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SPECIAL ISSUE ARTICLE

The Dynamics and Role of Gender in High-Value Avocado Farming in Kenya

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Abstract
We used two-wave panel data obtained from avocado growers in Murang'a County in Kenya to examine, through the perspective of gender, the dynamics of farmers' participation in avocado production and marketing organizations (PMOs), and test whether understanding group dynamics is important for analyzing contract farming. Using a multinomial logit (MNL) model, we identify the characteristics of men and women participating in PMOs categorized as early adopters, dis-adopters, late adopters, and non-adopters. We focus on dis-adopters and late adopters because these categories are most often ignored in the literature. Moreover, without considering the dynamics, we verify the influencing factors of PMOs by estimating a random-effects logit model that controls for unobserved heterogeneity across households. Furthermore, we estimate a sequential-choice model to test whether the process of selection into group membership affects the process of selection into contracting. Our results reveal heterogeneity with regard to household, farm, and resource characteristics across categories of farmers and between gender groups. Besides, the results reveal that group and contracting dynamics are related, and ignoring the former leads to biased estimates of the determinants of contracting dynamics. Policy efforts should focus on supporting women farmers to enhance their participation in PMOs, which ultimately affects contracting. Improving access to high-yielding avocado varieties and building capacity in orchard management would enhance women's decision-making including group participation, contracting, and marketing. Low-cost agricultural credit may also improve women's ownership of improved avocado trees and hence their participation in high-value markets.

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Résumé
Nous avons utilisé des données de panel à deux vagues obtenues auprès de producteurs d'avocats du comté de Murang'a au Kenya pour étudier, à travers le prisme du genre, la dynamique de la participation des agriculteurs et agricultrices aux organisations de production et de commercialisation de l'avocat, (PMO) et pour tester l'hypothèse selon laquelle il est important de comprendre la dynamique de groupe pour analyser l'agriculture contractuelle. À l'aide d'un modèle logit multinomial, nous identifions les caractéristiques des hommes et des femmes participant aux PMO qui sont classé·e·s dans différentes catégories: les adopteurs précoces, les dés-adopteurs, les adopteurs tardifs et les non-adopteurs. Nous nous concentrons sur les dés-adopteurs et les adopteurs tardifs car ces catégories sont le plus souvent ignorées dans la littérature. Par ailleurs, sans tenir compte de la dynamique, nous vérifions les facteurs d'influence des PMO en estimant un modèle logit à effets aléatoires qui contrôle l'hétérogénéité non observée entre les ménages. De plus, nous utilisons un modèle à choix séquentiel pour voir si le processus de sélection concernant la participation au sein d'un groupe affecte le processus de sélection concernant la contractualisation. Nos résultats révèlent une hétérogénéité en ce qui concerne les caractéristiques des ménages, des exploitations et des ressources entre les catégories d'agriculteurs et entre les groupes de genre différent. En outre, les résultats révèlent que les dynamiques de groupe et de contractualisation sont liées, et que le fait d'ignorer la dynamique de groupe conduit à des estimations biaisées des déterminants de la dynamique de contractualisation. Les efforts des politiques devraient se concentrer sur le soutien apporté aux agricultrices pour améliorer leur participation aux PMO, ce qui affecte en fin de compte la contractualisation. L'amélioration de l'accès aux variétés d'avocats à haut rendement et le renforcement des capacités de gestion des vergers amélioreraient la prise de décision des femmes, y compris la participation au sein d'un groupe, la contractualisation et la commercialisation. Le crédit agricole à faible coût peut également améliorer l'accès des femmes à la possession d'avocatiers améliorés et donc leur participation aux marchés à forte valeur ajoutée.

Introduction

Despite the high and sustained economic growth in many countries in Sub-Saharan Africa (SSA) in the last decade, a significant group of the poor and vulnerable populace remains excluded from the increased wellbeing. Because of the remarkable growth in recent years, high-value horticultural farming, has been identified as one of the fastest-growing agricultural sub-sectors and, as a result, is a possible driver of economic growth, inclusive development, and poverty reduction, especially among the most vulnerable groups of smallholder households (Henson and Jaffee 2008; Barrett et al. 2012). Innovative farming strategies have been devised to increase gains from the high-value markets, link smallholder farmers to markets, and make markets work for the poor (Njuki et al. 2011; Gramzow et al. 2018).

Such strategies have included organizing farmers into groups, associations, or cooperatives; contract farming and out-grower schemes; training on good agricultural practices; and providing market information, among others. Through such strategies, participant farmers have been able to tap the latent demand of more distance markets made accessible by the high-value agricultural chains, and therefore improve their productivity and profitability, which stimulates their welfare (Barrett et al. 2012). High-value markets, therefore, result from and contribute to economic and inclusive development. Although the pathway for integrating the poor in developing countries into a more commercialized sector of the economy, and assisting then access the gains from trade that depict the efficacious high-value market chains, the participation of smallholders in the global market remains limited (Muriithi and Matz 2014). How high-value market chains are executed towards achieving inclusive development among the smallholders is not entirely clear.

One of the challenges to understanding the participation of smallholders in commercialized high-value chains for enhanced wellbeing has been the lack of household-level longitudinal data, which is often due to limited resources for data collection. Panel data may facilitate analysis of the dynamics of smallholder participation in high-value markets that are important for informing policymakers seeking to stimulate rural economic growth and inclusive development data. Besides, the impact of the high-value market chain may be influenced by the gender of the target population. With the understanding that men and women participate differently in production and markets (Symes 1991), it is virtually important to investigate determinants of high-value market participation among the different gender groups for improved household welfare and inclusive development. Besides, women are marginalized in many aspects of farming due to limited access to productive resources in comparison with men farmers and thus lag in economic development (IFC 2013, p. 102).

We focused on two aspects of participation: (1) production and marketing organizations (hereafter, PMOs) and (2) contract farming. Originally produced mainly for home consumption, the avocado crop is referred to as "green gold" in Kenya and has overtaken traditional cash crops such as coffee and tea, whose profitability has declined over time. The fruit ranks fourth among the economically important fruits in the country, after banana, mangoes, and pineapples (Horticultural Crops Directorate, HCD 2017). Among fruit exports, avocados rank highest, contributing about 5.4 billion Kenyan shillings in 2017 and accounting for 74% of fruit exports by value (HCD 2017).

Contract farming (sometimes referred to as out-grower schemes) is a longstanding farming practice in developing countries. In Kenya, contract farming schemes date to the colonial period (Minot and Ngigi 2004). For farmers to participate in such contractual arrangements, they must be organized into special interest groups (Ashraf et al. 2009) commonly referred to as PMOs. Such groups have been particularly important in increasing market share among smallholder horticultural farmers, especially in export markets (Barrett et al. 2012). Contract arrangements help smallholders reduce market-associated suite of transaction costs including transportation costs of produce to market, searching for markets, and market information among other costs. The PMOs facilitate collective action that enables pooling volumes of products to attain economies of scale and to jointly invest in facilities needed to meet the good agricultural practices and safety standards that most exporters require.

Conversely, contract farming may exclude disadvantaged groups, mainly the poor, women, youth, and those with very little or no land at all or lack access to critical productive resources. The absence of women in contract farming in Africa and Asia has been documented in the past (e.g. Dolan 2001; Maertens and Swinnen, 2009, 2012). Generally, high rates of failure for contract farming are evident in Kenya (Ashraf et al. 2009; Minot and Ngigi 2004). These studies agree that certain constraints such as lack of capital, credit, information, and lack of access to land, have kept women from cash crop and contract farming.

The design of sustainable PMOs and contract-farming schemes requires an understanding of the dynamics of farmers' participation through the use of longitudinal data, which are limited in the literature. This paper addresses this knowledge gap with the help of panel data obtained from a sample of avocado-growing households in Murang'a County, Kenya. Specifically, the objective of this study is to examine the dynamics of farmers' participation in PMOs and test whether understanding group dynamics is important for analyzing contract farming. Besides, our analysis seeks to understand gender dynamics, an important determinant for sustainable social networks such as PMOs (Njuki et al. 2011; Fischer and Qaim 2012), which subsequently results in inclusive development.

