avocado exports to China reached seven billion Kenya shillings in 2022.

Further (Johnny et al., 2019), reported that the government of Kenya in collaboration with the Embassy of the Kingdom of the Netherlands and United States Agency for Development (USAID) promoted avocado production through provision of quality seedlings, training farmers in good agricultural practices and linking them to exporters. It is also expected that as farmers gain more understanding of the benefits of collective marketing e.g., increased price bargaining power and incomes, they will invest more in increasing production.

4.3. Selling of avocado

The results (Fig. 2) indicated that farmers who participated in collective marketing sold their avocado at higher prices compared to those that did not participate. In 2018, the price per piece for participants was approximately 7Ksh (0.07USD) and increased to 8Ksh (0.08USD) in 2019–2020. For non-participants, avocado price remained at 5Ksh (0.05USD) during the two consecutive years (2018–2019) and reached at 6Ksh (0.06USD) in 2020. In the three previous consecutive years, participants experienced an increase in price per piece of avocado compared to non-participants whose price did not change significantly. This suggests that collective marketing increases farmers bargaining power by eliminating brokers who have always exploited the farmers. The increasing price of avocado fruit for participants in collective marketing throughout the three years assessed in this study is consistent with the study of (Amare et al., 2019) and (Kamdem, 2016) who reported that participation in collective marketing increased avocado prices in Kenya and 6% on the individual sale price of Cocoa in Cameroon, respectively. Similarly (Mugwe et al., 2019), reported that better prices are among the key benefits of collective marketing participation. It is also consistent with the findings of (Bergaly & Tameko André, 2014) who reported that collective marketing participation had a positive influence on the net price received by Cocoa farmers in Cameroon.

4.4. Incomes from avocado

Income from avocado was significantly different between participants and non-participants in collective marketing (Table 4). In 2018, participants had a mean of 20,782Ksh (207.82USD) and 14,100Ksh (141USD) for non-participants and the difference in mean of income for the two groups of farmers was significant at 1% level (P = 0.0001). In 2019, the mean income for participants was approximately 31,167ksh (311.67USD) and 23,480ksh (234.80USD) for non-participants and the difference in mean between the two groups was statistically significant at 5% level (P = 0.003). This result may indicate the importance of collective marketing participation in increasing household farmers' income.

Table 4
Incomes from avocado and other businesses in Kenya shilling in Kigumo Sub-County.

Variables on Income	Participants N = 150	Non-participants N = 150	Difference	T- value
Income from avocado sales 2018	20782.37 (17596.3)	14099.98 (13960.38)	**6,683** 32.16%	−4.027 * * *
Income from avocado sales 2019	31167.24 (23227.3)	23480.13 (19051.30)	**7,687** 24.66%	−3.275 * *
Income from avocado sales 2020	36835.79 (27849.7)	25672.89 (19084.83)	**11,163** 30.30%	−3.605 * * *
Total Family Income from avocado and other businesses 2018	48317.15 (35837.99)	33090.50 (27538.15)	**15,227** 31.51%	−4.126 * * *
Total Family Income from Avocado and other businesses 2019	56256.49 (37149.62)	40930.01 (32957.04)	**15,326** 27.24%	−3.780 * * *
Total family Income from Avocado and other Businesses 2020	59837.49 (41565.05)	45707.77 (41148.36)	**14,130** 23.61%	−2.959 * *

Survey Data (2020) N = 300; * * and * * * denotes significant levels at 5% and 1%.

In 2020, the income was approximately 36,836ksh (368.36USD) and 25,673Ksh (256.73USD) for participants and non-participants respectively. The mean difference between the two groups was significant at 1% level. The results indicated that from 2018 to 2020, the income from avocado increased significantly for participants compared to their counterparts.

In 2018, the mean total income was 48,317Ksh (483.17USD) for participants and 33,090.5Ksh (330.90USD) for non-participants while in 2019, the mean total income was 56,256.5Ksh (562.57USD) for participants and 40,930Ksh (409.30USD) for their counterparts (Table 4). In 2020, the mean total income was 59,837.5Ksh (598.37USD) for participants and 45,708Ksh (457.08USD) for non-participants. This showed that participants experienced a higher total income compared to non-participants. This was highly significant at 1% level for the two consecutive years 2018 and 2019, but significant at 5% level for the year

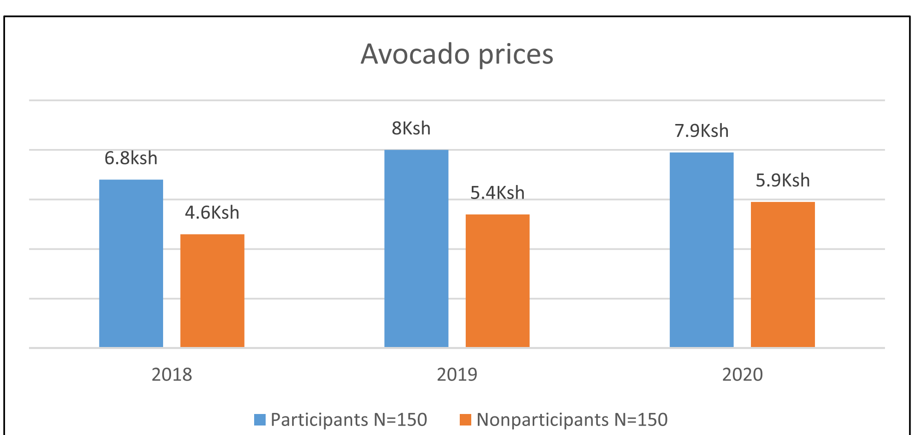


Fig. 2. Prices for avocado in Kenya Shilling in Kigumo Sub-County.

2020 (Table 4). The results on farmers avocado income and total income, were consistent with those of (Barrett, 2008; Nyasulu et al., 2019Nyasulu et al.,2019; Meier zu Selhausen, 2016) who reported collective action initiatives to increase significantly households' incomes and improve their livelihoods.

4.5. Effect of participation on incomes

Table 5 show the ATT estimation on impact of participation in collective marketing on avocado income for three consecutive years estimated using the four matching algorithms. The three outcome variables (avocado income 2018, 2019 and 2020) were analyzed for the average treatment of the treated (ATT), average treatment of the untreated (ATU) and the average treatment causal/effect (ATE) to find out the impact of participation in collective marketing on avocado income. The results revealed that participation in avocado collective marketing significantly increased the income of avocado farmers. The results contradict with those of (Zakari et al., 2021) who, by employing matching techniques, found negative effect of collective marketing on household income in Sahel, Niger. Adopting collective marketing increased avocado income by an average of 11,096Ksh in 2018; 18, 096Ksh in 2019 and 16,657Ksh in 2020 for NNM1; 12,266Ksh in 2018; 15,231Ksh in 2019 and 19,567Ksh in 2020 for NNM5; 10,185Ksh in 2018; 12,683Ksh in 2019; 14,413Ksh in 2020 for Kernel-Based Matching; 11,096Ksh in 2018; 18,009 in 2019; 16,659Ksh in 2020 for Caliper Based Matching. The impact for the four matching algorithms was significant (Table 5). The results indicated that the ATT estimate based on the four matching algorithms was vigorous across the three years (2018, 2019 and2020) and this result is consistent with those of (Arouna, 2018b) who reported bigger impact of collective marketing participation on Paddy rice by smallholder producers in Benin. Similarly (Sikwela & Mushunje, 2013), reported positive and significant impact of collective marketing activities on smallholder farmers 'welfare in Eastern Cape, KwaZulu Natal farmers in South Africa. In Malawi (Mango et al., 2017), reported that marketing collectively within the framework of innovation platforms increased household income while in Sahel, Niger (Mutonyi, 2019) found that farmers who adopted group membership improved significantly their households' income compared to their non-adopters.

The average avocado income gained ranged from 10,185Ksh to 12,266Ksh in 2018; 12,683Ksh to 18,096Ksh in 2019 and 14,413Ksh to 19,567Ksh in 2020, which were significant at 95% confidence level for all matching algorithms throughout the three years used in this study (Table 5). In terms of percentage increase, this translated to 20.43% in 2018; 42.67% in 2019 and 35.75% in 2020 with an overall average increase of 32.95% during the three consecutive years. This corroborates with findings of (Musa et al., 2022a) who reported a 73% increase in incomes due to collective marketing participation. These authors associated the increase to enhanced farmers bargaining power. In our study, the increase in income is highly associated with the better prices offered and increased production, especially in 2020.

The use of Propensity Score Matching model (PSM) in impact assessment, is mostly used to address selected biases with observable variables in an intervention program. But it may operate in the opposite way of its objective such as increasing inefficiency, imbalance, model dependence and increasing biases the worse in impact analysis. However, the current analysis did not realise such limitations as it was tested in section 3.6.

4.6. Balancing tests for propensity score matching quality indicators for the three years (2018, 2019, and 2020)

A balancing property test of the generated propensity scores was conducted (Table 6), accompanied by testing the matching quality using different matching methods as indicated in a brief guide to decisions at each step of the propensity score matching (Harris & Horst, 2016) and

Table 5
Estimated Average treatment effect on Treated for the impact on the income of collective marketing participation in Kigumo Sub-County (2018, 2019, and 2020).

