Drivers of Participation in Smallholders Banana Contract Farming in Kenya.

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Abstract
Smallholder banana farmers in Kenya face declining farm productivity and low market prices due to a fragmented, broker-dominated market. While the Kenya National Banana Development Strategy promotes contract farming as a potential solution, farmer participation remains surprisingly low. This study investigates the factors influencing smallholder participation in banana contract farming in Kenya. Employing a heteroskedastic probit model with robust standard errors to assess the drivers of participation in smallholder banana contract farming in Kenya, we identify key drivers such as household head education, credit access, cooperative membership, irrigation, and banana farm size. Based on these findings, we recommend policy interventions focusing on: Enhanced farmer extension services and technical assistance, facilitated credit access, cooperative development, investment in irrigation, and incentives for contract farming companies. By addressing these critical factors, policymakers can encourage wider smallholder participation in banana contract farming, unlocking its potential to improve livelihoods and contribute to sustainable agricultural development in Kenya.

Keywords: Banana; contract; Kenya; participation; smallholder

JEL Classification Codes : Q10, Q11, C13

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1. Introduction

Agriculture is pivotal in the economic development of Sub-Sahara Africa (SSA) countries, contributing significantly to GDP, employment, and livelihoods. In Kenya, agriculture directly constitutes 33% of the GDP, with an additional 27% indirectly, underscoring its essential role in national development (Organisation for Economic Co-operation and Development & Food and Agriculture Organization of the United Nations, 2016; World Bank, 2016; Republic of Kenya, 2019). Recognizing its significance, the government has strategically prioritized agriculture in key plans such as the Vision 2030 and the Agricultural Sector Transformation and Growth Strategy (2019—2029), with a specific focus on enhancing farm-level productivity and income (Republic of Kenya, 2019).

Recent decades have witnessed the emergence of horticulture as a linchpin of agricultural progress in Kenya, contributing substantially to foreign exchange earnings, food security, employment, and poverty alleviation (International Fund for Agricultural Development, 2019). Within this dynamic horticultural sector, the banana subsector has emerged as a prominent contributor, commanding 16% of the horticultural value in Kenya (Agriculture and Food Authority, 2021). Cultivated predominantly on smallholder farms with an average size of 0.1 to 3 hectares, banana farming has become an alternative income source amid the declining fortunes of other commodities (Obaga & Mwaura, 2018). Despite continuous growth, banana production faces challenges like high costs, low productivity, and inefficient marketing, threatening its sustainability (IFAD, 2019). In response, the government, non-governmental organizations, and private sector entities have implemented various interventions, including the Smallholder Horticulture Empowerment Project (SHEP) and the National Agricultural and Rural Inclusive Growth Project (NARIGP), aimed at enhancing productivity and value chain efficiencies (Kitajima & Shimada, 2020; Republic of Kenya, 2020).

Despite these efforts, approximately 90% of banana farmers encounter challenges selling their produce, relying on middlemen or local markets with depressed prices (USAID, 2016). In this context, contract farming emerges as a strategic intervention. Defined as agreements between organized buyers and farmers specifying production and marketing conditions, contract farming is increasingly recognized as a means to address challenges in smallholder banana farming (Republic of Kenya, 2014).

Contract farming offers a structured approach, providing farmers with production support, a reliable market, and predefined prices, mitigating business risks for both parties (USAID, 2016). Key corporate players like Stawi Foods and Fruits Limited, Neo-Kenya, and Twiga Foods, along with governmental and non-governmental initiatives, have embraced and promoted contract farming in the banana sector (Bismark-Osten, 2021). Despite these initiatives, smallholder participation remains low (East African Community, 2021).

Household utility maximization is central to the decision to participate in contract farming, with the Random Utility Model (RUM) providing a framework for analyzing this discrete choice. RUM posits that participation hinges on the perceived utility of participation compared to non-participation, influenced by observable household and institutional characteristics (covariates) (Obebo, 2018). This framework allows us to estimate drivers of participation in smallholder banana contract farming. Although the Linear Probability Model (LPM) is often used for binary outcomes like participation, it has significant drawbacks: its predictions can fall outside the 0-1 range, and it is not robust to heteroskedasticity (Verbeek, 2012). Therefore, probit regression is selected due to its suitability for the data characteristics. A Shapiro-Wilk test confirms the normality of the error distribution, supporting the use of the probit model. To address potential heteroskedasticity, a heteroskedastic probit model with robust standard errors is run to ensure reliable and unbiased results (Verbeek, 2012).