The contribution of this paper to the existing literature is threefold: first, we estimate the determinants of group membership dynamics [early adopter, late adopter, dis-adopter—joins and leaves-, or non-adopter (decides not to join)] defined with the help of the two rounds panel dataset. Second, while most past studies used contract farming as an independent variable, based on the premise that smallholder farmers can only be contracted as a group, we analyzed contract farming as conditional on group membership by designing a sequential-choice model based on a bivariate probit framework in which a farmer first chooses whether to join a group or not, then decides whether or not to enter into a contract. The unobserved factors that affect group non-adoption may be correlated with unobserved factors affecting contract non-adoption. Consequently, if the decisions were somehow correlated, ignoring group membership when analyzing contracting would lead to inconsistent estimates. Third, we tested whether gender matters in smallholder participation in high-value avocado chains. Success in agricultural development is greatly influenced by differences in roles between men and women, and greater gender equality can improve productivity and enhance inclusive development. Further, men's appropriation of women's spheres of influence and activity may negatively impact the adoption of agricultural innovations (Dolan 2001).

Our results showed heterogeneity with respect to farm and farmer characteristics across categories of PMOs. For instance, the gender-specific analysis showed that, among women-headed households (WHHs), early adopters were more educated, but had fewer Hass (a cultivar of avocado) avocado trees and were more credit-constrained compared to dis-adopters. The results of the sequential-decision model revealed that group and contracting dynamics were related and suggested that ignoring the former would lead to biased estimates. Gender of the head of household has an impact on the group-membership-participation decisions as shown by the random-effects model estimates; gender is, thus, indirectly important for contracting. These findings have important implications for the participation of smallholders and especially the resource-constrained women in high-value avocado chains and thus for inclusive development.

The remainder of the paper is organized into four sections. Section 2 describes the data and presents descriptive statistics. Section 3 provides the conceptual framework and estimation strategy. The results and discussion are given in Sect. 4, and Sect. 5 concludes.

Data and Dynamics of Avocado Farmers Participation in High-Value Horticultural Farming

Study Area and Data Collection

Data utilized in this study were collected from Kandara Sub-County, one of the eight sub-counties within Murang'a County, Central Kenya. The County is Kenya's leading avocado producer, and Kandara, as its highest-producing sub-county, has become a hub of avocado production and trade. Avocado production (both volume and exports) has expanded substantially since 2005 (HCD 2017) and therefore, was found to provide an interesting case study to analyze the implications for rural development (Amare et al. 2019). The baseline survey was carried out in November–December 2015, followed by an end-line household survey in July 2017. The baseline covered 790 farming households, but only 714 were interviewed in the end line.

At the baseline survey, three main household groups were identified from across the seven administrative locations in Kandara, based on their participation in avocado-marketing contracts. The first group (contract farmers) was composed of farm households involved in modern avocado marketing through contract arrangements with an established exporter. The lists were provided by the chairpersons of fourteen such groups and by Kandara Sub-County agricultural officers. Members of all the households in the lists provided by farmer groups were interviewed.

The second group of farmers included those who had recently signed contracts to sell avocados to exporters (transition farmers). Farmers in four groups, each of which consisted of 50–60 farmers on average, had already signed contracts with exporters (regarding price, quality, grade, and delivery of avocados). Thirty (30) to 40 farmers from each group were randomly sampled.

The third group included farmers involved in traditional avocado marketing who sold their avocados to middlemen or brokers (non-contract farmers). We selected 27 villages from the same sub-county whose farmers were not linked to exporters but whose production approaches and geographical locations were similar to those in the first and second groups. These villages were also similar in size, socio-economic

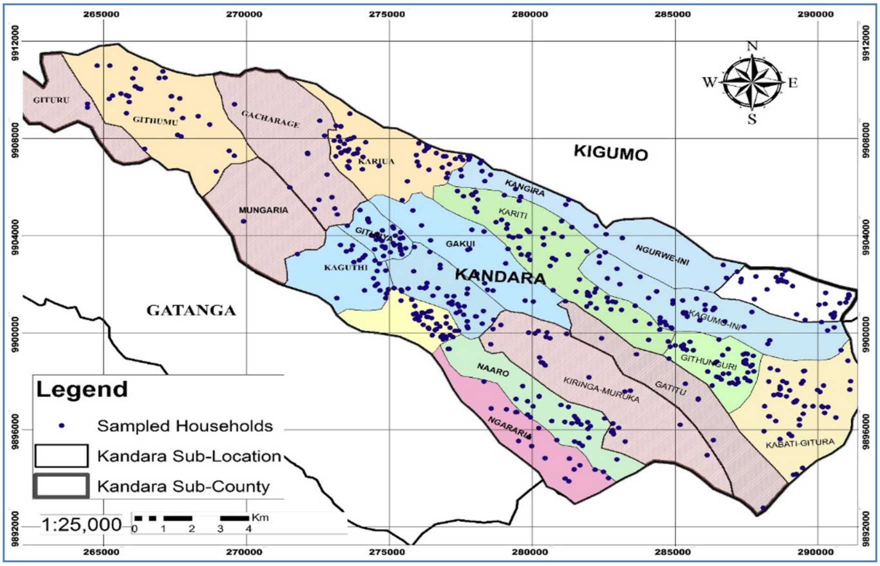

Fig. 1 Distribution of sampled households—Kandara sub-county

and agroclimatic conditions, and road and market access. From each of the villages, farmers who were not organized in any farmers' groups were randomly selected.[1]

Members of a total of 790 households[2] were interviewed (see Fig. 1 for sample distribution), though only 714 of these households were available for follow-up during the end-line survey. After cleaning the sample for missing data and enumerator errors, we analyzed a balanced sample of 674 households.

Dynamics of Avocado Farmers Participation in High-Value Horticultural Farming

We considered two different ways of participating in the high-value horticultural farming: (1) whether any member of the household was a member of an avocado-producing and/or marketing group; and (2) whether a farmer had a contract with an avocado trader (contract farming). The nature of our data (in two rounds of the survey) enabled us to define the dynamics of participation in the different pathways of high-value avocado farming. For ease of analysis, we use the terms "adopter" (a farmer who participated) and "non-adopter" (who did not).

Adopters were further categorized into (a) "late adopters,"—those who were not group or contract participants during the first round of the survey, but were

[1] Note that, for our study context, group membership was a prerequisite for contract farming. Implying that for smallholders to participate in contract farming, they were required to join an existing PMO.

[2] Among the three groups of farmers sampled, 266 households had existing contracts with local firms and exporters (first group), 144 households were in the transition groups who were newly organized into groups to sign contracts and 380 households did not have contracts.

Table 1 Dynamics of avocado farmers' participation in high-value horticulture farming

Dynamics	Group membership			Contract farming		
	Women-headed household (WHHs)	Men-headed household (MHHs)	Total	Women-headed household (WHHs)	Men-headed household (MHHs)	Total
Non-adopters	84	194	278	85	247	332
Late adopters	5	56	61	22	114	136
Dis-adopters	17	95	112	15	59	74
Early adopters	39	184	223	23	109	132
Total	145	529	674	145	529	674

participants by the time of the follow-up survey, (b) "dis-adopters," who were discovered during the follow-up survey to have ended their participation, and (c) "early adopters," who participated in both rounds of the survey.

Although the empirical analysis does not provide the dynamics of contract participation, Table 1 describes avocado farmers' participation in both group membership and contract farming, according to the gender of the household head. Most of the WHHs (59%) did not participate in contract farming (non-adopters), while about 10% (15 households) were no longer participating at the time of the follow-up survey (dis-adopters). This suggests a potential resource constraint among women farmers that may have hindered their participation in the high-value market, which collaborates with existing literature (e.g. Fischer and Qaim 2012). Similarly, most of the WHHs (58%) did not participate in avocado PMOs (non-adopters). Likewise, a large proportion of men-headed households (MHHs) did not participate in contract and group membership (47% and 37%, respectively).[3]

Conceptual Framework and Estimation Strategy

Our analysis is anchored on the assumption that the choice of a household whether to participate in high-value horticultural farming or not is determined by its expected utility associated with either option. Previous studies have revealed that participation in the avocado high-value market has important positive effects on household income and wealth, besides the direct gains, but also indirectly through established market access, better prices of produce due to existing arrangements with traders, and better access and use of technologies and inputs (Mithofer et al. 2008). Participation in the high-value market allows intensive use of land that increases farm

[3] Note that it is possible to have more people as contract non-adopters than group non-adopters, since there are farmers who had joined a group but not yet signed the contracts, especially the transitioning group. For the same reason, it is possible to have more late adopters into contract than in a group, since there are farmers who had joined a group during baseline but not singed contracts till during the second round of the survey.

productivity, household income, and poverty reduction (Amare et al. 2019). Besides the modern value chains provide a labor market especially for the disadvantaged groups, mainly the poor, women, youth, that is associated with increased rural employment and thus household income. Indirectly, participation of rural households in product and labor markets provides technology and managerial spill-over effects, investment linkages, and consumption linkages that drive economic growth, inclusive development, and poverty reduction (Maertens et al. 2012). However, participation in a high-value market also involves additional transaction costs, such as harvesting and transport costs, group membership fees, and the opportunity cost of time spent attending group meetings[4] (Ashraf et al. 2009). Subsequently, a household will participate in high-value markets if the expected benefits of participation exceed the utility of selling locally to brokers.