	Matching for year 2018						Matching for year 2019					Matching for year 2020				
Matching algorithm	Outcomes Var.	Tr.	Contr.	Diff.	Std. Err.	T-stat	Treat.	Contr.	Diff.	Std. Err.	T-stat	Treat.	Contr.	Diff.	Std. Err.	T-stat
Nearest Neighbor Matching (1)	ATT	21499	10403	**11096**	3402.85	**3.26**	31803	13795	**18096**	5344.77	**3.37**	36836	20177	**16657**	5807.50	**2.87**
	ATU	13740	11068	−2671			22507	17438.5	−5068			25655	19973	−5682		
	ATE			4235					6589					5717.5		
Nearest Neighbor Matching (5)	ATT	21499	9233	**12266**	2074.82	**5.91**	31803	16572.5	**15231**	3431	**4.44**	36836	17268	**19567**	3588	**5.45**
	ATU	13739.7	21938	8199			22507	33529	11022			25655	38071	12416		
	ATE			10239.5					13148					16065		
Kernel Matching	ATT	21499	11314	**10185**	2048.68	**4.97**	31803	19120	**12683**	3071	**4.13**	36836	22423	**14413**	3552	**4.06**
	ATU	13398	21833	8434.5			21723	33370	11647			24886.5	37516	12630		
	ATE			9322					12176					13549		
Caliper matching (0.5)	ATT	21499	10403	**11096**	3403	**3.26**	31803	13795	**18009**	5344.77	**3.37**	36836	20177	**16659**	5807.50	**2.87**
	ATU	13740	11068	−2671.5			22507	17438.5	−5068			25655	19973	−5682		
	ATE			4236					6589					5717.5		

Table 6
Balancing tests for propensity score matching quality indicators for the three years (2018, 2019, 2020).

	Matching for the year 2018				Matching for the year 2019				Matching for the year 2020			
	NN1	NN5	Kernel	Caliper	NN1	NN5	Kernel	Caliper	NN1	NN5	Kernel	Caliper
Pseudo R^2 Unmatched	0.089	0.089	0.089	0.089	0.087	0.087	0.087	0.087	0.088	0.088	0.088	0.088
Pseudo R^2 Matched	0.009	0.023	0.004	0.009	0.009	0.022	0.004	0.009	0.010	0.024	0.004	0.010
P-value Unmatched	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P-value Matched	0.825	0.329	0.987	0.825	0.802	0.334	0.990	0.802	0.756	0.286	0.991	0.756
Mean bias before matching	14.0	14.0	14.0	14.0	14.2	14.2	14.2	14.2	13.8	13.8	13.8	13.8
Mean bias after matching	7.5	11.8	4.3	7.5	8	12.4	4.4	8.0	8.6	12.9	5.0	8.6
%Bias reduction	45.4	15.7	69.3	45.4	43.7	11.4	69.1	47.7	37.7	6.5	63.8	37.7

(Rosenbaum & Rubin, 1983). These authors emphasize the importance of assessing the quality of matches to be sure that there is similarity of distribution of propensity scores between the comparison group and the intervention group. The results indicated the values of Pseudo R^2, P-value, mean bias, and %bias reduction before matching and after matching. Furthermore, the Pseudo R^2, the Mean bias were high before matching but reduced significantly after matching. The results also reported significant P-values before matching which became insignificant after matching for all matching methods, thus confirming success of the matching procedure.

The mean bias reduced from 14.2 to the range of 4.3 and 12.9, which goes with the bias reduction of 6.5–69.3 per cent. The same findings indicated that the values of Pseudo R^2 which were higher before matching reduced considerably from 0.089 to the range of 0.004 and 0.023 in 2018, from 0.087 to the range of 0.004 and 0.022 in 2019, from 0.088 to the range of 0.004 and 0.024 in 2020, all after matching (Table 6). The significant reduction of the values of Pseudo R^2 across the matching methods manifests that there were no systematic differences in the distribution of the covariates between the participants and non-participants in avocado collective marketing. This result is consistent with that of (Sianesi, 2004) who suggested that the Pseudo R^2 should be lower whereas the p-value of the likelihood ratio tested in the study should be insignificant (Table 6) to confirm a successful match. Across the matching algorithms, the reduction of the mean biasness after matching ranged from 69.3% to 6.5%.

4.7. Sensitivity analysis for estimated average treatment effects (ATT)

The effect of independent variables on dependent variables under certain specific conditions is understood using the sensitivity analysis concept to check the hidden biases that may arise and affect the matching estimators (Becker & Caliendo, 2007). The results (Table 7; 8; 9) indicated the results of P-value at different levels of gamma. When gamma equals to 1, the P-value (0.000) was similar to the one estimated in the matching analysis. The values of the p-values were the same for gamma equals to 1 up to gamma equals to 3. This helped to assume that due to unobserved confounders, there was no hidden biases for the three years (2018, 2019, and 2020). Moreover, there was no presence of outliers on the estimated parameters. The results showed also that, with an increase of gamma by 0.5 from 3 to 3.5 values of gamma, the P-value increase to 8.9e-16 in 2018, to 6.7e-16 in 2019 and 2020 which are very below the usual P-value (0.05). These results came to fortify the assumption that insures the non-presence of outliers on the estimated parameters.

The results (Table 7; 8; 9) did not show any value of gamma that indicates the insignificant level in the matching analysis. This implies that the results are not sensitive to hidden biases that may be caused by unobserved confounders. Therefore, the conclusion and interpretation of the results of the impact on the income of avocado collective marketing participation can be made without caution.

Table 7
Sensitivity analysis for Estimated Average Treatment Effects (ATT) for year 2018.

Gamma	Sig+	Sig-	t-hat+	t-hat-	CI+	CI-
1	0.000	0.000	15754	15754	13761	17979
1.5	0.000	0.000	13005	19248	11490	21408
2	0.000	0.000	11412	21492	10107.5	23922
2.5	0.000	0.000	10420	23200	8253	25836
3	0.000	0.000	9436.5	24984	6843	27480
3.5	8.9e-16	0.000	8001	26010	6030	28902
4	4.9e-14	0.000	7242	26997	5412	30000
4.5	1.1e-13	0.000	6492	27864	4992	31228
5	1.4e-12	0.000	6009	28980	4494	32481
5.5	1.1e-11	0.000	5511	29829	4047	33330
6	6.1e-10	0.000	5292	30021	3753	34437
6.5	2.6e-09	0.000	5001	31098	3510	34995
7	9.2e-09	0.000	4752	31743	3300	35335
7.5	2.7e-08	0.000	4494	32478	3120	36192
8	7.1e-08	0.000	4245	32601	2985	36660

Gamma -log odds of differential assignment due to unobserved factors.
Sig + -upper bound significance level.
Sig- -lower bound significance level.
t-hat + -upper bound Hodges-Lehmann point estimate.
t-hat- -lower bound Hodges-Lehmann point estimate.
CI + -upper bound confidence interval (a = 0.95).
CI− -lower bound confidence interval (a = 0.95).

Table 8
Sensitivity analysis for Estimated Average Treatment Effects (ATT) for year 2019.

Gamma	Sig+	Sig-	t-hat+	t-hat-	CI+	CI-
1	0.000	0.000	25520	25520	23250	28500
1.5	0.000	0.000	22009.5	30264	18498	33694.5
2	0.000	0.000	18297	33750	15000	37490
2.5	0.000	0.000	15750	36330	12498	40284
3	0.000	0.000	13959	38742	10791	42484
3.5	6.7e-16	0.000	12346.5	40611	9498	43993
4	4.0e-14	0.000	11152	41994	8319	45493
4.5	9.5e-13	0.000	10245	43218	7403	46699.5
5	1.2e-12	0.000	9492	43998	6744	47994
5.5	9.5e-11	0.000	8685	45000	6045	49428
6	5.4e-10	0.000	8104	45754.5	5556	50008
6.5	2.3e-09	0.000	7500	46683	5238	51697.5
7	8.2e-09	0.000	7091	47484	4875	52495
7.5	2.5e-08	0.000	6724	47995	4626	53490
8	6.4e-08	0.000	6255	48978	4371	54193.5

Gamma -log odds of differential assignment due to unobserved factors.
Sig + -upper bound significance level.
Sig- -lower bound significance level.
t-hat + -upper bound Hodges-Lehmann point estimate.
t-hat- -lower bound Hodges-Lehmann point estimate.
CI + -upper bound confidence interval (a = 0.95).
CI− -lower bound confidence interval (a = 0.95).

Table 9
Sensitivity analysis for Estimated Average Treatment Effects (ATT) for year 2020.