This study contributes to the literature on contract farming participation by addressing the drivers of participation in smallholder banana contract farming in Kenya, an area largely unexplored despite the significance of banana as a leading horticultural crop in the country (Agriculture and Food Authority, 2021). The existing literature on drivers of contract farming participation provides inconclusive insights, with variations across crops, enterprises, and regions (World Bank, 2017). Studies highlight factors such as the commercialization index, distance from collection centres, labour availability, age, production experience, and access to credit (Hussaini Yusuf et al., 2021; Akumu et al., 2020; Mulatu et al., 2017). Gender-related dynamics impact adoption, with male-headed households often being better adopters (Maganga-Nsimbila, 2021; Hirpesa et al., 2020; Ziyadhuma, 2020; Dubbert, 2019; Bellemare & Bloem, 2018; Wainaina et al., 2012; Bellemare, 2012). Internet access, education, information availability, and infrastructure also play vital roles (Maganga-Nsimbila, 2021; Ziyadhuma, 2020; Hirpesa et al., 2020; Dubbert, 2019; Amare et al., 2019; Mwambi et al., 2016).

The remainder of the paper is organized as follows: Section 2 outlines the methodological approach employed, Section 3 provides a presentation and discussion of the results, and Section 4 concludes the study and draws inferences regarding policy implications.

2. Methodological Approach

2.1 Theoretical Model

The theoretical foundation for understanding the drivers of participation in smallholder banana contract farming in Kenya is rooted in Singh *et al.*'s (1986) theory of household utility maximization. This framework delves into the complex decisions made by households regarding production, consumption, and labour allocation, offering essential linkages to describe a farm household's engagement in contract farming.

The household's objective is to maximize the utility function, represented as U, which encompasses the household-produced good C_h market-purchased good C_m, leisure τ and a vector of household variables influencing consumption M^h:

$$Max\ U = U(C_h, C_m, \tau; M^h) \tag{1}$$

The household faces a production constraint expressed as:

$$Q_h = f(X, L^h) \tag{2}$$

Where Q_h represents the total household production, that is shared between household consumption and market sale, X represents inputs other than labour and L^h is household labour. Moreover, the household faces an income constraint. The potential sources of income include sale of some of the household good, sale of labour in the market, and borrowing to purchase the market good and inputs for production of the household good such that:

$$Y^* = P_h(Q_h - C_h) + w\,L_w + NB = P_m\,C_m + P_x\,X \quad (3)$$

Whereby Y^* represents the total household income, P_h is the price of the household-produced good in the market, $(Q_h - C_h)$ is the quantity of household good that is sold in the market, w is the wage rate, L_w is the amount of household labour sold in the market, NB is the net borrowing by the household, P_m is price of the market good, C_m is the quantity of the market good consumed by the household, P_x is the input price and X is the quantity of inputs used by the household in the production of the household good.

The household also faces a time constraint. It allocates its total time (T) between production of the home good (L_h), participation in the labour market (L_w) and leisure (τ).

$$T = L_w + L_h + \tau \quad (4)$$

Equations 2, 3, and 4 can be rearranged to form the full income constraint as follows:

$$[P_h\ f(X, L_h) - P_x\,X - wL_h\ ] + wT + NB = P_h\,C_h + P_mC_m + w\tau \quad (5)$$

While the left-hand side represents income from the household production less the cost of production, total value of time, and net borrowing, the right-hand side represents the cost of the household good consumed in the household, market good consumed in the household and leisure.