Estimation Approach

Methodologies for evaluating the dynamics of agricultural technology vary across studies, largely depending on the objective of the study. Most studies, however, have evaluated static adoption vs. non-adoption decisions (e.g. Kassie et al. 2011; Shiferaw et al. 2014; Sunding and Zilberman 2001), but often limited by the available data, mainly cross-sectional datasets. Analyzing the dynamics of technology adoption requires the use of longitudinal data. Only a few studies have examined what happens when technologies are abandoned (e.g. Neill and Lee 2001; Moser and Barrett 2003). Such studies are, however, limited in Africa.

Neill and Lee (2001) used bivariate probit to analyze the adoption and abandonment of cover crops. The model considered dichotomous decisions (adopt, yes/no: abandon yes/no) and the potential correlation between them. In estimating the adoption and abandonment of precision soil sampling in cotton production in the Southeastern USA, Walton et al. (2008) used the probit model, while Rigby et al. (2001) used logit model to explore reasons for the abandonment of organic farming in the UK. Moser and Barrett (2003) used a probit model and asymmetrically trimmed least-squares estimation of a dynamic Tobit model to analyze the decisions to adopt, expand, and abandon SRI technology in Madagascar. It is evident from these and related studies that the adoption of agricultural technologies is dynamic—widely and spontaneously accepted by the farmers at the initial stages but later abandoned.

Similar to the adoption of agricultural technology, the participation of smallholders in high-value-market farming is a dynamic process, but most studies on this topic are based on static models that have used cross-sectional data (e.g. Ashraf et al. 2009). Smallholders follow different pathways, for instance through contracts offered by exporters or selling through brokers. While some maintain one production-marketing pathway, others abandon one channel to follow a different one from season to season and may eventually retreat to the previous path

[4] These transaction costs may exclude resource poor farmers from the high-value markets as well as their incapacity to invest in the infrastructure required to meet the good agricultural practices and acquire certification of products as required for the international markets (Ashraf et al. 2009).

or follow a new one altogether. Capturing the dynamics of market participation decisions may provide more information on behaviors and differences among households who continue to participate, those who abandon the market, those who participate later, and those who never participate, as these dynamics influence their welfare and thus inclusive development. Using static models, biased results arise from ignoring the dynamic effect of learning and the inability to control for unobserved heterogeneity (Moser and Barrett 2003). Treating early adopters and late or recent adopters the same, as is often done in static models, may result in misleading and biased coefficient estimates because early adopters may have more experience and, subsequently, may be more likely to continue with technology in comparison to late adopters (Cameron 1999).

Even when panel data is available, controlling for endogeneity that arises from the household self-selection is still a challenge in adoption models. To address this challenge, Barham et al. (2004) used a MNL model, incorporating household characteristics from the baseline to describe the current period. Self-selection could arise when households change from one market choice to another (for instance late adopters and dis-adopters). Similarly, Diederen et al. (2003) applied nested logit models, an extension of a MNL model, to analyze farmers' adoption behavior in choosing to be laggards (late and non-adopters), early adopters, or innovators of a dairy farming technology.

We adopted a MNL model following (Barham et al. 2004) to establish the factors that influence farmers' participation in either of the four group categories. A second estimation uses the panel nature of our data to control for unobserved variables in a random-effects logit model. The random-effects logit model provides a means of testing the reliability of the MNL model (Barham et al. 2004). Based on the evidence that smallholder farmers in Kenya can only be contracted by exporters as a group (Ashraf et al. 2009), and especially those exporting avocado (Gyau et al. 2016), we did not estimate contract farming as an independent decision. Rather, we estimated the factors that affect contract farming conditional on group membership by designing a sequential choice model based on the bivariate probit framework following Chang and Boisvert (2005) and Khanna (2001).

The choice of the determinants of the adoption of PMOs and contract farming are guided by the agriculture technology adoption literature, which includes human capital theory and sociological research including gender analysis, and contextual characteristics that may influence the participation of smallholder farmers in high-value markets including group membership and contract farming. The explanatory variables can be broadly classified into five categories: household and farm characteristics (including gender, age, education and occupation of the household head, and household size) (Doss 2001; Kassie et al. 2011; Quisumbing & Pandolfelli 2010; Rogers 1995), household resources (including the number of avocado trees in production, farm size, the value of assets, livestock ownership, access to off-farm income and credit constraint (Feder et al. 1990; Kassie et al. 2011; Simtowe et al. 2016), access to market and information (Muriithi & Matz 2014; Shiferaw et al. 2011), social capital (including trust among neighbors and cooperation with other avocado farmers) (Fischer & Qaim 2012;

Key et al. 2000), and, perceptions towards avocado production (Fischer & Qaim 2012). We also controlled for location fixed effects.

Group Dynamics Estimation

Multinomial Logit We estimated a MNL model using panel data to capture the determinants of participation in high-value avocado markets (PMOs) of each household category (early adopters, late adopters, dis-adopters, and non-adopters). This study follows an analytical framework developed by Moser and Barrett (2003) who employed separate dynamic probit models to establish who adopted and who abandoned SRI technology. The dynamic model allowed us to explore the role of selected explanatory factors in adoption decisions.

Participation in the high-value market in any of our categories was not ordered. Given the unordered nature of the dependent variables, we motivated the selection of categories through a random utility model following Greene (2012). The utility model assumes that each household makes its market- or group-participation choice for each period or season according to a latent utility function y^*_{it}, such that

$$y^*_{ikt} = \beta' x_{it} + \varepsilon_{ikt}, \tag{1}$$

where y^*_{it} is the utility household i derives from high-value market participation choice k (0, 1, 2, 3) at time t, x_{it} are the observed explanatory variables that may influence participation decisions, β' is a vector of parameters to be estimated, and ε_{ikt} is the error term. Consider the multiple high-value market participation categories (i.e. $k=0, 1, 2, 3$) and time, $t=0, 1$ (two survey rounds, $t=0$ if 2015 and $t=1$ if 2017), such that the categories can be expressed as follows:

$$\begin{aligned}
&k = 0 \quad \text{if } y^*_{ikt} \leq 0 \quad \text{for } t = 0\text{, and} \quad y^*_{ikt} \leq 0 \text{ for } t = 1\\
&\text{High - value market participation non - adopters}\\
&k = 1 \quad \text{if } y^*_{ikt} > 0 \quad \text{for } t = 0 \text{ and } t = 1\\
&\text{Early high - value market participants (early adopters)}\\
&k = 2 \quad \text{if } y^*_{ikt} \leq 0 \quad \text{for } t = 0\text{, but} \quad y^*_{ikt} > 0 \text{ for } t = 1\\
&\text{Late high - value market participants (late adopters)}\\
&k = 3 \quad \text{if } y^*_{ikt} > 0 \quad \text{for } t = 0\text{, but} \quad y^*_{ikt} \leq 0 \text{ for } t = 1\\
&\text{High - value market participation dis - adopters.}
\end{aligned} \tag{2}$$

The PMOs' participation is dynamic as presented in the above formulation. If characteristics that determine the category into which a farming household falls can be sufficiently defined in the baseline period, then the analysis can be reduced to a single-period estimation. Our interest was to describe the probability of adoption of either of the four high-value-market participation choices given a set of specific household explanatory variables (x_{it});

$$\Pr(y_{it} = 0|x_i) = P_{ik} = \frac{\exp(\beta' x_{it})}{1 + \sum_{k=0}^{K} \exp(\beta' x_{it})}, \quad (3)$$

where Pr(.) is the probability of the i^{th} household to make the K^{th} market choice conditional on observed explanatory variables $\boldsymbol{x}$. With K (0, 1, 2, 3) categories, K log-odds are computed. Because the probabilities of the outcomes must add to the unit value, 1, a benchmark outcome ($k=0$) can be assigned to identify the coefficients in the estimation of different market participation choices relative to the benchmark outcome, such that:

$$\Pr(y_{it} = 0|x_i) = P_{ik} = \frac{1}{1 + \sum_{k=0}^{K} \exp(\beta' x_{it})}. \quad (4)$$

The above specification is an MNL model. The regression estimates how marginal changes in observable farm and farmer characteristics affect the probability of being in one category relative to another. The above estimation was repeated three times to estimate the factors that affected PMOs' participation among the interviewed households and gender-specific factors based on the head of the sampled household (i.e., the respondent).