Gamma	Sig+	Sig-	t-hat+	t-hat-	CI+	CI-
1	0.000	0.000	30226	30226	25875.5	32505
1.5	0.000	0.000	24125.5	33976	21300	38265.5
2	0.000	0.000	21225.5	38600	17000	42200
2.5	0.000	0.000	17750	41473	13800	45630.5
3	0.000	0.000	15440.5	44137	12000	49471
3.5	6.7e-16	0.000	13590	46196	10500	50139
4	3.7e-14	0.000	12450	48600	9200	51976
4.5	8.7e-13	0.000	11250	50008	8250	54000
5	1.1e-12	0.000	10490	50200	7500	55144
5.5	8.8e-11	0.000	9565	51200	7000	57500
6	5.0e-10	0.000	8800	52293	6500	58952
6.5	2.2e-09	0.000	8317	53600	6000	59476
7	7.7e-09	0.000	8000	54500	5750	59742
7.5	2.3e-08	0.000	7500	55180	5500	60625.5
8	6.1e-08	0.000	7200	56502	5250	61000

Gamma -log odds of differential assignment due to unobserved factors.
Sig + -upper bound significance level.
Sig- -lower bound significance level.
t-hat + -upper bound Hodges-Lehmann point estimate.
t-hat- -lower bound Hodges-Lehmann point estimate.
CI + -upper bound confidence interval (a = 0.95).
CI− -lower bound confidence interval (a = 0.95).

5. Conclusion and policy implication

This study determined the impact of participation in collective marketing on smallholder farmers' income in Kigumo Sub-County, Kenya. This comparative study showed that participants and non-participants differed in five key characteristics. They differed in terms of size of land under avocado, distance to regular avocado market, number of active members providing labor for avocado production, perception of government support in market infrastructure and perception of accessibility road to market.

Participants produced more avocado than non-participants during 2019 and 2020. They also consistently received better prices than non-participants across the three years (2018, 2019, and 2020). This translated to better incomes from avocado for participants compared to non-participants.

The results from the propensity score matching estimates revealed that farmers who participated in collective marketing obtained higher avocado income than non-participants by a margin of 10,185Ksh (101.85USD) to 12,266Ksh (122.66USD) in 2018; 12,683Ksh (126.83USD) to 18,093Ksh (180.96USD) in 2019 and 14,413Ksh (144.13USD) to 19,567Ksh (195.67USD) in 2020. On average incomes increased by 32.95% for those participating in collective marketing. Policymakers should therefore encourage smallholder avocado farmers to intensify the land allocated to avocado cultivation and promote collective marketing strategy. This is expected to lead to increased avocado production, spur domestic consumption, and increase local and international markets.

We recommend that the county government and avocado stakeholders should support farmers with improved roads to enable farmers to access local markets and avocado collection centers. Promotion of participation in collective marketing can be done through interventions such as providing training and improvement of market infrastructures. These activities are envisaged to empower smallholder avocado farmers and motivate them to participate in collective marketing.

CRediT authorship contribution statement

Samuel Kwizerimana: Conceptualization, Methodology, Formal analysis, Writing – original draft. **Jayne Mugwe:** Conceptualization, Investigation, Project administration, Writing – review & editing. **Bekele Nigat:** Investigation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

The authors appreciate the farmers who participated in this study. This research did not receive any specific grant from funding agencies in the public, commercial, or not for profit sector.

Appendix A. Results of Propensity Scores

```
. pscore MAINLYSellAvocado HHGender1_A HHeducationStatus LabourSufficiency GovernmentSupport_CreditAccess GovernmentSupport_Agrochemicals Governm
> entSupport_MarketingInfra GeneralCreditAccess AgriculturalCreditAccess MarketingInformationAvailablity, pscore(mypscore) comsup logit


****************************************************
Algorithm to estimate the propensity score
****************************************************


The treatment is MAINLYSellAvocado

MAINLYSellAvoca |
             do |      Freq.     Percent        Cum.
----------------+-----------------------------------
Nonparticipants |        150       50.00       50.00
   Participants |        150       50.00      100.00
----------------+-----------------------------------
          Total |        300      100.00
```

```
Note: the common support option has been selected
The region of common support is [.22757973, .92085532]
```

```
Description of the estimated propensity score
in region of common support

                 Estimated propensity score
-------------------------------------------------------------
      Percentiles      Smallest
 1%     .2275797       .2275797
 5%     .2927205       .2275797
10%     .2927205       .2275797       Obs                 291
25%     .3633113       .2275797       Sum of Wgt.         291

50%     .5126625                      Mean           .5142563
                        Largest       Std. Dev.      .1690437
75%     .6574659       .7907973
90%     .7234658       .8911368       Variance       .0285758
95%     .7809321       .8911368       Skewness      -.0056981
99%     .8911368       .9208553       Kurtosis       1.840056
```

```
******************************************************
Step 1: Identification of the optimal number of blocks
Use option detail if you want more detailed output
******************************************************


The final number of blocks is 5

This number of blocks ensures that the mean propensity score
is not different for treated and controls in each blocks



**********************************************************
Step 2: Test of balancing property of the propensity score
Use option detail if you want more detailed output
**********************************************************


The balancing property is satisfied


This table shows the inferior bound, the number of treated
and the number of controls for each block

  Inferior |
  of block |   MAINLYSellAvocado
  of pscore |  Nonpartic  Participa |     Total
-----------+----------------------+----------
        .2 |         65         18 |        83
        .4 |         39         54 |        93
        .6 |         36         76 |       112
        .8 |          1          2 |         3
-----------+----------------------+----------
     Total |        141        150 |       291

Note: the common support option has been selected
```

APPENDIX B. Results of PSM analysis from matching stage

1. PSM matching with nearest neighbor 1 (avocadosellingincome2018)

```
. psmatch2 MAINLYSellAvocado, outcome( AvocadoSellingIncome2018 ) pscore(mypscore) neighbor(1) ate
```

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
AvocadoSe~me2018	Unmatched	21499.0069	13739.7292	7759.27773	1847.04224	4.20
	ATT	21499.0069	10403.3103	11095.6966	3402.85178	3.26
	ATU	13739.7292	11068.2083	-2671.52083	.	.
	ATE			4235.90657	.	.

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support On suppor	Total
Untreated	144	144
Treated	145	145
Total	289	289

```
.
.
. pstest HHGender1_A HHeducationStatus LabourSufficiency GovernmentSupport_CreditAccess GovernmentSupport_Agrochemicals GovernmentSupport_Marketi
> ngInfra GeneralCreditAccess AgriculturalCreditAccess MarketingInformationAvailablity, both graph
```

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|	V(T)/ V(C)
HHGender1_A	U	.75172	.72917	5.1		0.44	0.663	.
	M	.75172	.78621	-7.8	-52.9	-0.69	0.488	.
HHeducationStatus	U	1.6483	1.625	3.3		0.28	0.776	1.17
	M	1.6483	1.6276	3.0	11.1	0.25	0.800	1.17
LabourSufficiency	U	.64138	.68056	-8.3		-0.70	0.484	.
	M	.64138	.6	8.7	-5.6	0.72	0.469	.
GovernmentSupport_CreditAccess	U	0	0	.		.	.	.
	M	0	0	.	.	.	.	.
GovernmentSupport_Agrochemicals	U	.0069	.02083	-11.9		-1.01	0.312	.
	M	.0069	0	5.9	50.5	1.00	0.318	.
GovernmentSupport_MarketingInfra	U	.09655	.11111	-4.8		-0.40	0.686	.
	M	.09655	.09655	0.0	100.0	0.00	1.000	.
GeneralCreditAccess	U	.13103	.08333	15.4		1.31	0.191	.
	M	.13103	.08276	15.6	-1.2	1.33	0.185	.
AgriculturalCreditAccess	U	.06207	.05556	2.8		0.23	0.815	.
	M	.06207	.02759	14.6	-429.4	1.42	0.157	.
MarketingInformationAvailablity	U	1.7172	1.4167	60.7		5.16	0.000	0.90
	M	1.7172	1.6966	4.2	93.1	0.36	0.717	0.96

* if variance ratio outside [0.72; 1.39] for U and [0.72; 1.39] for M

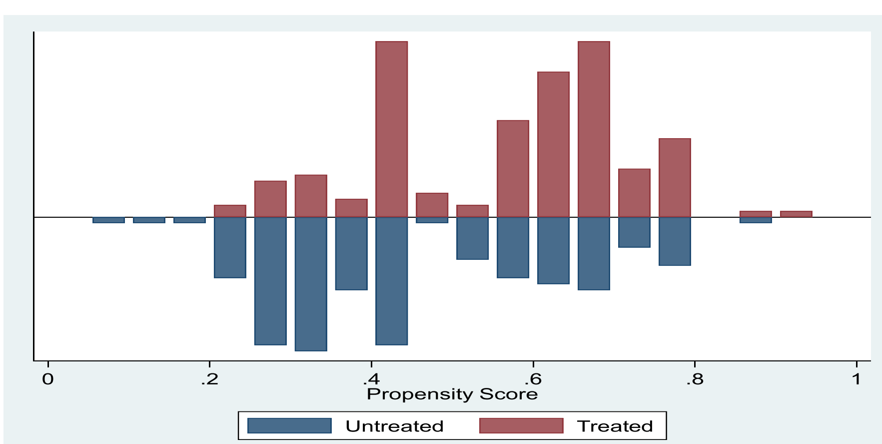
Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.089	35.53	0.000	14.0	6.7	72.6*	0.73	0
Matched	0.009	3.59	0.825	7.5	6.9	22.3	1.18	0

* if B>25%, R outside [0.5; 2]

```
.
.
. psgraph

.
```

Graph.



2. Nearest neighbor 5 (avocadosellingincome2018

. psmatch2 MAINLYSellAvocado, outcome(AvocadoSellingIncome2018) pscore(mypscore) neighbor(5) ate

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
AvocadoSe~me2018	Unmatched	21499.0069	13739.7292	7759.27773	1847.04224	4.20
	ATT	21499.0069	9232.74207	12266.2648	2074.82145	5.91
	ATU	13739.7292	21938.4028	8198.67361	.	.
	ATE			10239.5066	.	.