Given the full income constraint, the augmented utility function may be defined as:

$$L = U(.) + \lambda[P_h\,f(X, L_h) - P_xX - wL_h + wT + NB - P_h\,C_h - P_m\ C_m - w\tau] \quad (6)$$

The first order necessary conditions are as follows:

$$dL/_{dC_h} = U_{Ch} - \lambda P_h = 0 \quad (7)$$

$$dL/_{dC_m} = U_{Cm} - \lambda P_m = 0 \quad (8)$$

$$dL/_{d\tau} = U_\tau - \lambda w = 0 \quad (9)$$

$$dL/_{d\lambda} = U_\lambda - [P_h\,f(X, L_h) - P_xX - wL_h + wT + NB - P_hC_h - P_mC_m - w\tau] = 0 \quad (10)$$

Solving the first-order conditions from the joint system of equations: (7), (8), (9), and (10), yields normal demand functions of the household produced good, market purchased good, and leisure. The demands are a function of the price of household good (P_h), the price of market good (P_m), wage rate (w), input price of household produced good (P_x), level of inputs (X), net borrowing (NB) and a vector of household variables affecting consumption (M^h).

In addition, the optimal production decisions of the household can be deduced from the system of equations and depend on the variables in equations (7), (8), (9), and (10). Following Sadoulet & De Janvry (1995), Huffman (2010), and Obebo (2018), the first order conditions may be used to derive the reduced form of the consumption and production decisions of the households such that:

$$C_i = C_i (P_h , P_x , P_m , X , NB;\ M^h)\ for\ i = h,m \tag{11}$$

$$Q_h = Q_h(P_h , P_x , P_m , X , NB;\ M^h) \tag{12}$$

Equations 11 and 12 infer that the household's optimal consumption and production decisions depend on the price of the household good, price of inputs used in the production of the household good, level of inputs used and net borrowing among other parameters. In the context of contract farming, a participating farm household may benefit from higher and steady prices for the farm produce as secured by the contract, better access to affordable farm inputs, and access to credit thus affecting the utility of the household.

The subsequent application of the theory introduces the random utility model (RUM) postulated by Marschak (1960). This probabilistic representation of household preferences explores the discrete choice of participating or not in contract farming. The decision-making process is modelled as a binary choice problem, where participating households have an indirect utility V_P *(w)* and non-participating households have an indirect utility V_N *(w)*, with *w* representing a set of covariates. The latent variable (D_i) reflects the household's choice, influenced by an unobservable threshold utility V^* *(w)*.

$$V^w(w) = V_{P(w)} - V_{N(w)} \tag{13}$$

$$Di = 1\ if\ V^*(w) > 0\ and\ Di = 0\ if\ V^x(w) \leq 0 \tag{14}$$

The choice model (Equation 15) estimates the probability of a household participating in contract farming using probit regression (Equation 16). X' is a vector of covariates that would potentially influence the decision to participate or not, β is a vector of unknown parameters, ε is a stochastic error term, while ϕ represents the cumulative distribution function of a standard normal random variable.

$$Di = X'\beta + \varepsilon \tag{15}$$

$$Pr(Di = 1) = \phi(X'\beta) \tag{16}$$

In cases of heteroskedasticity, a heteroskedastic probit (hetprobit) model (Equation 17) is considered, allowing for variance in the error term based on covariates suspected of heteroskedasticity.

$$Pr(Di = 1) = \phi\left({(X'\beta)}/{exp(\rho\omega)}\right) \tag{17}$$

Where X, β , ϕ are as aforementioned while ρ represents a vector of covariates that are suspected of having heteroskedasticity and ω is a vector of parameters associated with ρ variables. If ω = 0, then the hetprobit becomes the probit.

2.2 Empirical Model

Based on Equation 16, the probit model to be used to assess the drivers of farm household participation in small-holder banana contract farming can be specified as:

$$D_i = X'\beta + \varepsilon \tag{18}$$

Where participation decision (D) is the dependent variable coded as one if the farm household participates and zero if otherwise. i denotes the farm household. X is a vector of covariates that include age of household head, household size, gender of household head, education level of household head, total land size, banana farm size, off-farm income, income from other agricultural production, adoption of tissue-culture banana plantlets, use of irrigation facilities, farm-gate price of banana, distance to market, access to banana related training, access to market information, access to hired labour, access to credit and membership to banana cooperative. β is a vector of parameters to be estimated and ε is the stochastic error term assumed to be normally distributed. If heteroskedasticity is detected, a heteroskedastic probit (hetprobit) – a variation of the Probit model shown by equation 17- is preferred.