Barham et al. (2004) noted that, using explanatory variables from the baseline to describe the adoption process from baseline to the current period, as done above, the MNL partially addresses endogeneity. The authors, however, cautioned that, while baseline explanatory variables were conceivably exogenous for all categories of farmers who made participation decisions later, the model did not remove potential endogeneity for early participants (early adopters). To ameliorate this concern, the authors suggested following the panel nature of the data by estimating a random effect regression model described below.

Random-Effects Logit Model For the random-effects logit specification, we specify farmers' participation in PMOs as follows.

$$y_{it}^{*} = \boldsymbol{\beta x}_{it} + a_i + \mu_{it}, \quad (5)$$

where a_i controls for the unobserved heterogeneity across households because it is distributed normally with mean zero and variance σ_a^2, and the error term μ_{it} has a logistic distribution with mean zero and variance σ_ε^2. The fact that the model controls for the unobserved heterogeneity across households, and that it focuses on changes within households over time, rather than on average effects across households, plausibly addresses the problem of self-selection into group membership. $\boldsymbol{x}_{it}$ and $\boldsymbol{\beta}$ are as described above in the MNL model. The random effect logit panel data model also accounts for omitted variables and the possible endogeneity of some independent variables.

Sequential Farmers' Participation in High-Value Market Decisions Based on Bivariate Probit Framework

In a given period, say every year, the farmer's choice of whether or not to participate in high-value horticulture production is determined by the expected utility or benefits associated with either option. Let U_{G} and U_0 represent, respectively, farmers' expected utility from joining an avocado PMO and not. Subsequently, a farmer decides to join a group if $U_{\mathrm{G}}^{*} = U_{\mathrm{G}} - U_0 > 0$. As highlighted earlier, we assumed, based on previous literature, that the decision to participate in contract farming would be conditional on PMO membership. A farmer first joins a group and then decides whether to participate in contract farming. The contract-participation decision is determined by comparing the expected benefits from selling through brokers and selling through a contract (U_{C}), and the farmer participates if $U_{\mathrm{C}}^{*} = U_{\mathrm{C}} - U_{\mathrm{G}} > 0$. The net benefits U_{G}^{*} and U_{C}^{*} for an avocado-growing household are latent variables, assumed to be random functions of the vectors of observed explanatory variables $\boldsymbol{X}_{\mathbf{G}}$ and $\boldsymbol{X}_{\mathbf{C}}$, respectively.

$$U_{\mathrm{G}}^{*} = \boldsymbol{Z}_{\mathbf{G}}\boldsymbol{\beta}_{\mathbf{G}} + \varepsilon_{\mathrm{G}}, \tag{6}$$

$$U_{\mathrm{C}}^{*} = \boldsymbol{Z}_{\mathbf{C}}\boldsymbol{\beta}_{\mathbf{C}} + \varepsilon_{\mathrm{C}}, \tag{7}$$

where ε_{G} and ε_{C} are random errors distributed normally with mean zero and variance one and $\boldsymbol{\beta}_{\mathbf{G}}$ and $\boldsymbol{\beta}_{\mathbf{C}}$ are vectors of coefficients of the explanatory variables to be estimated. The observable choices of the farmer are presented as follows:

$$I_{\mathrm{G}} = 1 \text{ if } U_{\mathrm{G}}^{*} > 0; \text{or } I_{\mathrm{G}} = 0, \text{ otherwise}, \tag{8}$$

$$I_{\mathrm{C}} = 1 \text{ if } U_{\mathrm{C}}^{*} > 0; \text{and } I_{\mathrm{G}} = 1, \text{ or } I_{\mathrm{C}} \text{ otherwise}, \tag{9}$$

where I_{G} is the observable decision to join a group given as 1 if the between expected benefits (U_{G}^{*}) of group membership are higher than 0, while I_{C} is the subsequent decision to join contract farming, given as 1 if the expected benefits (U_{C}^{*}) from being under contract are higher than 0. The covariance of the errors terms $\mathrm{Cov}(\varepsilon_{\mathrm{G}}, \varepsilon_{\mathrm{C}}) = \rho$ when the random factors affecting the group and contract participation decisions are not independent because of the unobservable factors that could affect either participation decision. Subsequently, the joint distribution $(\varepsilon_{\mathrm{G}}, \varepsilon_{\mathrm{C}})$ have a bivariate normal distribution with mean vector zero and covariance matrix $\begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$, where the correlation coefficient (ρ) captures the joint nature of these two decisions, which can be estimated using a bivariate probit procedure (Hausman and Wise 1978). However, because the nature of group membership and contact decisions are sequential rather than joint, the above needs to be modified to account for the sequential participation process. Because the contract decision (Eq. 9), can be defined only over the sub-sample where group membership I_{G}=1 (we assumed only farmers in a group are contracted), we get three-way regimes of observations with a non-zero ρ that leads to a bivariate sequential model (Khanna 2001). The probabilities of the three outcomes are:

$$P_{GC} = \Pr\left(I_G = 1; I_C = 1\right) = \boldsymbol{\Phi}_1(\mathbf{Z_G}\boldsymbol{\beta}_\mathbf{G}, \mathbf{Z_C}\boldsymbol{\beta}_\mathbf{C}, \rho), \tag{10}$$

$$P_{G0} = \Pr\left(I_G = 1; I_C = 0\right) = \boldsymbol{\Phi}\left(\mathbf{Z_G}\boldsymbol{\beta}_\mathbf{G}\right) - \rho_{GC}, \tag{11}$$

$$P_{00} = \Pr\left(I_G = 0; I_C = 0\right) = 1 - \boldsymbol{\Phi}\left(\mathbf{Z_G}\boldsymbol{\beta}_\mathbf{G}\right), \tag{12}$$

where $\boldsymbol{\Phi}$ and $\boldsymbol{\Phi}_1$ are the cumulative distribution functions of the standard normal distribution and the standard bivariate normal distribution with correlation coefficient $\boldsymbol{\rho}$ **,** respectively (Alpu and Fidan 2004; Khanna 2001). The above models can be estimated by the Full Information Maximum Likelihood (FIML) using the likelihood function:

$$L = \prod_{I_G=1, I_C=1} \boldsymbol{\Phi}_1(\mathbf{Z_G}\boldsymbol{\beta}_\mathbf{G}, \mathbf{Z_C}\boldsymbol{\beta}_\mathbf{C}, \rho). \prod_{I_G=1, I_C=0} \boldsymbol{\Phi}\left(\mathbf{Z_G}\boldsymbol{\beta}_\mathbf{G}\right) - \rho_{GC}). \prod_{I_G I_C} 1 - \boldsymbol{\Phi}\left(\mathbf{Z_G}\boldsymbol{\beta}_\mathbf{G}\right). \tag{13}$$

Results and Discussion

Descriptive Statistics of Farm and Farmer Characteristics

Table 2 provides a summary of statistics of selected farms and farmer characteristics that are likely to influence the participation of smallholder avocado farmers in the high-value market. On average, MHHs were larger than WHHs. Men who were heads of households were younger and had more years of schooling than did women who led households. While bigger families may hinder participation in high-value crop production because subsistence needs are prioritized over commercial activities (Braun et al. 1991), they may provide labor required in the management of the commercial crops. Better educated farmers are expected to possess skills and the ability to use better market information, which may reduce market and other transaction costs and thus make them participate in profitable high-value markets (Geoffrey et al. 2013). A significantly larger proportion of WHHs reported farming as their main occupation. While relying on agriculture alone may motivate farmers to invest in commercial production for high-value products, it may also suggest limited opportunities to receive the capital required to finance production.