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support On suppor	Total
Untreated	144	144
Treated	145	145
Total	289	289

. pstest HHGender1_A HHeducationStatus LabourSufficiency GovernmentSupport_CreditAccess GovernmentSupport_Agrochemicals GovernmentSupport_Marketi
> ngInfra GeneralCreditAccess AgriculturalCreditAccess MarketingInformationAvailablity, both graph

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|	V(T)/ V(C)
HHGender1_A	U	.75172	.72917	5.1		0.44	0.663	.
	M	.75172	.83586	-19.1	-273.0	-1.77	0.077	.
HHeducationStatus	U	1.6483	1.625	3.3		0.28	0.776	1.17
	M	1.6483	1.5724	10.9	-225.9	0.96	0.337	1.36
LabourSufficiency	U	.64138	.68056	-8.3		-0.70	0.484	.
	M	.64138	.60138	8.4	-2.1	0.70	0.484	.
GovernmentSupport_CreditAccess	U	0	0	.		.	.	.
	M	0	0	.	.	.	.	.
GovernmentSupport_Agrochemicals	U	.0069	.02083	-11.9		-1.01	0.312	.
	M	.0069	.00414	2.4	80.2	0.32	0.752	.
GovernmentSupport_MarketingInfra	U	.09655	.11111	-4.8		-0.40	0.686	.
	M	.09655	.06207	11.3	-136.8	1.09	0.279	.
GeneralCreditAccess	U	.13103	.08333	15.4		1.31	0.191	.
	M	.13103	.05517	24.5	-59.0	2.23	0.026	.
AgriculturalCreditAccess	U	.06207	.05556	2.8		0.23	0.815	.
	M	.06207	.04276	8.2	-196.5	0.74	0.462	.
MarketingInformationAvailablity	U	1.7172	1.4167	60.7		5.16	0.000	0.90
	M	1.7172	1.669	9.7	83.9	0.86	0.392	1.02

* if variance ratio outside [0.72; 1.39] for U and [0.72; 1.39] for M

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.089	35.53	0.000	14.0	6.7	72.6*	0.73	0
Matched	0.023	9.16	0.329	11.8	10.3	35.3*	2.31*	0

* if B>25%, R outside [0.5; 2]

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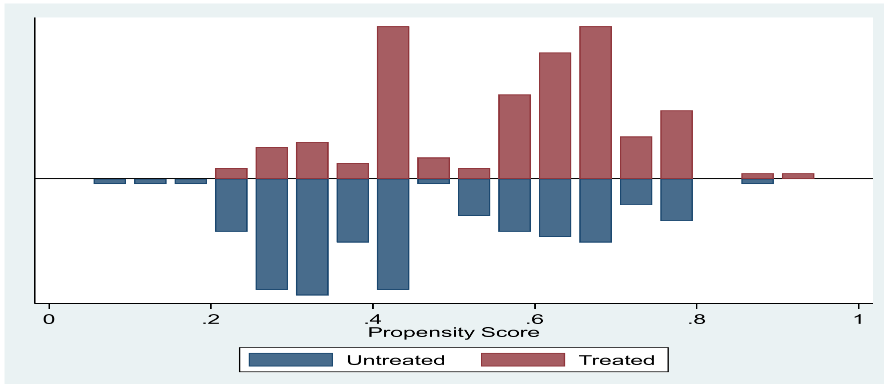
. psgraph

Graph.



3. Kernel (avocadosellingincome2018)

```
. psmatch2 MAINLYSellAvocado, outcome( AvocadoSellingIncome2018 ) pscore(mypscore) kernel ate
```

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
AvocadoSe~me2018	Unmatched	21499.0069	13739.7292	7759.27773	1847.04224	4.20
	ATT	21499.0069	11314.0983	10184.9086	2048.68755	4.97
	ATU	13398.3121	21832.8528	8434.54077	.	.
	ATE			9321.96501	.	.

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support Off suppo	On suppor	Total
Untreated	3	141	144
Treated	0	145	145
Total	3	286	289

```
. pstest HHGender1_A HHeducationStatus LabourSufficiency GovernmentSupport_CreditAccess GovernmentSupport_Agrochemicals GovernmentSupport_Marketi
> ngInfra GeneralCreditAccess AgriculturalCreditAccess MarketingInformationAvailablity, both graph
```

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|	V(T)/ V(C)
HHGender1_A	U	.75172	.72917	5.1		0.44	0.663	.
	M	.75172	.79526	-9.9	-93.0	-0.88	0.378	.
HHeducationStatus	U	1.6483	1.625	3.3		0.28	0.776	1.17
	M	1.6483	1.639	1.3	60.1	0.11	0.911	1.10
LabourSufficiency	U	.64138	.68056	-8.3		-0.70	0.484	.
	M	.64138	.63788	0.7	91.1	0.06	0.951	.
GovernmentSupport_CreditAccess	U	0	0	.		.	.	.
	M	0	0	.	.	.	.	.
GovernmentSupport_Agrochemicals	U	.0069	.02083	-11.9		-1.01	0.312	.
	M	.0069	.00193	4.2	64.3	0.64	0.525	.
GovernmentSupport_MarketingInfra	U	.09655	.11111	-4.8		-0.40	0.686	.
	M	.09655	.10113	-1.5	68.6	-0.13	0.897	.
GeneralCreditAccess	U	.13103	.08333	15.4		1.31	0.191	.
	M	.13103	.09951	10.2	33.9	0.84	0.402	.
AgriculturalCreditAccess	U	.06207	.05556	2.8		0.23	0.815	.
	M	.06207	.0515	4.5	-62.3	0.39	0.698	.
MarketingInformationAvailablity	U	1.7172	1.4167	60.7		5.16	0.000	0.90
	M	1.7172	1.7074	2.0	96.7	0.17	0.863	0.98

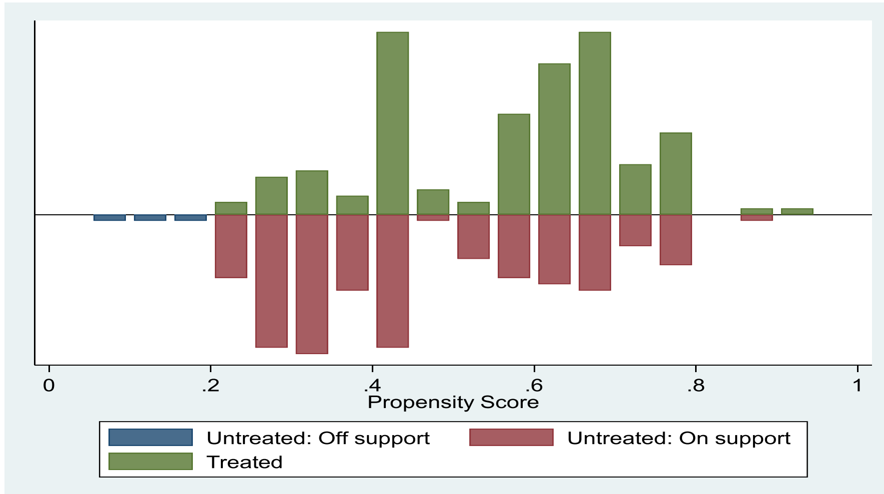
* if variance ratio outside [0.72; 1.39] for U and [0.72; 1.39] for M

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.089	35.53	0.000	14.0	6.7	72.6*	0.73	0
Matched	0.004	1.79	0.987	4.3	3.1	15.6	1.36	0

* if B>25%, R outside [0.5; 2]

```
.
.
. psgraph
.
```

Graph.



4. Caliper matching 0.5 (avocadosellingincome2018)

```
. psmatch2 MAINLYSellAvocado, outcome( AvocadoSellingIncome2018 ) pscore(mypscore) caliper (0.5) ate
```

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
AvocadoSe~me2018	Unmatched	21499.0069	13739.7292	7759.27773	1847.04224	4.20
	ATT	21499.0069	10403.3103	11095.6966	3402.85178	3.26
	ATU	13739.7292	11068.2083	-2671.52083	.	.
	ATE			4235.90657	.	.