2.3 Data

The study used secondary data from the 'Initiative to Build a Competitive Banana Industry in Kenya' Project, funded by the Alliance for Green Revolution in Africa (AGRA) and the International Fund for Agricultural Development (IFAD). The University of Sydney and the University of Nairobi jointly executed the project, supported by the International Initiative for Impact Evaluation (3ie). Twiga Foods played a crucial role by enrolling willing farmers into contract farming and providing essential extension services to enhance agricultural practices and productivity among smallholders. The firm also ensured reliable and consistent market access for smallholder banana farmers, specifying pricing mechanisms and payment terms in the contracts.

The data was collected from 2,231 households in Kirinyaga County in October–December 2016. This comprehensive dataset encompasses diverse aspects, including socioeconomic details, land ownership, banana production practices, decision-making in banana production, technology adoption, involvement in contract farming, household labour allocation, income and expenditure, banana cooperative participation, training, time preferences, risk preferences, and social networks.

2.4 Diagnostic Checks

The investigation into multicollinearity utilized the Variance Inflation Factor (VIF), measuring the strength of correlation among independent variables—a condition known as multicollinearity, which poses challenges in regression analysis (Salmeron *et al*., 2018). A VIF surpassing 4 suggests potential multicollinearity, warranting further scrutiny, while a VIF exceeding 10 signals significant multicollinearity requiring correction (Salmeron *et al*., 2018). The VIF test results, shown in Table 1, revealed that the VIFs for all variables were below 4, indicating the absence of multicollinearity in the regression model.

Table 1: Multicollinearity Test Results for Probit Model of Drivers of Participation in Banana Contract Farming

Variable	VIF
Age years	1.26
Gender	1.16
Household size	1.17
Education level	1.76
Total land size	1.70
Land under banana	1.73
Banana sale income	1.40
Tissue culture banana	1.15
Credit	1.10
Banana cooperative membership	1.28
Average banana gate price	1.06
Hired labour	1.13
Off farm income	1.09
Other agri prod income	1.03
Irrigation	1.24
Productivity	1.29

Note: The presence of the multicollinearity problem is indicated by a VIF > 10.

Source: Own Computation from Study Data (2023)

The normality of data and probit model residuals was assessed through a Shapiro-Wilk test. The interpretation involves scrutinizing the p-value in relation to the chosen significance level, typically 0.05. A p-value below 0.05 implies rejecting the null hypothesis of normality, indicating non-normally distributed data (Royston, 1982). As shown in Table 2, the Shapiro-Wilk test yielded a p-value of 0.6, suggesting that the null hypothesis of normality cannot be rejected. This implies that the residuals of the probit model can be reasonably assumed to follow a normal distribution (Royston, 1982).

Table 2: Results of the Shapiro-Wilk Normality Test for Probit Model of Drivers of Households' Participation in Banana Contract Farming

W-statistic	0.999101
P-value	0.587313

Source: Own Computation from Study Data (2023)

To evaluate the model's goodness of fit, a McFadden Pseudo R-squared test was employed. According to Allison (2014), values between 0.2 and 0.4 indicate an excellent model fit. The test's value of 0.347, shown in Table 3, confirmed that the proposed model aligned well with the data.

Table 3: Results of McFadden's Pseudo R-Squared Test for Probit Model of Drivers of Households' Participation in Banana Contract Farming

McFadden's Pseudo R-Squared	0.347

Source: Own Computation from Study Data (2023)

To identify heteroscedasticity, a Studentized Breusch-Pagan test was conducted. A p-value below the significance threshold (usually 0.05) rejects the null hypothesis of homoskedasticity, indicating heteroskedasticity (Koenker, 1981). As shown in Table 4, the test yielded a p-value of 0, which is less than the alpha level of 0.05, confirming the presence of heteroskedasticity. To address this issue, the study employed the heteroskedastic probit proposed by Harvey (1976) and generalized by Alvarez & Brehm (1995). This modification adapts the probit model, allowing the variance in a normal cumulative distribution function to vary as a function of independent variables. Consequently, the model corrects for unequal variances with binary outcomes by generating heteroskedastic-robust standard errors (Obebo, 2018).