As a measure of the wealth of the household, we included the total number of productive Hass, and Fuerte avocado trees, farm size, the value of major farm assets, and livestock ownership (in tropical livestock units; TLU). We also included dummy variables equal to 1 if the household had access to off-farm income including remittances, businesses, or employment from other sources, and a second dummy equal to 1 if a household was credit-constrained as an indicator of working capital. We

Table 2 Selected household, farm, market, and social capital characteristics based on baseline data

	Full sample		Women-head households (WHHs)		Men-headed households (MHHs)		Difference (WHHs – MHHs)
	(n = 674)		(n = 145)		(n = 529)		
	Mean	SD	Mean	SD	Mean	SD	
Household and farm characteristics							
Household size (adult equivalent)	2.11	0.71	1.83	0.69	2.19	0.70	– 0.354***
Age of household head (years)	63.42	12.37	65.48	11.80	62.85	12.47	2.633***
Education of household hear (years of schooling)	8.20	3.71	6.27	3.76	8.73	3.51	8.203***
Farming main head occupation (1 = Yes 0 = No)	0.70	0.46	0.85	0.36	0.67	0.47	0.183***
Resource constraints							
Number of Hass avocado trees	8.67	15.48	5.12	6.30	9.64	17.04	– 4.515***
Number of Fuerte avocado trees	5.24	9.38	5.05	5.53	5.29	10.19	– 0.247
Owned cultivated land (ha)	0.70	0.72	0.68	0.61	0.71	0.75	– 0.028
Major farm assets and furniture ('000 KES)	54.33	161.96	42.31	99.31	57.62	175.19	– 15.303
Access to off-farm income (1 = Yes 0 = No)	0.79	0.41	0.79	0.41	0.79	0.41	– 0.002
Credit constrained household (1 = Yes, 0 = No)	0.16	0.37	0.08	0.28	0.18	0.39	– 0.099***
Livestock owned in TLU	1.38	1.65	1.17	1.34	1.44	1.73	– 0.266*
Hire labor (1 = Yes, 0 = No)	0.51	0.50	0.54	0.50	0.50	0.50	0.0496
Market access							
Distance to local market (km)	3.03	5.49	3.75	10.49	2.83	2.87	0.914*
Distance to market (walking minutes)	39.26	27.57	38.34	26.52	39.50	27.87	– 1.160
Social capital networks							
Trust neighbors (1 = Yes, 0 = No)	0.40	0.49	0.40	0.49	0.40	0.49	0.003
Cooperate with other avocado farmers (1 = Yes, 0 = No)	0.05	0.22	0.06	0.23	0.05	0.22	0.004
Avocado production perceptions							
Stability for avocado farming (1 = Stable, 0 = Otherwise)	0.81	0.39	0.83	0.37	0.81	0.39	0.027

Table 2 (continued)

	Full sample		Women-head households (WHHs)		Men-headed households (MHHs)		Difference (WHHs – MHHs)
	(n = 674)		(n = 145)		(n = 529)		
	Mean	SD	Mean	SD	Mean	SD	
Avocado working conditions (1 = Strenuous 0 = Otherwise)	0.73	0.44	0.72	0.45	0.73	0.44	− 0.007
Keep avocado related records (1 = Yes, 0 = No)	0.10	0.30	0.08	0.28	0.10	0.30	− 0.019
Risk preference (1 = Yes, 0 = No)	0.73	0.44	0.64	0.48	0.76	0.43	− 0.117***
Location dummies							
Gaichanjiru	154		23		131		
Ithiru	179		46		133		
Kagunduini	184		41		143		
Others	157		35		122		

Above analysis is based on baseline data from 674 households

KES Kenya Shillings; 100 KES are equivalent to 1 US dollar, *TLU* tropical livestock units

Statistical significance at *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

also included a dummy variable equal to 1 if farmers hired labor for agricultural activities.

The number of improved productive avocado trees is a prerequisite for participating in high-value avocado markets. On average, MHHs had significantly more Hass trees than WHHs, while the two groups of households had more or less the same number of Fuerte trees. Farm size is often used as collateral for obtaining credit and, consequently, may positively influence farmers' decisions to participate in commercial production. Following Feder et al. (1990), we defined credit-constrained farmers as those who needed credit but were unable to get it. On average, a significantly larger proportion of MHHs was credit-constrained compared to WHHs.

Market access variables are directly associated with the transaction costs related to both input and output marketing activities and can negatively influence the smallholder's participation in production for the high-value market (Key et al. 2000). We measured market access as distance to the local and main markets, in kilometers and walking minutes, respectively. The average distance to the local market was 3 km, with WHHs reporting significantly longer distances than did MHHs.

Following Shiferaw et al. (2011), we also controlled for social capital and networks that could influence high-value market participation decisions among avocado growers. We considered two measures of social capital; household relationships with neighbors, defined as whether the household trusted neighbors; and household relationships with other avocado producers, defined as whether the household cooperated with other avocado farmers in the village. Different forms of social capital and networks may affect farmer's participation in high-value markets through information sharing, stable market contracts, bargaining for better prices, labor sharing, soothing credit constraints, mitigation of risks, and other ways (Shiferaw et al. 2011; Fischer and Qaim 2012; Wossen et al. 2017). The two variables, however, are not significantly different between the MHHs and WHHs.

We also considered some perceptions regarding avocado production that were likely to influence smallholder participation in the high-value market including stability of avocado farming and working conditions (input application, harvesting, record-keeping by farmers, and risk preferences e.g., all measured as dummy variables). Risk-preferring households are likely to try new markets or technological innovations such as producing crops for high-value markets through contracts. On the other hand, risk-averse farmers tend to join a group to mitigate the risks associated with non-payments from traders.[5]

Empirical Results and Discussions

As mentioned in the previous section, we applied the multinomial regression and random-effects models to estimate the determinants of dynamic participation in PMO membership among avocado farmers in Murang'a County, and a sequential bivariate model approach to assess determinants of contract farming conditional on group membership. To determine whether certain factors affected farmers

[5] The sample characteristics of different categories of PMOs membership and contract adoption groups were also tabulated and available under supplementary materials.

differently by gender, we conducted separate MNL and random-effects estimations for households headed by women and those headed by men. Sequential bivariate models were, however, estimated for the pooled sample, with a focus on gender as our variable of interest. The random-effects model used the panel nature of our data; therefore, it did not incorporate farmer dynamics in group membership. Before running the models, we conducted a multicollinearity test for the variables included in the analysis. The results showed no strong correlation because the value of the variance inflation factor (VIF) was far less than 10.

Factors Affecting Dynamics of Smallholder Farmers Participation in Avocado Production and Marketing Groups

Multinomial Logit Regression Results Table 3 reports estimates derived using the MNL model for the determinants of avocado farmer's behavior in PMOs participation. Tables 4 and 5 report gender-specific estimations. Because the set of late group participants was small among WHHs (see Table 1), we merged this group with the non-adopters while analyzing the WHHs models. Analyzing the two groups together is supported by Diederen et al. (2003) who compared laggards and frontrunners (innovators and early adopters). Similarly, Rogers (1995) depicts the characteristics of the late adopters and non-adopters as very similar.

With respect to full sample regression (Table 3), household and farm characteristics matter for the choice of different participation decisions. Early group participants have smaller families than non-adopters and dis-adopters. The gender variable is also significant, with late adopters and early adopters likely to be MHHs in comparison with non-adopters. This suggests the existence of a resource gap among WHHs relative to households headed by men, thus affecting group participation. As noted in the literature, women have less access to productive resources that might limit them from participating in commercialized value chains (Quisumbing and Pandolfelli 2010). Besides, hidden transaction costs such as information search costs that are not controlled in the model, due to difficulties in measurement, may also constrain women more than men. As observed by Rogers (1995), relative to non-adopters, early adopters have more years of formal education and are more likely to depend upon farming as their main occupation.

