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Article

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Cogent Economics & Finance

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Suggested Citation: Murigi, Michael; Ngui, Dianah; Ogada, Maurice Juma (2024) : Impact of smallholder banana contract farming on farm productivity and income in Kenya, Cogent Economics & Finance, ISSN 2332-2039, Taylor & Francis, Abingdon, Vol. 12, Iss. 1, pp. 1-12, https://doi.org/10.1080/23322039.2024.2364353

This Version is available at:
https://hdl.handle.net/10419/321512

Cogent Economics & Finance

ISSN: 2332-2039 (Online) Journal homepage: www.tandfonline.com/journals/oaef20

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COGENT ECONOMICS & FINANCE
2024, VOL. 12, NO. 1, 2364353
https://doi.org/10.1080/23322039.2024.2364353

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Impact of smallholder banana contract farming on farm productivity and income in Kenya

Michael Murigi[a], Dianah Ngui[b] and Maurice Juma Ogada[c]

[a]School of Economics, Kenyatta University and Partnership for Economic Policy (PEP), Nairobi, Kenya; [b]Africa Economic Research Consortium (AERC), Nairobi, Kenya; [c]Taita Taveta University, Nairobi, Kenya

ABSTRACT
Smallholder banana farmers in Kenya grapple with declining farm productivity and low market prices in a fragmented, broker-dominated market. To address these challenges, the Kenya National Banana Development Strategy advocates for the adoption of contract farming. This research utilizes Difference-in-Differences (DID) regression analysis to assess the impacts of smallholder participation in banana contract farming on farm productivity and income. The empirical results reveal positive impacts, emphasizing the potential of contract farming to enhance productivity, increase incomes for smallholder farmers, and invigorate rural economies. These findings provide valuable insights into the efficacy of contract farming as a strategy for addressing challenges in banana farming. To maximize this potential, the study recommends policy interventions, including increased government support, improvements in infrastructure and market accessibility, reinforced institutional backing, and the promotion of sustainable practices. These measures aim to secure enduring benefits for both farmers and food marketing firms in Kenya.

IMPACT STATEMENT
This study examines the effectiveness of contract farming in addressing the struggles of Kenyan smallholder banana farmers. The study finds that participating in contract farming leads to increased farm productivity and income for these farmers. These findings highlight the potential of contract farming to revitalize rural economies. To maximize these benefits, the research recommends policy changes, such as increased government support and improved infrastructure, to create a sustainable and mutually beneficial system for both farmers and food companies in Kenya.

ARTICLE HISTORY
Received 9 February 2024
Revised 22 April 2024
Accepted 29 May 2024

KEYWORDS
Banana; contract; impact; income; Kenya; productivity; smallholder

REVIEWING EDITOR
Goodness Aye, University of Agriculture, Nigeria

SUBJECTS
Rural Development; Development Studies; Economics; Research Methods in Development Studies; Sustainable Development

Introduction

Agriculture serves as a critical driver of economic development in Sub-Saharan Africa (SSA) countries, significantly contributing to employment, livelihoods, and GDP. In Kenya, where agriculture directly constitutes 33% of the GDP with an additional 27% indirectly, the horticultural sector stands out as a linchpin, contributing substantially to foreign exchange earnings, food security, and poverty alleviation (IFAD, 2019; Republic of Kenya, 2019). However, despite its growth, challenges such as high production costs, low farm productivity, and inadequate marketing systems pose threats to the sustainability of the horticultural sector.

Of particular importance within Kenya's horticultural domain is banana farming, emerging as the leading horticultural crop, comprising 16 percent of the total value of horticulture and 33 percent of the total value of fruits (AFA, 2021). Most bananas are cultivated on smallholder farms, reflecting a shift towards this crop as a means of enhancing household food security and providing an alternative income source (Obaga & Mwaura, 2018). The significance of the banana crop is evident in its continuous expansion, with the production area growing from 113,660 acres in 2008 to 179,040 acres in 2020 (AFA, 2021).

CONTACT Michael Murigi micmurigi@gmail.com School of Economics, Kenyatta University and Partnership for Economic Policy (PEP), Nairobi, Kenya

Unlike other horticultural crops, banana is produced year-round, with rising demand both domestically and internationally due to changing consumption habits (Obaga & Mwaura, 2018).

However, the success of the banana sector faces challenges, including high production costs, low farm productivity, and suboptimal marketing systems (IFAD, 2019). In response, various interventions, including the promotion of contract farming, have been implemented by governmental, non-governmental, and private sector entities. Contract farming, involving agreements between buyers and farmers, is seen as a strategy to address production and marketing challenges. Major corporate entities such as Stawi Foods and Fruits Limited, Neo-Kenya, and Twiga Foods, along with governmental and non-governmental initiatives like the Smallholder Horticulture Empowerment Project (SHEP), Kenya Agricultural Value Chain Enterprises (KAVES) project, National Agricultural and Rural Inclusive Growth Project (NARIGP), and the 'Initiative to Build a Competitive Banana Industry in Kenya' Project, have actively endorsed and advanced the cause of contract farming within the banana sector (AGRA, 2017; Bismarck-Osten, 2021; Republic of Kenya, 2020; USAID., 2018). Despite these efforts, banana production per unit area in Kenya has notably declined from about 14,800 kilogrammes per acre in 2008 to 8,200 kilogrammes per acre in 2020, posing a substantial shortfall from the National Banana Development Strategy's targeted 16,000 tonnes per acre, while income for smallholder banana farmers remains stagnant (AFA, 2021; Republic of Kenya, 2014).