Table 4: Results of the Studentized Breusch-Pagan Test for Probit Model of Drivers of Households' Participation in Banana Contract Farming

BP	224
Degrees of freedom	18
P-value	0.0000

Source: Own Computation from Study Data (2023)

3. Empirical Results and Discussion

The **descriptive statistics** are shown in table 5. The total sample used in the study was 2,231 banana–farming households. Of these households, 35 percent enrolled in banana contract farming, while 65 percent did not. This level of contract farming adoption is relatively low despite the sustained efforts by state and non-state actors over the past decade, to promote contract farming as a viable means of revitalizing the banana industry and improving the welfare of farmers.

Table 5: Descriptive Statistics for Continuous Variables

Variable	Total Sample	Participants	Non-Participants	Difference	P-value
	Mean (S.D)	**Mean (S.D)**	**Mean (S.D)**		
Household head age (years)	51.690 (14.537)	51.5 (14.46)	52.02 (14.69)	-0.52	0.446
Household size	3.000 (1.363)	3 (1)	3 (1)	0.00	0.640
Total land size (acre)	1.473 (1.266)	1.49 (1.35)	1.45 (1.09)	0.04	0.161
Banana farm size (acre)	0.223 (0.202)	0.23 (0.21)	0.21 (0.18)	0.02	0.280
Banana farm income	12406.410 (78651.702)	10475.19 (20138.02)	15647.87 (130387.26)	-5172.68	0.667
Banana farm-gate price	19.750 (5.668)	19.69 (5.59)	19.87 (5.82)	-0.18	0.695
Off farm income	144104.700 (307328.093)	138919.1 (319209.14)	154065.82 (283238.71)	-15146.72	0.311
Banana farm productivity	2612.950 (3805.451)	2632.72 (3735.95)	2576.17 (3933.64)	56.55	0.660
Observations	**2231**	**780**	**1451**		

S.D = Standard deviation in parenthesis; P. value is probability value associated with differences in means between the enrolled/participants and non-enrolled/participants.

Source: Own Computation from Study Data (2023)

The total sample used in the study was 2,231 banana–farming households. Of these households, 35 percent enrolled in banana contract farming, while 65 percent did not. This level of contract farming adoption is relatively low despite the sustained efforts by state and non-state actors over the past decade, to promote contract farming as a viable means of revitalizing the banana industry and improving the welfare of farmers. The descriptive statistics also showed that the average size of the farm households in the sample was three members. This compares favourably with the 2019 Kenya Population and Housing Census report that the national average household size was 3.9 members and Kirinyaga County's was 3 members (Kenya National Bureau of Statistics, 2020). The average age of a farm household head was 52 years. There was no significant difference in the average age of the household head between the enrolled/participating households and non-enrolled/participating households since the associated probability of the t-value was 0.446. The total agricultural land owned by a farm household averaged 1.5 acres, while banana farm size averaged 0.2 acres. This confirms that banana is predominantly cultivated in smallholder farms, measuring under 5 acres (Kenya Agricultural and Livestock Research Organization, 2019).

The average banana farm productivity in the study sample was 2613 kilogrammes per acre. For the enrolled farm household, productivity was 2633 kilogrammes of banana per acre, while it was 2576 kilograms of banana per acre for the non-enrolled farm households. A difference of about 57 but statistically insignificant as the associated probability of the t-value was 0.660.