The number of Hass avocado trees had a positive impact on group participation decisions across different categories compared to non-participants. Surprisingly, the size of the farm has a negative influence on late adopters and dis-adopters in relation to the non-adopters, suggesting that non-adopters have larger farms than their counterparts. This is plausible as larger-scale farmers may prefer to market their produce independently and not collectively through groups. Early group participation relative to late participation decisions is likely to be positively influenced by access to hired labor, supporting the importance of extra effort in commercialized agricultural value chains. While market access characteristics don't seem to matter in group-participation decisions, social capital networks (developed through trust of neighbors) are likely to positively influence group-exiting decisions in comparison to late or non-participation. This implies that socio-capital networks alone are not enough for sustainable participation in high-value chains. In accordance with our expectations, satisfaction with avocado farming and record-keeping correlated positively with the

Table 3 Factors that affect participation in avocado production and marketing groups

	Late adopters vs. non-adopters	Dis-adopters vs. non-adopters	Early adopters vs. non-adopters	Dis-adopters vs. late adopters	Early adopters vs. late adopters	Early adopters vs. dis-adopters
Household and farm characteristics						
Household size (adult equivalent)	−0.265	0.152	−0.336	0.416	−0.071	−0.487
	(0.231)	(0.185)	(0.167)**	(0.243)*	(0.238)	(0.179)***
Gender of household head (1 = male, 0 = female)	1.169	0.557	0.542	−0.611	−0.626	−0.015
	(0.552)**	(0.348)	(0.305)*	(0.612)	(0.573)	(0.368)
Age of household head (years)	0.015	0.031	0.004	0.016	−0.011	−0.027
	−0.014	(0.012)***	(0.010)	(0.016)	(0.015)	(0.012)**
Education of household head (years of schooling)	0.108	0.047	0.066	−0.061	−0.042	0.019
	(0.055)**	−0.041	(0.037)*	(0.058)	(0.053)	(0.038)
Farming main head occupation (1 = Yes 0 = No)	0.4	−0.111	0.635	−0.510	0.235	0.745
	(0.359)	(0.286)	(0.259)**	(0.386)	(0.368)	(0.283)***
Resource constraints						
Number of Hass avocado trees	0.104	0.124	0.124	0.020	0.020	0.00
	(0.031)***	(0.027)***	(0.026)***	(0.019)	(0.018)	(0.007)
Number of Fuerte avocado trees	0.013	0.006	−0.012	−0.008	−0.026	−0.018
	(0.016)	(0.012)	(0.016)	(0.015)	(0.016)	(0.014)
Owned cultivated land (ha)	−0.657	−0.666	−0.269	−0.009	0.388	0.397
	(0.310)**	(0.261)**	(0.173)	(0.373)	(0.311)	(0.264)
Major farm assets and furniture ('000 KES)	0.000	0.000	0.001	0.000	0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Access to off-farm income (1 = Yes 0 = No)	0.225	−0.078	0.038	−0.303	−0.187	0.115
	(0.427)	(0.342)	(0.300)	(0.450)	(0.390)	(0.321)
Credit constrained household (1 = Yes, 0 = No)	−0.343	−0.383	−0.525	−0.039	−0.181	−0.142
	(0.448)	(0.351)	(0.293)*	(0.472)	(0.434)	(0.350)

Table 3 (continued)

	Late adopters vs. non-adopters	Dis-adopters vs. non-adopters	Early adopters vs. non-adopters	Dis-adopters vs. late adopters	Early adopters vs. late adopters	Early adopters vs. dis-adopters
Livestock owned in TLU	0.105	−0.079	0.053	−0.183	−0.052	0.131
	(0.089)	(0.110)	(0.084)	(0.114)	(0.052)	(0.111)
Hire labor (1 = Yes, 0 = No)	−0.328	−0.035	0.321	0.293	0.649	0.356
	(0.332)	(0.287)	(0.247)	(0.357)	(0.321)**	(0.273)
Market access						
Distance to local market (km)	−0.019	0.019	0.012	0.037	0.031	−0.007
	(0.043)	(0.017)	(0.022)	(0.038)	(0.037)	(0.020)
Distance to main market (walking minutes)	0.001	0.001	0.001	0.000	0.000	0.000
	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.004)
Social capital networks						
Trust neighbors (1 = Yes, 0 = No)	−0.116	0.537	0.311	0.653	0.427	−0.226
	(0.357)	(0.266)**	(0.231)	(0.378)*	(0.346)	(0.257)
Cooperate with other avocado farmers (1 = Yes, 0 = No)	1.05	−0.337	0.146	−1.387	−0.903	0.484
	(0.677)	(0.848)	(0.610)	(0.706)**	(0.546)*	(0.615)
Avocado farming perceptions and practice						
Satisfaction with avocado farming (1 = Satisfied 0 = Otherwise)	−0.274	0.022	0.61	0.296	0.885	0.589
	(0.388)	(0.337)	(0.319)*	(0.432)	(0.382)**	(0.342)*
Avocado working conditions (1 = Strenuous 0 = Otherwise)	0.442	0.571	0.224	0.129	−0.217	−0.347
	(0.380)	(0.316)*	(0.246)	(0.420)	(0.363)	(0.315)
Keep avocado related records (1 = Yes, 0 = No)	0.158	0.944	0.827	0.786	0.669	−0.117
	(0.594)	(0.415)**	(0.372)**	(0.599)	(0.560)	(0.359)
Risk preference (1 = Yes, 0 = No)	0.418	0.584	0.267	0.166	−0.151	−0.317

Table 3 (continued)

	Late adopters vs. non-adopters	Dis-adopters vs. non-adopters	Early adopters vs. non-adopters	Dis-adopters vs. late adopters	Early adopters vs. late adopters	Early adopters vs. dis-adopters
	(0.426)	(0.316)*	(0.267)	(0.458)	(0.418)	(0.302)
Location dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	− 6.527	− 4.861	− 2.66	1.666	3.867	2.201
	(1.642)***	(1.223)***	(1.026)***	(1.817)	(1.687)**	(1.247)*
Number of observations		674				
Wald $\chi^2(72)$		270.17***				
Pseudo R^2		0.231				
Log pseudo likelihood		− 646.29				

Presented above are the odds ratio coefficients (standard error)

Statistical significance at *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Table 4 Factors affecting participation in avocado production and marketing groups by women-headed households

	Dis-adopters vs. laggards	Early adopters vs. laggards	Early adopters vs. dis-adopters
Household and farm characteristics			
Education of household head (years of schooling)	−0.187	0.118	0.305
	(0.133)	(0.087)	(0.142)**
Resource constraints			
Number of Hass avocado trees	0.224	0.116	−0.107
	(0.065)***	(0.048)**	(0.049)**
Credit constrained household (1 = Yes, 0 = No)	−15.829	0.199	16.027
	(2.041)***	(1.021)	(1.977)***
Hire labor (1 = Yes, 0 = No)	−1.939	−0.260	1.679
	(1.014)*	(0.586)	(0.979)*
Market access			
Distance to local market (km)	1.528	1.536	0.008
	(0.870)*	(0.869)*	(0.021)
Social capital networks	Yes	Yes	Yes
Avocado farming perceptions and practice			
Keep avocado related records (1 = Yes, 0 = No)	2.460	1.409	−1.051
	(1.203)**	(0.863)	(1.167)
Risk preference (1 = Yes, 0 = No)	1.584	0.550	−1.034
	(0.934)*	(0.651)	(1.042)
Location dummies	Yes	Yes	Yes
Constant	2.236	−3.500	−5.736
	(4.223)	(3.092)	(4.662)
Number of observations	145		
Wald $\chi^2(46)$	1291.1***		
Pseudo R^2	0.33		
Log pseudo likelihood	−88.13		

Laggards comprise late adopters and non-adopters; presented above are the odds ratio coefficients (standard error); all the independent variables in Table 3 were used in the above analysis, but only the significant variables are reported; the full model results are available as Supplementary Materials

Statistical significance at *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

probability of being an early adopter compared to non-adopters. This is plausible, as record-keeping is a vital business skill for the successful commercialization of agriculture value chains (Fischer and Qaim 2012). Relative to non-participation, group dis-adoption was also positively related to record-keeping, again querying

Table 5 Factors affecting participation in avocado production and marketing groups among households headed by men