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support On suppor	Total
Untreated	144	144
Treated	145	145
Total	289	289

```
. pstest HHGender1_A HHeducationStatus LabourSufficiency GovernmentSupport_CreditAccess GovernmentSupport_Agrochemicals GovernmentSupport_Marketi
> ngInfra GeneralCreditAccess AgriculturalCreditAccess MarketingInformationAvailablity, both graph
```

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|	V(T)/V(C)
HHGender1_A	U	.75172	.72917	5.1		0.44	0.663	.
	M	.75172	.78621	-7.8	-52.9	-0.69	0.488	.
HHeducationStatus	U	1.6483	1.625	3.3		0.28	0.776	1.17
	M	1.6483	1.6276	3.0	11.1	0.25	0.800	1.17
LabourSufficiency	U	.64138	.68056	-8.3		-0.70	0.484	.
	M	.64138	.6	8.7	-5.6	0.72	0.469	.
GovernmentSupport_CreditAccess	U	0	0	.		.	.	.
	M	0	0	.	.	.	.	.
GovernmentSupport_Agrochemicals	U	.0069	.02083	-11.9		-1.01	0.312	.
	M	.0069	0	5.9	50.5	1.00	0.318	.
GovernmentSupport_MarketingInfra	U	.09655	.11111	-4.8		-0.40	0.686	.
	M	.09655	.09655	0.0	100.0	0.00	1.000	.
GeneralCreditAccess	U	.13103	.08333	15.4		1.31	0.191	.
	M	.13103	.08276	15.6	-1.2	1.33	0.185	.
AgriculturalCreditAccess	U	.06207	.05556	2.8		0.23	0.815	.
	M	.06207	.02759	14.6	-429.4	1.42	0.157	.
MarketingInformationAvailablity	U	1.7172	1.4167	60.7		5.16	0.000	0.90
	M	1.7172	1.6966	4.2	93.1	0.36	0.717	0.96

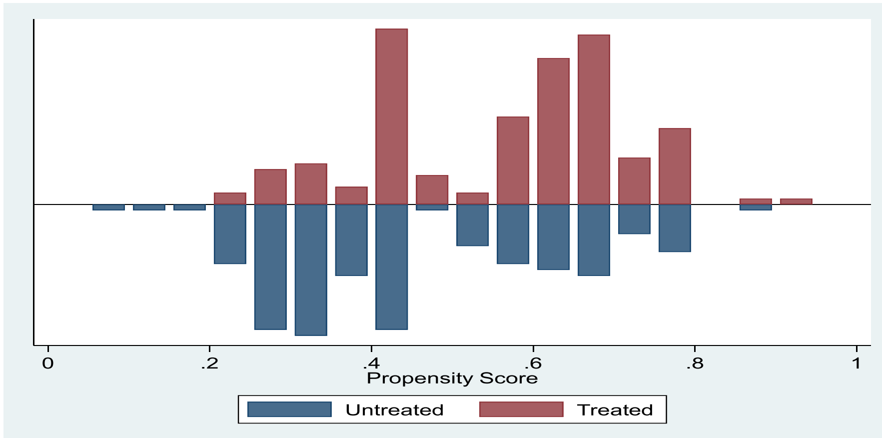
* if variance ratio outside [0.72; 1.39] for U and [0.72; 1.39] for M

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.089	35.53	0.000	14.0	6.7	72.6*	0.73	0
Matched	0.009	3.59	0.825	7.5	6.9	22.3	1.18	0

* if B>25%, R outside [0.5; 2]

```
. psgraph

.
```

Graph.



1. Nearest neighbor 1 (avocadosellingincome2019)

```
. psmatch2 MAINLYSellAvocado, outcome( AvocadoSellingIncome2019 ) pscore(mypscore) neighbor(1) ate
```

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
AvocadoSe~me2019	Unmatched	31803.3061	22506.8681	9296.43807	2704.47097	3.44
	ATT	31803.3061	13794.6531	18008.6531	5344.77582	3.37
	ATU	22506.8681	17438.5764	-5068.29167	.	.
	ATE			6589.13402	.	.

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support On suppor	Total
Untreated	144	144
Treated	147	147
Total	291	291

```
. pstest HHGender1_A HHeducationStatus LabourSufficiency GovernmentSupport_CreditAccess GovernmentSupport_Agrochemicals GovernmentSupport_Market
> ingInfra GeneralCreditAccess AgriculturalCreditAccess MarketingInformationAvailablity, both graph
```

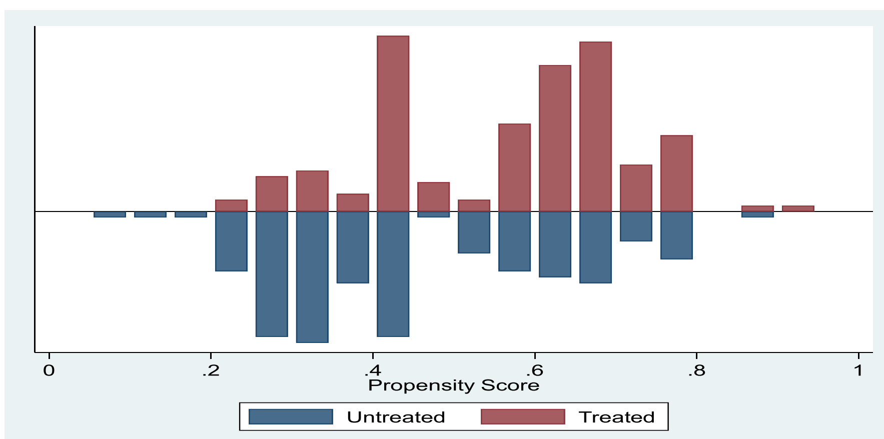
Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|	V(T)/ V(C)
HHGender1_A	U	.7619	.72917	7.5		0.64	0.523	.
	M	.7619	.78912	-6.2	16.9	-0.56	0.578	.
HHeducationStatus	U	1.6395	1.625	2.1		0.18	0.858	1.14
	M	1.6395	1.6463	-1.0	52.9	-0.08	0.933	1.13
LabourSufficiency	U	.63946	.68056	-8.7		-0.74	0.461	.
	M	.63946	.59864	8.6	0.7	0.72	0.473	.
GovernmentSupport_CreditAccess	U	0	0	.		.	.	.
	M	0	0	.	.	.	.	.
GovernmentSupport_Agrochemicals	U	.0068	.02083	-12.0		-1.03	0.306	.
	M	.0068	0	5.8	51.5	1.00	0.318	.
GovernmentSupport_MarketingInfra	U	.10204	.11111	-2.9		-0.25	0.803	.
	M	.10204	.08844	4.4	-50.0	0.40	0.692	.
GeneralCreditAccess	U	.12925	.08333	14.9		1.27	0.206	.
	M	.12925	.08163	15.4	-3.7	1.33	0.185	.
AgriculturalCreditAccess	U	.06803	.05556	5.2		0.44	0.660	.
	M	.06803	.02721	16.9	-227.3	1.65	0.101	.
MarketingInformationAvailablity	U	1.7143	1.4167	60.0		5.12	0.000	0.90
	M	1.7143	1.6871	5.5	90.9	0.48	0.633	0.95

* if variance ratio outside [0.72; 1.38] for U and [0.72; 1.38] for M

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.087	35.18	0.000	14.2	8.1	71.9*	0.70	0
Matched	0.009	3.81	0.802	8.0	6.0	22.7	1.48	0

* if B>25%, R outside [0.5; 2]

Graph.



2. Nearest Neighbor 5 (avocadosellingIncome 2019)

```
.  psmatch2 MAINLYSellAvocado, outcome( AvocadoSellingIncome2019 ) pscore(mypscore) neighbor(5) ate
```

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
AvocadoSe~me2019	Unmatched	31803.3061	22506.8681	9296.43807	2704.47097	3.44
	ATT	31803.3061	16572.5306	15230.7755	3431.31217	4.44
	ATU	22506.8681	33528.8833	11022.0153	.	.
	ATE			13148.09	.	.

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support On suppor	Total
Untreated	144	144
Treated	147	147
Total	291	291

```
.
. pstest HHGender1_A HHeducationStatus LabourSufficiency GovernmentSupport_CreditAccess GovernmentSupport_Agrochemicals GovernmentSupport_Marketi
> ngInfra GeneralCreditAccess AgriculturalCreditAccess MarketingInformationAvailablity, both graph
```

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|	V(T)/ V(C)
HHGender1_A	U	.7619	.72917	7.5		0.64	0.523	.
	M	.7619	.84218	-18.4	-145.2	-1.73	0.085	.
HHeducationStatus	U	1.6395	1.625	2.1		0.18	0.858	1.14
	M	1.6395	1.5755	9.3	-342.4	0.82	0.411	1.33
LabourSufficiency	U	.63946	.68056	-8.7		-0.74	0.461	.
	M	.63946	.59592	9.2	-5.9	0.77	0.444	.
GovernmentSupport_CreditAccess	U	0	0	.		.	.	.
	M	0	0	.	.	.	.	.
GovernmentSupport_Agrochemicals	U	.0068	.02083	-12.0		-1.03	0.306	.
	M	.0068	.00408	2.3	80.6	0.32	0.752	.
GovernmentSupport_MarketingInfra	U	.10204	.11111	-2.9		-0.25	0.803	.
	M	.10204	.0585	14.1	-380.0	1.37	0.171	.
GeneralCreditAccess	U	.12925	.08333	14.9		1.27	0.206	.
	M	.12925	.05442	24.3	-63.0	2.23	0.026	.
AgriculturalCreditAccess	U	.06803	.05556	5.2		0.44	0.660	.
	M	.06803	.04218	10.7	-107.3	0.97	0.333	.
MarketingInformationAvailablity	U	1.7143	1.4167	60.0		5.12	0.000	0.90
	M	1.7143	1.6599	11.0	81.7	0.97	0.334	1.01

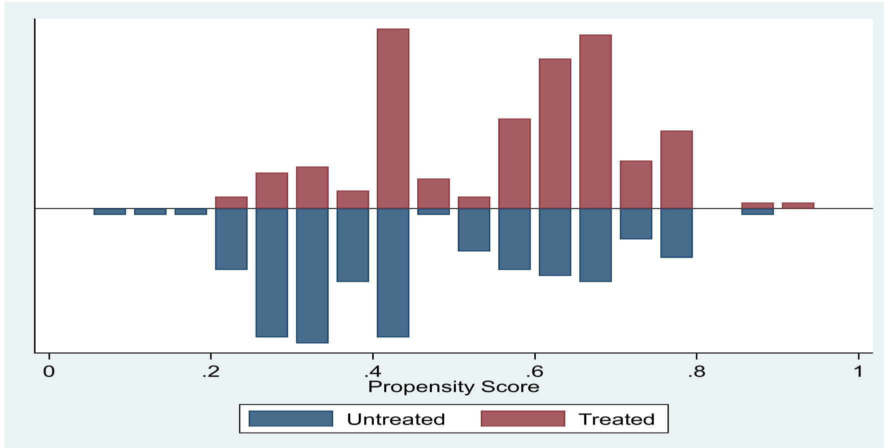
* if variance ratio outside [0.72; 1.38] for U and [0.72; 1.38] for M

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.087	35.18	0.000	14.2	8.1	71.9*	0.70	0
Matched	0.022	9.10	0.334	12.4	10.8	35.0*	2.23*	0

* if B>25%, R outside [0.5; 2]

```
. psgraph

.
```

Graph.