Table 6: Descriptive Statistics for Categorical Variables

Category	**Total Sample n = 2231**			**Participants (1) n = 780 (34.96%)**		**Non-Participants (0) n = 1451 (65.04%)**	
	Measurement	**n**	**%**	**n**	**%**	**n**	**%**
Gender of the household head	Female	464	21	146	19	318	22
	Male	1767	79	634	81	1133	78
Education level of household head	No Education	31	1	12	2	19	1
	Primary	527	24	273	35	254	18
	Secondary	1121	50	423	54	698	48
	Tertiary	552	25	72	9	480	33
Used tissue culture banana plantlets	No	1922	86	675	87	1247	86
	Yes	309	14	105	13	204	14
Credit access	No	1791	80	589	76	1202	83
	Yes	440	20	191	24	249	17
Membership in banana co-operative	No	1921	86	669	86	1252	86
	Yes	310	14	111	14	199	14
Hired labour	No	817	37	268	34	549	38
	Yes	1414	63	512	66	902	62
Irrigation	No	1906	85	692	89	1214	84
	Yes	325	15	237	16	88	11

*n = Number of observations; ***, **, * denote levels of statistical significance at 1%, 5% and 10%, respectively; and P. value is probability value associated with differences in proportions between the enrolled/participants and non-enrolled/non-participants.*

Source: Own Computation from Study Data (2023)

Generally, 79 percent of the sampled households were male-headed while 21 percent were female-headed. Among the households that enrolled into contract farming, 81 percent were male headed, while 19 percent were female headed. In the non-participating group, 78 percent were male headed while 22 were female headed. This observation is consistent with a finding from a World Bank survey that about 81 percent of agricultural households in Kenya are male-headed and 19 percent are female headed (World Bank, 2018).

Regarding the education level of the household head, the secondary school level had the highest frequency at 50 percent, followed by the tertiary level (25 percent) and the primary level at 24 percent. For participants, the secondary level was the most common at 54 percent, followed by the primary and the tertiary levels at 35 percent and 9 percent respectively. Among the non-participants, the distribution by education levels stood at 48 percent for the secondary level, 33 percent for the tertiary level and 18 percent for the primary level. Participation in contract farming was higher for households whose heads had secondary-level education than those with less. This observation shows that more educated farmers are more likely to embrace innovative agricultural technologies and approaches like contract farming (Yeboah & Jayne, 2016).

In the study sample, only 14 percent of the banana farmers had embraced tissue-culture technology and planted tissue-culture banana plantlets. The proportion of farmers that planted tissue-culture banana plantlets within the participating group was 13 percent while among the non-participants was 14 percent. This attests to the finding by Ndungu-Thuo *et al*. (2017) that the adoption of tissue-culture banana plantlets is very low in Kenya.

Of the sampled farm households, 80 percent had never accessed any credit for use in their banana farming. Only 20 percent of the households had. About 25 percent of the participating households had accessed credit while 17 percent of the non-participating households reported accessing credit. Njiru and Mwikamba (2020) also found that less than 20 percent of households accessed agricultural credit in Kenya. Regarding membership in banana farmers' cooperatives, only 14 percent of the households in either category claimed membership.

A majority of the sampled farm households, 63 percent, had used hired labour in one or more banana orchard management practices. The proportions of the farm households that hired farm labour in the participating and non-participating groups were 66 and 62 percent respectively. On access to irrigation, 15 percent of the households used community or individual irrigation facilities to water their banana crop. Use of irrigation facilities by the participating and the non-participating groups stood at 16 and 11 percent respectively. This confirms the finding by Karienye and Kamiri (2020) that most of the banana farming in Kenya is rainfed rather than irrigated.

3.1 Empirical results

The results of the hetprobit model fitted using the maximum likelihood estimation (MLE) are presented in Table 3 and Table 4 which also shows the robust standard errors.

Table 7: Drivers of Participation in Banana Contract Farming: Heteroskedastic Probit Regression Results

Heteroskedastic Probit Regression Results	
Dependent variable = 1 if a farm household participated in small-holder banana contract farming and 0 otherwise	
Independent Variables	**Marginal effects (dy/dx)**
Age (years)	0.000 (0.001)
Gender (Male)	0.033 (0.041)
Household size	-0.002 (0.013)
Education Level (Primary)	0.134 (0.124)
Education level (Secondary)	0.246* (0.132)
Education level (Tertiary)	0.445*** (0.070)
Total land size	0.000 (0.018)
Banana farm size	0.234** (0.115)
Banana sale income	0.000 (0.000)
Tissue culture banana (Yes)	0.054 (0.052)
Credit (Yes)	0.151*** (0.045)
Banana cooperative membership (Yes)	0.138*** (0.042)
Average banana gate price	-0.003 (0.004)
Hired labour (Yes)	0.021 (0.036)
Off farm income	0.000 (0.000)
Other agri prod income	0.000 (0.000)
Irrigation (Yes)	0.168*** (0.044)
Productivity	0.000 (0.000)