	Late adopters vs. non-adopters	Dis-adopters vs. non-adopters	Early adopters vs. non-adopters	Dis-adopters vs. late adopters	Early adopters vs. late adopters	Early adopters vs. dis-adopters
Household and farm characteristics						
Household size (adult equivalent)	−0.355	0.236	−0.376	0.591	−0.021	−0.613
	(0.247)	(0.218)	(0.198)*	(0.254)**	(0.249)	(0.205)***
Age of household head (years)	0.017	0.044	0.006	0.027	−0.011	−0.038
	(0.016)	(0.013)***	(0.012)	(0.017)	(0.016)	(0.013)***
Education of household head (years of schooling)	0.108	0.062	0.058	−0.046	−0.05	−0.004
	(0.058)*	(0.046)	(0.042)	(0.061)	(0.055)	(0.042)
Farming main head occupation (1 = Yes 0 = No)	0.362	−0.268	0.545	−0.63	0.182	0.812
	(0.383)	(0.301)	(0.284)*	(0.405)	(0.388)	(0.303)***
Resource constraints						
Number of Hass avocado trees	0.109	0.127	0.128	0.018	0.02	0.001
	(0.035)***	(0.032)***	(0.032)***	(0.018)	(0.018)	(0.007)
Owned cultivated land (ha)	−0.829	−1.032	−0.45	−0.203	0.379	0.582
	(0.372)**	(0.318)***	(0.240)*	(0.433)	(0.362)	(0.306)*
Credit constrained household (1 = Yes, 0 = No)	−0.479	−0.231	−0.631	0.248	−0.153	−0.401
	(0.465)	(0.365)	(0.312)**	(0.487)	(0.453)	(0.369)
Hire labor (1 = Yes, 0 = No)	−0.458	0.115	0.32	0.574	0.778	0.205
	(0.372)	(0.320)	(0.286)	(0.394)	(0.353)**	(0.305)
Market access						
Distance to local market (km)	−0.076	0.056	−0.231	0.132	−0.155	−0.287
	(0.103)	(0.063)	(0.148)	(0.074)*	(0.141)	(0.135)**
Distance to main market (walking minutes)	0.004	−0.001	0.017	−0.005	0.012	0.018
	(0.010)	(0.008)	(0.011)	(0.007)	(0.010)	(0.009)*
Social capital networks						

Table 5 (continued)

	Late adopters vs. non-adopters	Dis-adopters vs. non-adopters	Early adopters vs. non-adopters	Dis-adopters vs. late adopters	Early adopters vs. late adopters	Early adopters vs. dis-adopters
Trust neighbors (1 = Yes, 0 = No)	−0.327	0.496	0.276	0.824	0.603	−0.221
	(0.391)	(0.294)*	(0.261)	(0.413)**	(0.374)	(0.290)
Cooperate with other avocado farmers (1 = Yes, 0 = No)	1.094	−0.407	0.328	−1.501	−0.766	0.735
	(0.750)	(0.951)	(0.679)	(0.808)*	(0.584)	(0.707)
Avocado farming perceptions and practice						
Satisfaction with avocado farming (1 = Satisfied 0 = Otherwise)	−0.389	−0.018	0.653	0.371	1.043	0.671
	(0.412)	(0.364)	(0.355)*	(0.459)	(0.411)**	(0.378)*
Keep avocado related records (1 = Yes, 0 = No)	0.208	0.775	0.752	0.567	0.545	−0.022
	(0.620)	(0.467)*	(0.418)*	(0.634)	(0.592)	(0.409)
Location dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−5.221	−4.96	−1.843	0.26	3.378	3.117
	(1.951)***	(1.363)***	(1.195)	(2.113)	(1.986)*	(1.347)**
Number of observations	529					
Wald $\chi^2(69)$	214.1***					
Pseudo R^2	0.2379					
Log pseudo likelihood	−516.53					

Presented above are the odds ratio coefficients (standard error); all the independent variables in Table 3 were used in the above analysis, but only the significant variables are reported; the full model results are available as Supplementary Materials

Statistical significance at $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

sustainability of participation in high-value chains despite possession of the important agriculture commercialization ingredients such as record-keeping skills.[6]

Table 4 shows the MNL estimations for WHHs. As noted earlier, the analysis of WHHs is composed of three categories of group participation: early adopters, dis-adopters, and laggards. Among such households, the education of the household head matters for early group participation decisions in comparison to dis-adopters. Similarly, the number of Hass avocado trees has a positive impact on early adoption and abandonment decisions in comparison to late and non-adopters. This finding is consistent with most of the gender literature which shows that access to resources among women increases their capacity to participate in rural institutions and subsequently adopt new technologies (Doss 2001; Quisumbing and Pandolfelli 2010). Credit constrained households headed by women are more likely to be late adopters or non-adopters in comparison to dis-adopters. This is plausible as participation in PMOs requires contributions for group membership and other group maintenance expenses, hence cash outlay. However, credit-constrained WHHs are more likely to be early adopters in comparison with dis-adopters. This implies that credit-constrained female farmers may choose to remain in groups where they receive credit and other financial services that may be required for the production and marketing of their produce (Quisumbing and Pandolfelli 2010).

Consistent with agriculture commercialization literature (e.g. Muriithi and Matz 2014), farmers located far away from the market have limited market opportunities for their produce and hence may choose to join rural institutions to facilitate their marketing activities. Surprisingly, none of the social capital networks influenced group participation among WHHs, while dis-adopters had a high probability of keeping records in comparison with late and non-adopters.

Table 5 presents the regression results for the MHHs. Early adopters have smaller families, while dis-adopters have older household heads, both in comparison to non-adopters. Dis-adopters, however, have larger families in comparison with early adopters. Similarly, the size of Hass avocado orchards positively affects PMOs participation compared to those who do not participate, suggesting the need to encourage the production of improved avocado tree crops, and hence participation in rural institutions. Interestingly, we found a negative relationship to all group-adoption categories in comparison with non-adopters with regard to the size of land cultivated. The finding contrasts with Rogers' (1995) argument on the adoption of agricultural technologies. Farmers with less land probably use rural groups for marketing to maximize earnings from their small plots. In the same way as WHHs, credit-constrained MHHs are likely to be early adopters in comparison with non-adopters. MHHs that exit from groups are more likely to trust their neighbors in comparison with late and non-adopters, while early adopters are more likely to be satisfied with avocado

[6] The similarities in some variables such as record-keeping between early adopters and dis-adopters is not surprising since the two groups were both participants at the baseline; this is in contrast with late adopters and non-adopters who were not participating in PMOs and/or contract farming at baseline.

Table 6 Random-effects logit model for participation in avocado production and marketing groups

	Full sample		Women-headed households		Men-headed households	
Household and farm characteristics						
Gender of the household head	0.073	(0.035)**				
Education of household hear (years of schooling)	0.008	(0.004)**	0.010	(0.007)	0.005	(0.004)
Resource constraints						
Number of Hass avocado trees	0.010	(0.002)***	0.010	(0.009)	0.01	(0.002)***
Number of Hass avocado trees squared	0.000	(0.000)***	0.000	(0.000)	0.000	(0.000)**
Number of Fuerte avocado trees squared	0.000	(0.000)**	−0.001	(0.000)*	0.000	(0.000)**
Owned cultivated land (ha)	−0.004	(0.019)	0.089	(0.041)**	−0.018	(0.019)
Access to off-farm income (1 = Yes 0 = No)	−0.049	(0.027)*	0.011	(0.058)	−0.06	(0.032)*
Livestock owned in TLU	−0.013	(0.006)**	0.000	(0.010)	−0.016	(0.008)**
Hire labor (1 = Yes, 0 = No)	0.067	(0.029)**	0.064	(0.062)	0.061	(0.033)*
Market access						
Distance to local market (km)	0.000	(0.003)	0.002	(0.002)	−0.017	(0.006)***
Distance to main market (walking minutes)	0.000	(0.001)	0.001	(0.001)	0.002	(0.001)**
Social capital networks						
Trust neighbors (1 = Yes, 0 = No)	0.041	(0.024)*	0.024	(0.046)	0.056	(0.028)**
Avocado farming perceptions and practice						
Satisfaction with avocado farming (1 = Satisfied 0 = Otherwise)	0.080	(0.030)***	0.083	(0.046)*	0.079	(0.037)**
Keep avocado related records (1 = Yes, 0 = No)	0.081	(0.042)*	0.017	(0.101)	0.094	(0.046)**
Location fixed effects	Yes		Yes		Yes	
Constant	0.005	(0.115)	−0.070	(0.222)	0.089	(0.135)
Number of observations	1348		299		1049	
Wald $\chi^2(29)$	638.58***		289.27		432.22	
R^2	0.2811		0.3543		0.2659	

Robust standard errors in parenthesis; the above regression analysis includes all the independent variables provided in Table 3, but only the significant ones are presented above; full model results are provided as Supplementary Materials

Statistical significance at $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

farming compared with the same groups, while both those who exit and those who stay keep records of their production activities.[7]

Random-Effects logit Model Estimations Table 6 presents the random-effects logit model results for farmer's participation in group membership (Eq. 5). The first columns present the estimations for the full sample; subsequent rows show results by gender. Similar to the MNL results, the gender of the household head had a significant positive impact on the probability of participating in PMOs, implying that MHHs are more likely to join groups than WHHs, again suggesting the existence of a resource gap among the latter group. As highlighted earlier, the invisible transaction costs of participating in PMOs such as time to attend PMO meetings and unlimited capacity to make group decisions, in addition to limited access to productive resources, may pressure women more than men.