3. Kernel matching (avocadosellingincome2019)

```
. psmatch2 MAINLYSellAvocado, outcome( AvocadoSellingIncome2019 ) pscore(mypscore) kernel ate
```

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
AvocadoSe~me2019	Unmatched	31803.3061	22506.8681	9296.43807	2704.47097	3.44
	ATT	31803.3061	19120.4367	12682.8695	3071.45182	4.13
	ATU	21722.6738	33369.7097	11647.036	.	.
	ATE			12175.7427	.	.

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support Off suppo	On suppor	Total
Untreated	3	141	144
Treated	0	147	147
Total	3	288	291

```
. pstest HHGender1_A HHeducationStatus LabourSufficiency GovernmentSupport_CreditAccess GovernmentSupport_Agrochemicals GovernmentSupport_Marketi
> ngInfra GeneralCreditAccess AgriculturalCreditAccess MarketingInformationAvailablity, both graph
```

Variable	Unmatched Matched	Mean Treated	Control	%bias	%reduct |bias|	t-test t	p>|t|	V(T)/ V(C)
HHGender1_A	U	.7619	.72917	7.5		0.64	0.523	.
	M	.7619	.80169	-9.1	-21.5	-0.82	0.411	.
HHeducationStatus	U	1.6395	1.625	2.1		0.18	0.858	1.14
	M	1.6395	1.6427	-0.5	77.3	-0.04	0.968	1.07
LabourSufficiency	U	.63946	.68056	-8.7		-0.74	0.461	.
	M	.63946	.63331	1.3	85.0	0.11	0.913	.
GovernmentSupport_CreditAccess	U	0	0	.		.	.	.
	M	0	0	.	.	.	.	.
GovernmentSupport_Agrochemicals	U	.0068	.02083	-12.0		-1.03	0.306	.
	M	.0068	.0019	4.2	65.1	0.64	0.525	.
GovernmentSupport_MarketingInfra	U	.10204	.11111	-2.9		-0.25	0.803	.
	M	.10204	.1005	0.5	83.0	0.04	0.965	.
GeneralCreditAccess	U	.12925	.08333	14.9		1.27	0.206	.
	M	.12925	.0989	9.8	33.9	0.82	0.415	.
AgriculturalCreditAccess	U	.06803	.05556	5.2		0.44	0.660	.
	M	.06803	.05065	7.2	-39.4	0.63	0.530	.
MarketingInformationAvailablity	U	1.7143	1.4167	60.0		5.12	0.000	0.90
	M	1.7143	1.7005	2.8	95.4	0.24	0.808	0.98

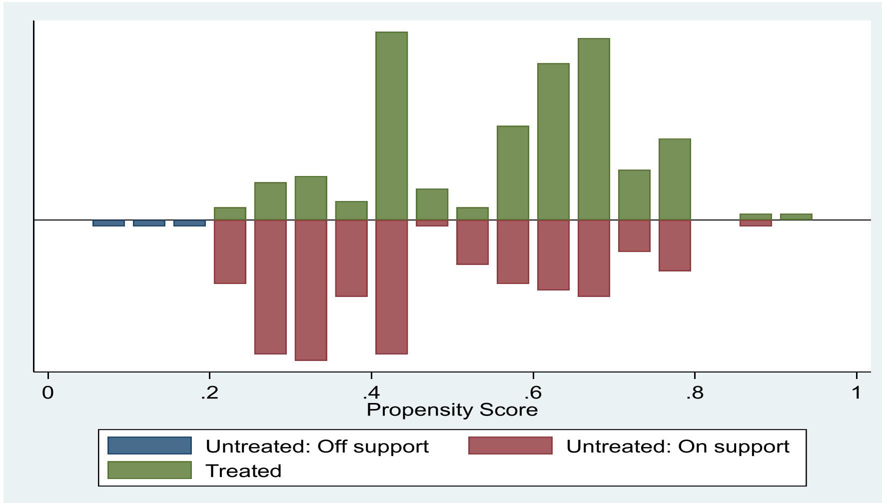
* if variance ratio outside [0.72; 1.38] for U and [0.72; 1.38] for M

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.087	35.18	0.000	14.2	8.1	71.9*	0.70	0
Matched	0.004	1.67	0.990	4.4	3.5	14.9	1.52	0

* if B>25%, R outside [0.5; 2]

```
. psgraph

.
```

Graph.



4. Caliper 0.5 (avocadosellingIncome2019)

```
. psmatch2 MAINLYSellAvocado, outcome( AvocadoSellingIncome2019 ) pscore(mypscore) caliper(0.5) ate
```

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
AvocadoSe~me2019	Unmatched	31803.3061	22506.8681	9296.43807	2704.47097	3.44
	ATT	31803.3061	13794.6531	18008.6531	5344.77582	3.37
	ATU	22506.8681	17438.5764	-5068.29167	.	.
	ATE			6589.13402	.	.

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support On suppor	Total
Untreated	144	144
Treated	147	147
Total	291	291

```
. pstest HHGender1_A HHeducationStatus LabourSufficiency GovernmentSupport_CreditAccess GovernmentSupport_Agrochemicals GovernmentSupport_Marketi
> ngInfra GeneralCreditAccess AgriculturalCreditAccess MarketingInformationAvailablity, both graph
```

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|	V(T)/V(C)
HHGender1_A	U	.7619	.72917	7.5		0.64	0.523	.
	M	.7619	.78912	-6.2	16.9	-0.56	0.578	.
HHeducationStatus	U	1.6395	1.625	2.1		0.18	0.858	1.14
	M	1.6395	1.6463	-1.0	52.9	-0.08	0.933	1.13
LabourSufficiency	U	.63946	.68056	-8.7		-0.74	0.461	.
	M	.63946	.59864	8.6	0.7	0.72	0.473	.
GovernmentSupport_CreditAccess	U	0	0	.		.	.	.
	M	0	0	.	.	.	.	.
GovernmentSupport_Agrochemicals	U	.0068	.02083	-12.0		-1.03	0.306	.
	M	.0068	0	5.8	51.5	1.00	0.318	.
GovernmentSupport_MarketingInfra	U	.10204	.11111	-2.9		-0.25	0.803	.
	M	.10204	.08844	4.4	-50.0	0.40	0.692	.
GeneralCreditAccess	U	.12925	.08333	14.9		1.27	0.206	.
	M	.12925	.08163	15.4	-3.7	1.33	0.185	.
AgriculturalCreditAccess	U	.06803	.05556	5.2		0.44	0.660	.
	M	.06803	.02721	16.9	-227.3	1.65	0.101	.
MarketingInformationAvailablity	U	1.7143	1.4167	60.0		5.12	0.000	0.90
	M	1.7143	1.6871	5.5	90.9	0.48	0.633	0.95

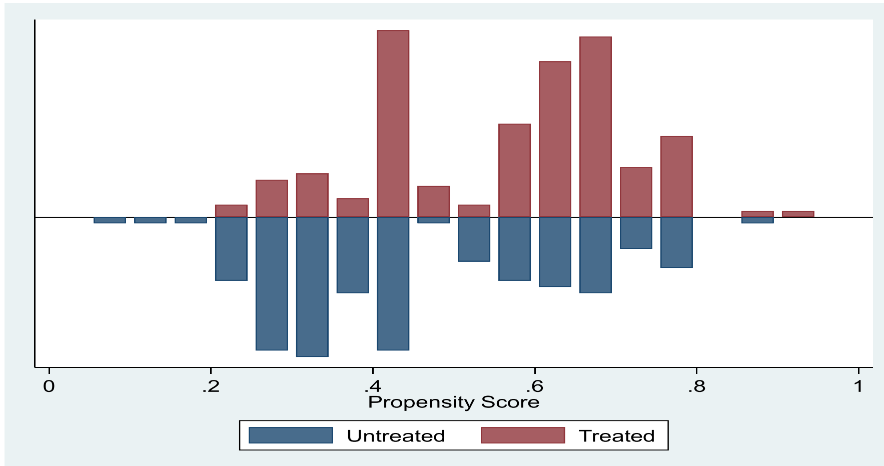
* if variance ratio outside [0.72; 1.38] for U and [0.72; 1.38] for M

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.087	35.18	0.000	14.2	8.1	71.9*	0.70	0
Matched	0.009	3.81	0.802	8.0	6.0	22.7	1.48	0

* if B>25%, R outside [0.5; 2]

.
.