*Number of Observations =2231; Wald Chi square (19) = 167.6; Prob > chi2 = 0.00; Standard errors are in parentheses; No education is the reference level; ***, **, * denote levels of statistical significance at 1%, 5% and 10%, respectively; dy/dx is for discrete change of dummy variable from 0 to 1.*

Source: Own Computation from Study Data (2023)

From the results presented in Table 7, the education level of the household head, access to credit, membership in banana co-operative, access to irrigation facilities, and size of land under banana significantly influenced farm households' participation in small-holder banana contract farming. However, the rest of the identified variables including household head's age and gender, household size, total land size, income from banana sale, use of tissue-culture banana, average banana farm gate price, access to hired labour, amount of off-farm income, amount of income from other agricultural production and banana farm productivity did not significantly influence participation in banana contract farming.

Within the context of this hetprobit analysis, while conventionally reported standard errors presume homoscedasticity of error terms, the inclusion of robust standard errors offers a complementary perspective (Alvarez and Brehm, 1995). This approach acknowledges the potential for heteroscedasticity and strengthens the reliability of coefficient estimates. By contrasting the standard errors with their robust counterparts, potential violations of the homoscedasticity assumption can be unveiled. More importantly, robust standard errors provide statistically rigorous confidence intervals for the coefficients, even without a priori concerns regarding heteroscedasticity. This ultimately fosters a more robust and generalizable analysis (Alvarez and Brehm, 1995). The findings of the hetprobit model estimated with robust standard errors are presented in Table 8.

Table 8: Drivers of Participation in Banana Contract Farming: Heteroskedastic Probit Regression Results with Robust Standard Errors

Heteroskedastic Probit Regression Results	
Dependent variable = 1 if a farm household participated in small-holder banana contract farming and 0 otherwise	
Independent Variables	**Marginal effects (dy/dx)**
Age (years)	0.000 (0.002)
Gender (Male)	0.033 (0.045)
Household size	-0.002 (0.015)
Education Level (Primary)	0.134 (0.130)
Education level (Secondary)	0.246* (0.140)
Education level (Tertiary)	0.445*** (0.075)
Total land size	0.000 (0.020)
Banana farm size	0.234** (0.120)
Banana sale income	0.000 (0.000)
Tissue culture banana (Yes)	0.054 (0.055)
Credit (Yes)	0.151*** (0.048)
Banana cooperative membership (Yes)	0.138*** (0.045)
Average banana gate price	-0.003 (0.005)
Hired labour (Yes)	0.021 (0.038)
Off farm income	0.000 (0.000)
Other agri prod income	0.000 (0.000)
Irrigation (Yes)	0.168*** (0.047)
Productivity	0.000 (0.000)

*Number of Observations =2231; Wald Chi square (19) = 167.6; Prob > chi2 = 0.00; Robust standard errors are in parentheses; No education is the reference level; ***, **, * denote levels of statistical significance at 1%, 5% and 10%, respectively; dy/dx is for discrete change of dummy variable from 0 to 1.*

Source: Own Computation from Study Data (2023)

The hetprobit analysis with robust standard errors, consistent with the results in Table 7, indicated that the education level of the household head, access to credit, membership in banana co-operative, access to irrigation facilities, and size of land under banana significantly influenced farm households' participation in small-holder banana contract farming.