Consistent with the MNL pooled data results for early adopters, education of the household head, the number of improved avocado trees (Hass), satisfaction with avocado farming, and record-keeping are significant and positively related to participation in groups. For gender-disaggregated analysis, ownership of a large amount of land had a positive impact on the probability that WHHs would join an avocado production and marketing group.

Factors Affecting Contract Farming Conditional on Group Membership

Table 7 shows the estimates of the sequential participation in the high-value market value chain using bivariate probit (Eqs. (8) and (9)), together with the marginal effects of the explanatory variables. A bivariate probit model estimation requires an identification condition for Eqs. (8) and (9), suggesting establishing variables that correlate with group membership but not directly with contract farming. We achieve this by including the "group membership fees" in Eq. (9). The model estimation shows that the null hypothesis (i.e., that ρ is 0) is rejected at a 1% level, suggesting the validity of estimating the two selection equations jointly. The ρ is positive, implying that the unobserved factors that affect participation in groups also increased the probability of contract farming participation.

Our variable of interest, the gender of the household head, was positive but not significant. The positive sign implies that households headed by men are likely to join a group or enter into a contracting than women, however, the difference is not significant between the two groups. The result contradicts those from random-effects estimation, perhaps because the bivariate probit estimation did not account for omitted variables and the potential endogeneity of some independent variables, which are both addressed in the former regression model. However, as in the previous estimation, ownership of a higher number of Hass avocado trees has a significant

[7] In addition to the separate analysis of the female- vs. male-headed households, we assessed whether mechanism and determinants of PMOs systematically differ by gender, thanks to an anonymous reviewer. We run the main analysis on the full sample with interaction terms between the key explanatory variables and a female-headed household dummy. Consistent with existing literature on gender and agricultural commercialization, land cultivated systematically differed by gender with respect to adoption of the PMOs.

positive impact on the probability of joining a farmer group and of contract farming, supporting the hypothesis that participation in income-enhancing agricultural activities is not scale neutral. Risk preference, one of the social capital measures of this study, has a significant positive effect on contract farming as hypothesized.

Conclusions and Policy Recommendations

We used panel data consisting of two waves of household-level data obtained from one of the avocado-producing counties in Kenya, Murang'a County, to examine, on a gender lens, the factors associated with smallholder participation in the high-value export markets. The study contributes to the limited literature on the dynamics of smallholder horticultural farmers' participation in high-value markets. We diverged from previous studies that considered adoption using binary models using panel data to construct the dynamics of market participation. Besides, our analysis focused on the gender of the household head, based on existing evidence that men and women participate in markets differently, an aspect that is often ignored in many studies of the adoption of agricultural technology. We considered two forms of high-value market participation: group membership and contract farming. Based on existing evidence that the majority of smallholder farmers in Kenya can only be contracted by exporters as a group, we estimate the factors that affected contract farming conditional on group membership.

Given the nature of our data, we divided group participation dynamics into four categories: late adopters, early adopters, dis-adopters, and non-adopters. Our descriptive results show a significant proportion of respondents exited (dis-adopters) from groups (17%) and contract farming (11%), hence demonstrating the need to model smallholder market participation beyond binary analysis.

We estimated the model using the full sample and then separated estimations for households headed by men or by women for group participation and pooled model for contract farming. Our results show that the categories of farmers differed with regard to household and farm characteristics, resource constraints, market access, and avocado farming perceptions and practices. We found that early adopters had smaller families, their household heads were younger, were more likely to rely on farming as their main occupation, and perceived greater satisfaction with avocado farming than did dis-adopters. Among the WHHs, we found that early adopters were more educated, had fewer Hass avocado trees, and were more credit-constrained than were dis-adopters. Laggards (late and non-adopters) also owned less of the improved avocado variety (Hass) in comparison with dis-adopters and early adopters. With regard to MHHs, dis-adopters had bigger families, their household heads were older, they were closer to the local market, their household heads less likely to be dependent on farming as their main occupation, and they were less satisfied with avocado farming in comparison to early adopters. In terms of contract farming conditional on group membership, the gender variable is positive but not significant. The finding follows the previous random-effects estimation which showed that households headed by men were more likely to participate in both groups and in contracting. The number of

Table 7 Determinants of the probability of participation in the high-value avocado market

	Bivariate model		Marginal effects[a]	
	Group membership	Contract farming	Both group and contract	Group only
Household and farm characteristics				
Household size (adult equivalent)	−0.233	0.064	0.003	−0.095
	(0.108)**	(0.116)	(0.019)	(0.038)**
Gender of household head (0 = Female 1 = Male)	0.25	0.183	0.035	0.064
	(0.157)	(0.187)	(0.029)	(0.057)
Farming main head occupation (1 = Yes 0 = No)	0.146	0.353	0.057	0.001
	(0.128)	(0.150)**	(0.024)**	(0.046)
Resource constraints				
Number of Hass avocado trees	0.036	0.027	0.005	0.009
	(0.009)***	(0.011)**	(0.002)***	(0.003)***
Number of Hass avocado trees (squared)	−0.0002	−0.0003	−0.00005	−0.0001
	(0.000)***	(0.000)*	(0.00002)**	(0.00003)
Owned cultivated land (ha)	0.191	0.103	0.0210	0.054
	(0.120)	(0.143)	(0.023)	(0.043)
Access to off-farm income (1 = Yes 0 = No)	−0.319	−0.143	−0.0308	−0.096
	(0.131)**	(0.141)	(0.023)	(0.047)**
Market access indicators	Yes	Yes	Yes	Yes
Social capital networks				
Cooperate with other avocado farmers (1 = Yes, 0 = No)	0.522	−0.257	−0.0229	0.230
	(0.277)*	(0.300)	(0.047)	(0.103)**
Satisfaction with avocado farming (1 = Satisfied 0 = Otherwise)	0.534	0.321	0.0637	0.148
	(0.165)***	(0.210)	(0.033)*	(0.060)**
Risk preference (1 = Yes, 0 = No)	−0.017	0.549	0.0815	−0.088
	(0.141)	(0.178)***	(0.028)***	(0.052)**

Table 7 (continued)

	Bivariate model		Marginal effects[a]	
	Group membership	Contract farming	Both group and contract	Group only
Group membership fees (KES)	0.015		0.0004	0.006
	(0.004)***		(0.000)***	(0.002)***
Location fixed effects	Yes	Yes	Yes	Yes
Constant	−0.84	−2.764		
	(0.552)	(0.669)***		
RHO (ρ)	0.612 (0.068)***			
Number of observations	658			
Log-likelihood	−529.55			
LR test	207.53***			

Standard errors in parenthesis

Statistical significance at $*p<0.1$, $**p<0.05$, $***p<0.01$

[a]Contract participation is only observed if a farmer participates in a group ($I_C \neq 1 \text{ if } I_G = 0$); the above results show only the significant variables, full regression results are provided as Supplementary Materials

improved avocado trees and risk preference were also likely to positively influence contract farming.

While we found useful insights into the dynamics of smallholder participation in high-value markets, we acknowledge limitations in our analysis. One was the short period between surveys, which may not have allowed us to answer critical policy questions regarding adoption dynamics. Second, was the lack of an adequate sample of households headed by women to model dynamics. A third limitation was the comparison between households headed by women and households headed by men, which may not have been a perfect gender indicator: in fact, the management of farm plots depends upon the gender of the decision-maker rather than of the head of the household. More research is required to close these gaps.

Even with these caveats, the results suggest important implications, especially for woman farmers. Primary among these is that larger orchards of improved avocado varieties (Hass) can increase and sustain smallholders' participation in high-value markets, both through contracts and group membership. Efforts in this direction are evident, and, driven mainly by international demand, the Murang's County government is already promoting the adoption of the improved avocado variety. Another significant implication is that policy measures to discourage farmers from abandoning high-value markets should include improvement of household-level education, including quality extension services and other training platforms. Social networks that build trust among community members, as well as between traders and farmers, may also be considered to encourage non-adopters to participate in production for high-value markets.

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Declarations

Conflict of interest The author declares that there is no conflict of interest.

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