Graph.



1. Nearest Neighbor 1 (avocadosellingIncome 2020)

```
. psmatch2 MAINLYSellAvocado, outcome( AvocadoSellingIncome2020 ) pscore(mypscore) neighbor(1) ate
```

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
AvocadoSell~2020	Unmatched	36835.7852	25655.2517	11180.5335	3154.48977	3.54
	ATT	36835.7852	20177.1745	16658.6107	5807.50216	2.87
	ATU	25655.2517	19972.7692	-5682.48252	.	.
	ATE			5717.59589	.	.

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support On suppor	Total
Untreated	143	143
Treated	149	149
Total	292	292

```
. pstest HHGender1_A HHeducationStatus LabourSufficiency GovernmentSupport_CreditAccess GovernmentSupport_Agrochemicals GovernmentSupport_Marketi
> ngInfra GeneralCreditAccess AgriculturalCreditAccess MarketingInformationAvailablity, both graph
```

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|	V(T)/ V(C)
HHGender1_A	U	.75168	.72727	5.5		0.47	0.636	.
	M	.75168	.78523	-7.6	-37.5	-0.68	0.494	.
HHeducationStatus	U	1.6443	1.6294	2.2		0.18	0.854	1.15
	M	1.6443	1.6376	1.0	55.0	0.08	0.934	1.15
LabourSufficiency	U	.63758	.67832	-8.6		-0.73	0.465	.
	M	.63758	.58389	11.3	-31.8	0.95	0.344	.
GovernmentSupport_CreditAccess	U	0	0	.		.	.	.
	M	0	0	.	.	.	.	.
GovernmentSupport_Agrochemicals	U	.00671	.02098	-12.2		-1.05	0.296	.
	M	.00671	0	5.7	53.0	1.00	0.318	.
GovernmentSupport_MarketingInfra	U	.10067	.1049	-1.4		-0.12	0.906	.
	M	.10067	.08725	4.4	-217.8	0.40	0.693	.
GeneralCreditAccess	U	.12752	.08392	14.2		1.21	0.228	.
	M	.12752	.08054	15.3	-7.8	1.33	0.185	.
AgriculturalCreditAccess	U	.06711	.05594	4.6		0.40	0.693	.
	M	.06711	.02685	16.7	-260.5	1.64	0.101	.
MarketingInformationAvailablity	U	1.7181	1.4126	61.8		5.28	0.000	0.89
	M	1.7181	1.6846	6.8	89.0	0.59	0.553	0.94

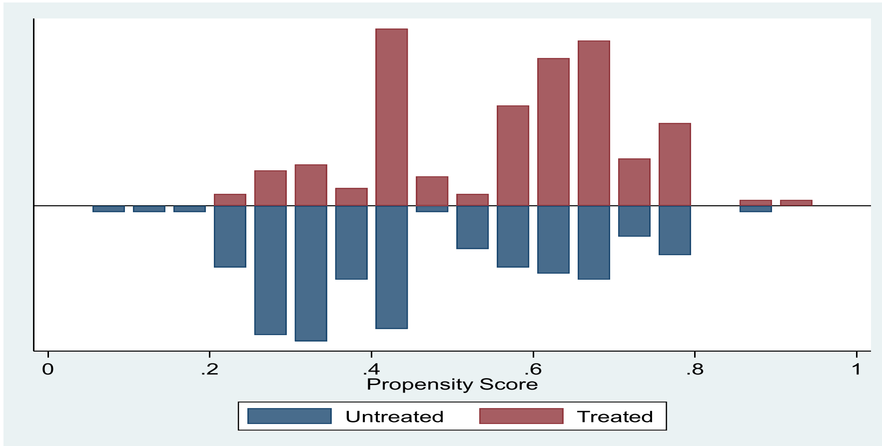
* if variance ratio outside [0.72; 1.38] for U and [0.72; 1.38] for M

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.088	35.73	0.000	13.8	7.1	72.3*	0.69	0
Matched	0.010	4.20	0.756	8.6	7.2	23.7	1.49	0

* if B>25%, R outside [0.5; 2]

```
.
.
. psgraph

. psgraph
```

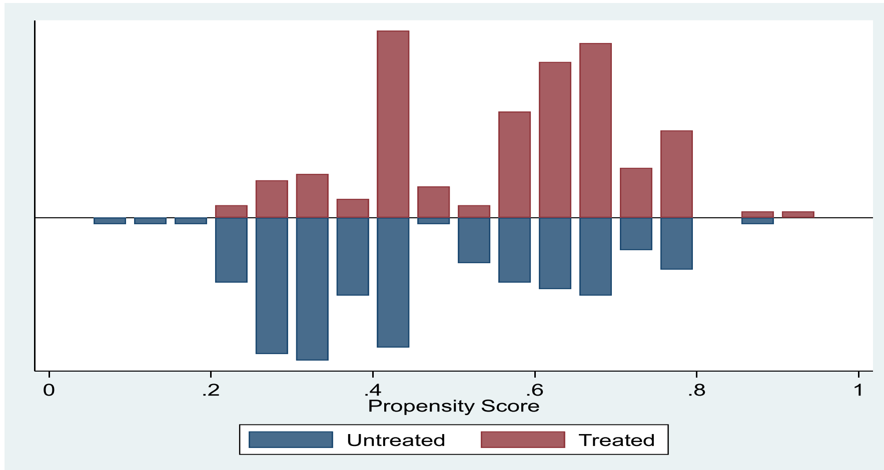
Graph.



2. Nearest Neighbor 5 (avocadosellingincome2020)

```
.  psmatch2 MAINLYSellAvocado, outcome( AvocadoSellingIncome2020 ) pscore(mypscore)  neighbor(5) ate

        Variable     Sample |    Treated     Controls   Difference         S.E.   T-stat
----------------------------+-----------------------------------------------------------
AvocadoSell~2020  Unmatched | 36835.7852   25655.2517   11180.5335   3154.48977     3.54
                        ATT | 36835.7852   17268.3893    19567.396   3588.40745     5.45
                        ATU | 25655.2517   38071.1063   12415.8545            .        .
                        ATE |                              16065.1            .        .
----------------------------+-----------------------------------------------------------
Note: S.E. does not take into account that the propensity score is estimated.

           | psmatch2:
 psmatch2: |   Common
 Treatment |  support
assignment | On suppor |     Total
-----------+-----------+----------
 Untreated |       143 |       143
   Treated |       149 |       149
-----------+-----------+----------
     Total |       292 |       292

. pstest HHGender1_A HHeducationStatus LabourSufficiency GovernmentSupport_CreditAccess GovernmentSupport_Agrochemicals GovernmentSupport_Marketi
> ngInfra GeneralCreditAccess AgriculturalCreditAccess MarketingInformationAvailablity, both graph

-----------------------------------------------------------------------------------------
                        Unmatched |       Mean               %reduct |     t-test    |  V(T)/
Variable                  Matched | Treated Control    %bias  |bias| |    t    p>|t| |  V(C)
----------------------------------+----------------------------------+---------------+----------
HHGender1_A                     U | .75168   .72727      5.5         |   0.47  0.636 |     .
                                M | .75168    .8349    -18.9  -241.0 |  -1.78  0.077 |     .
                                  |                                  |               |
HHeducationStatus               U | 1.6443   1.6294      2.2         |   0.18  0.854 |  1.15
                                M | 1.6443   1.5732     10.3  -376.7 |   0.92  0.360 |  1.34
                                  |                                  |               |
LabourSufficiency               U | .63758   .67832     -8.6         |  -0.73  0.465 |     .
                                M | .63758   .58523     11.0   -28.5 |   0.93  0.356 |     .
                                  |                                  |               |
GovernmentSupport_CreditAccess  U |      0        0        .         |      .      . |     .
                                M |      0        0        .       . |      .      . |     .
                                  |                                  |               |
GovernmentSupport_Agrochemicals U | .00671   .02098    -12.2         |  -1.05  0.296 |     .
                                M | .00671   .00403      2.3    81.2 |   0.32  0.752 |     .
                                  |                                  |               |
GovernmentSupport_MarketingInfra U | .10067   .1049     -1.4         |  -0.12  0.906 |     .
                                M | .10067   .05638     14.5  -948.7 |   1.42  0.156 |     .
                                  |                                  |               |
GeneralCreditAccess             U | .12752   .08392     14.2         |   1.21  0.228 |     .
                                M | .12752   .05369     24.0   -69.3 |   2.23  0.026 |     .
                                  |                                  |               |
AgriculturalCreditAccess        U | .06711   .05594      4.6         |   0.40  0.693 |     .
                                M | .06711   .04161     10.6  -128.3 |   0.97  0.333 |     .
                                  |                                  |               |
MarketingInformationAvailablity U | 1.7181   1.4126     61.8         |   5.28  0.000 |  0.89
                                M | 1.7181   1.6591     11.9    80.7 |   1.06  0.290 |  1.00
                                  |                                  |               |
-----------------------------------------------------------------------------------------
* if variance ratio outside [0.72; 1.38] for U and [0.72; 1.38] for M

-----------------------------------------------------------------------------------
 Sample    | Ps R2   LR chi2   p>chi2   MeanBias   MedBias      B       R     %Var
-----------+-----------------------------------------------------------------------
 Unmatched | 0.088     35.73    0.000     13.8        7.1     72.3*   0.69      0
 Matched   | 0.024      9.71    0.286     12.9       11.5     35.9*   2.16*     0
-----------------------------------------------------------------------------------
* if B>25%, R outside [0.5; 2]

. psgraph

.
```

Graph.