Regarding the education level of the household head, the coefficients of tertiary level education and secondary level education were positive and statistically significant at one percent and ten percent levels respectively. Other factors being constant, the probability of participation of a household whose head had tertiary level education was 44.5 percent more than that whose head had no education. A household whose head had secondary-level education was 24.6 percent more likely to participate in banana contract farming compared to one that had no education. According to the descriptive statistics presented in Table 2, participation in contract farming was higher for households whose heads had secondary-level education than those with less. The study aligns with the findings of Ziyadhuma (2020), Mwambi et al. (2016), Kutawa (2016) and Yeboah & Jayne (2016), indicating that farmers with higher levels of education are more likely to engage in contract farming, as they are more inclined to embrace innovative agricultural technologies and approaches. The study however contradicts Maganga-Nsimbila (2021), who found that the education of the household head did not influence the decision to participate in contract farming.

Although the coefficient of the total land size available to a household was not statistically significant, the coefficient of the banana farm size was positive and statistically significant at five percent level. An increase in the banana farm size by one acre increased the probability of banana contract-farming participation by 23.4 percent, implying that the size of land under banana was a crucial determinant in the participation decision. These results support the findings by Kutawa (2016) that the larger the land size under a crop, the higher the likelihood of participating in contract farming. Plausibly, if productivity levels are maintained, as the acreage under a crop expands, a household is likely to produce enough to sell to a food marketing firm.

The coefficient of access to credit was positive and significant at one percent level. On average, the probability of households that previously accessed agricultural credit for their banana farming to participate in contract farming was higher than those who didn't previously access it by 15.1 percent. The descriptive statistics in Table 2 also showed that a higher percentage of households that accessed credit participated in contract farming. Agricultural credit utilization is a critical driver of contract farming participation as credit borrowers seek to make their farm enterprises commercially viable to meet all the loan and other obligations (Akumu et al., 2020, Mulatu et al.,2017, Mwambi et al., 2016).

The results of membership in the banana production cooperative movement showed that households that had joined a banana cooperative were more likely to participate in contract farming. The probability of participation by banana cooperative members was 13.8 percent higher than non-members. Descriptive statistics in Table 2 indeed showed that a higher proportion of banana cooperative members participated in contract farming. This could be attributed to the fact that cooperatives help to bridge the information asymmetries members face as they produce individually and expose their members to superior production and marketing dynamics (Mwambi et al., 2016).

Irrigation also significantly influenced participation in banana contract farming. Other things being equal, the probability of participation in contract farming by households that irrigated their banana crop was 16.8 percent higher than those that did not. According to the descriptive statistics in Table 2, a higher proportion of banana farmers that irrigated their banana crop participated in contract farming. Irrigation can boost farm production, enabling farmers to have surplus crops for sale to contracting companies, as Swain (2012) discovered that farmers who irrigated their crops were more inclined to sell their produce to contract firms.

4. Conclusion and Policy Implications

This study utilized a heteroskedastic probit model with maximum likelihood estimation to assess the key drivers influencing smallholder farmers' participation in banana contract farming in Kenya. The analysis unveiled that education level of the farmers, access to credit, membership in banana cooperatives, access to irrigation facilities, and banana farm size significantly shaped participation decisions. Notably, farmers that were more likely to participate in banana contract farming tended to possess higher education, larger landholdings, credit and irrigation access, and membership in banana cooperatives. To enhance participation, it is recommended that stakeholders tackle barriers to participation through targeted measures such as establishing and/or strengthening banana cooperative societies, providing appropriate farmer extension and technical assistance programmes especially to banana farmers with lower levels of education, promoting irrigation access, and offering financial support to contract farming firms via subsidies, grants, low-interest loans, or tax incentives. These interventions can help reduce setup costs, foster research, and bolster the capacity of food marketing companies to enroll more farmers in contract farming schemes.

Author Contributions
All authors have made substantial contributions to the design and implementation of the research, the analysis of the results, and the writing of the manuscript. All authors agree to be accountable for all aspects of the work.

Disclosure statement
The authors report that there are no competing interests to declare.

Data Availability Statement
The study used secondary data sourced from a research project in Kenya by the University of Sydney and the University of Nairobi. The data are available from the corresponding author or the AEA RCT registry upon reasonable request.

The original project was approved by the Human Research Ethics Committee, University of Sydney (IRB Approval Number: 2015/618) and the Kenya National Commission for Science, Technology, and Innovation (Research Licence Number: 265590).

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