3. Kernel (avocadosellingincome2020)

```
. psmatch2 MAINLYSellAvocado, outcome( AvocadoSellingIncome2020 ) pscore(mypscore)  kernel ate
```

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
AvocadoSell~2020	Unmatched	36835.7852	25655.2517	11180.5335	3154.48977	3.54
	ATT	36835.7852	22423.1586	14412.6267	3551.74132	4.06
	ATU	24886.5714	37516.2868	12629.7154	.	.
	ATE			13548.9326	.	.

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support Off suppo	On suppor	Total
Untreated	3	140	143
Treated	0	149	149
Total	3	289	292

```
. pstest HHGender1_A HHeducationStatus LabourSufficiency GovernmentSupport_CreditAccess GovernmentSupport_Agrochemicals GovernmentSupport_Marketi
> ngInfra GeneralCreditAccess AgriculturalCreditAccess MarketingInformationAvailablity, both graph
```

Variable	Unmatched Matched	Mean Treated	Control	%bias	%reduct |bias|	t-test t	p>|t|	V(T)/ V(C)
HHGender1_A	U	.75168	.72727	5.5		0.47	0.636	.
	M	.75168	.79366	-9.5	-72.0	-0.86	0.389	.
HHeducationStatus	U	1.6443	1.6294	2.2		0.18	0.854	1.15
	M	1.6443	1.6468	-0.4	83.3	-0.03	0.976	1.09
LabourSufficiency	U	.63758	.67832	-8.6		-0.73	0.465	.
	M	.63758	.61975	3.7	56.2	0.32	0.751	.
GovernmentSupport_CreditAccess	U	0	0	.		.	.	.
	M	0	0	.	.	.	.	.
GovernmentSupport_Agrochemicals	U	.00671	.02098	-12.2		-1.05	0.296	.
	M	.00671	.00191	4.1	66.3	0.63	0.528	.
GovernmentSupport_MarketingInfra	U	.10067	.1049	-1.4		-0.12	0.906	.
	M	.10067	.09417	2.1	-53.9	0.19	0.851	.
GeneralCreditAccess	U	.12752	.08392	14.2		1.21	0.228	.
	M	.12752	.09944	9.1	35.6	0.76	0.447	.
AgriculturalCreditAccess	U	.06711	.05594	4.6		0.40	0.693	.
	M	.06711	.05161	6.4	-38.8	0.56	0.573	.
MarketingInformationAvailablity	U	1.7181	1.4126	61.8		5.28	0.000	0.89
	M	1.7181	1.6956	4.6	92.6	0.40	0.689	0.96

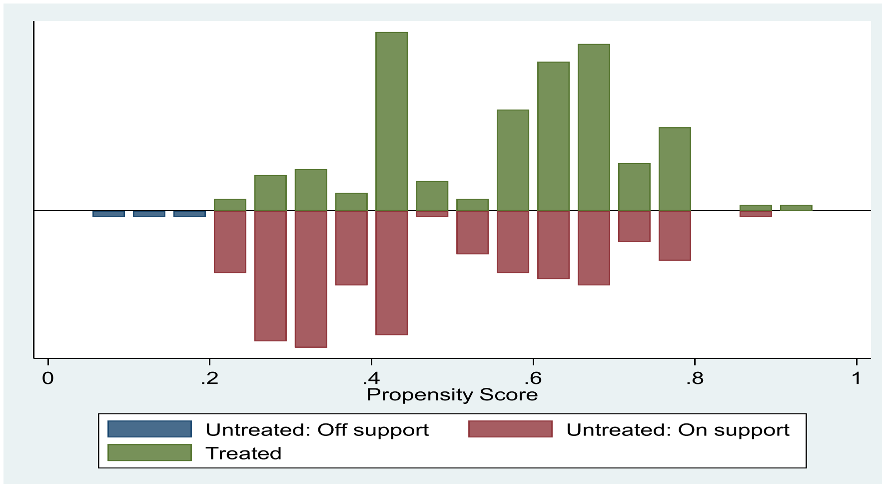
* if variance ratio outside [0.72; 1.38] for U and [0.72; 1.38] for M

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.088	35.73	0.000	13.8	7.1	72.3*	0.69	0
Matched	0.004	1.60	0.991	5.0	4.3	14.5	1.67	0

* if B>25%, R outside [0.5; 2]

```
. psgraph
```

Graph.



4. Caliper .5 (avocadosellingincome2020)

```
. psmatch2 MAINLYSellAvocado, outcome( AvocadoSellingIncome2020 ) pscore(mypscore) caliper (0.5) ate
```

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
AvocadoSell~2020	Unmatched	36835.7852	25655.2517	11180.5335	3154.48977	3.54
	ATT	36835.7852	20177.1745	16658.6107	5807.50216	2.87
	ATU	25655.2517	19972.7692	-5682.48252	.	.
	ATE			5717.59589	.	.

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support On suppor	Total
Untreated	143	143
Treated	149	149
Total	292	292

```
. pstest HHGender1_A HHeducationStatus LabourSufficiency GovernmentSupport_CreditAccess GovernmentSupport_Agrochemicals GovernmentSupport_Marketi
> ngInfra GeneralCreditAccess AgriculturalCreditAccess MarketingInformationAvailablity, both graph
```

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduct |bias|	t-test t	t-test p>|t|	V(T)/ V(C)
HHGender1_A	U	.75168	.72727	5.5		0.47	0.636	.
	M	.75168	.78523	-7.6	-37.5	-0.68	0.494	.
HHeducationStatus	U	1.6443	1.6294	2.2		0.18	0.854	1.15
	M	1.6443	1.6376	1.0	55.0	0.08	0.934	1.15
LabourSufficiency	U	.63758	.67832	-8.6		-0.73	0.465	.
	M	.63758	.58389	11.3	-31.8	0.95	0.344	.
GovernmentSupport_CreditAccess	U	0	0	.		.	.	.
	M	0	0	.	.	.	.	.
GovernmentSupport_Agrochemicals	U	.00671	.02098	-12.2		-1.05	0.296	.
	M	.00671	0	5.7	53.0	1.00	0.318	.
GovernmentSupport_MarketingInfra	U	.10067	.1049	-1.4		-0.12	0.906	.
	M	.10067	.08725	4.4	-217.8	0.40	0.693	.
GeneralCreditAccess	U	.12752	.08392	14.2		1.21	0.228	.
	M	.12752	.08054	15.3	-7.8	1.33	0.185	.
AgriculturalCreditAccess	U	.06711	.05594	4.6		0.40	0.693	.
	M	.06711	.02685	16.7	-260.5	1.64	0.101	.
MarketingInformationAvailablity	U	1.7181	1.4126	61.8		5.28	0.000	0.89
	M	1.7181	1.6846	6.8	89.0	0.59	0.553	0.94

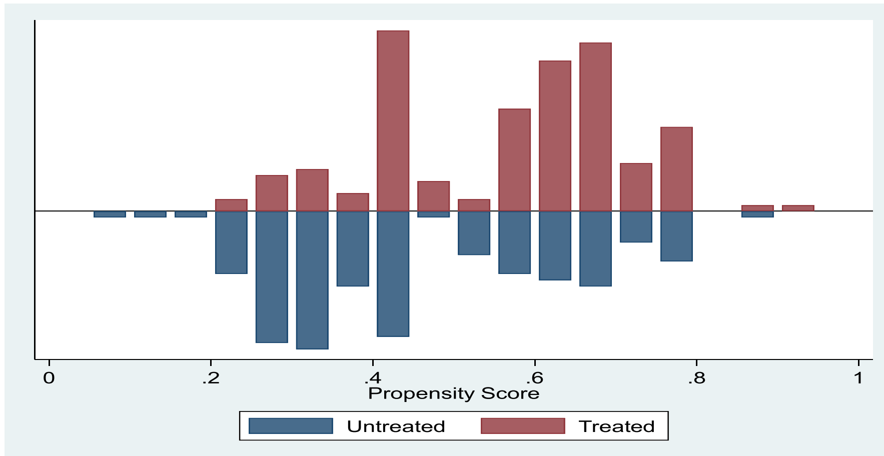
* if variance ratio outside [0.72; 1.38] for U and [0.72; 1.38] for M

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	B	R	%Var
Unmatched	0.088	35.73	0.000	13.8	7.1	72.3*	0.69	0
Matched	0.010	4.20	0.756	8.6	7.2	23.7	1.49	0

* if B>25%, R outside [0.5; 2]

```
. psgraph

.
```

Graph.



APPENDIX C. Images of avocado trees intercropped

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