Studies across various regions and crops paint a mixed picture of contract farming's impact on farm productivity and income. Igweoscar (2014) highlights significantly higher cassava farm productivity for contract farmers in Nigeria. Similarly, in Tanzania, Mpeta et al. (2018) found that sunflower farmers under contracts increased land productivity by 20.8–25.1 kilograms per acre, while Khan et al. (2019) revealed significantly higher productivity for potato contract farmers in Pakistan. Conversely, Maganga-Nsimbila (2021) using a treatment effects model found no significant impact of contract farming on smallholder cotton farmers' productivity in Tanzania. Mwambi et al. (2016) in Kenya reported no significant difference in incomes between contract and non-contract avocado farmers. In Nepal, Mishra et al. (2016) found positive impacts of contract High Yielding Varieties (HYV) seed farming on revenues and profits, while Olounlade et al. (2020) in Benin reported a significantly negative effect of contract rice farming on income. These diverse findings underscore the need to consider context in evaluating the effectiveness of contract farming strategies for enhancing farm productivity and income.

This study adds to the existing literature on contract farming, which has yielded inconclusive findings regarding its impact on farm productivity and income, with variations observed across crops, agricultural enterprises, and regions (World Bank, 2017). Specifically focusing on smallholder banana farming in Kenya, a sector often overlooked in research, this study employs the Difference-in-Differences (DID) methodology to analyse the impact of contract farming on farm productivity and income.

While propensity score matching is commonly used in the literature to estimate the impact of contract farming on farm productivity or income, it relies heavily on the conditional independence assumption and only considers observed (and observable) characteristics, disregarding unobservable factors (Fredriksson & Oliveira, 2019). This limitation becomes particularly challenging in the context of contract farming, where farmers self-select based on typically unobserved traits such as their risk or time preferences, perceptions, or entrepreneurial abilities. Studies employing matching techniques often do so with cross-sectional data, which poses further limitations. However, as noted by Fredriksson and Oliveira (2019), DID methodology integrates insights from both cross-sectional treatment-control comparisons and before-after studies, offering a more robust estimation of causal effects. Therefore, it is deemed appropriate to provide a comprehensive understanding of the average treatment effect (ATE) within the context of banana contract farming in Kenya.

The subsequent sections of the paper are structured as follows: 'Materials and methods' section delineates the methodological approach employed, 'Empirical results and discussion' section presents and discusses the results, and 'Conclusion and policy implications' section concludes the study while drawing inferences regarding policy implications.

Materials and methods

Data

The study utilized secondary data sourced from the 'Initiative to Build a Competitive Banana Industry in Kenya' Project, which received funding from 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 collaborated on the project, facilitated by the International Initiative for Impact Evaluation (3ie). Twiga Foods played a crucial role in engaging willing farmers in contract farming and delivering vital extension services to improve agricultural practices and productivity among smallholders. The company also facilitated reliable and steady market access for smallholder banana farmers by outlining pricing mechanisms and payment terms within the contract. The contract guaranteed the farmers an appealing price, exceeding the local market rate, with payment made directly at the farm gate upon banana collection. Furthermore, the contract mandated that Twiga Foods provide extension services to the farmers at no additional expense. In return, the farmers were obliged to follow the prescribed guidelines for banana cultivation and sell their harvest exclusively to the contracting firm.

Data collection took place in Kirinyaga County from 2,231 households during two survey rounds conducted between 2016 and 2020: the Baseline round (October–December 2016) and the Endline round (October 2019–January 2020). This extensive dataset covers a wide range of aspects, including socioeconomic details, land ownership, banana production practices, decision-making in banana production, technology adoption, participation in contract farming, household labour allocation, income and expenditure, banana cooperative involvement, training, time preferences, risk preferences, and social networks.

Theoretical model

Random Utility Theory (RUT) provides a useful framework for analysing the impact of contract farming participation on household utility by considering how it influences farm productivity and income. Since participation in contract farming is a discrete choice, RUT allows for comparing a household's expected utility if they engage in contract farming, such as banana farming, with their expected utility if they do not (Olounlade et al., 2020). Contract farming can influence utility through its effects on productivity (e.g. access to better inputs, extension services) and income (e.g. guaranteed prices, credit for inputs). If households anticipate greater utility from participation due to these potential improvements in productivity and income, they are more inclined to participate in contract farming (Olounlade et al., 2020).

To estimate the impact of banana contract farming participation on farm productivity and income, a DID design was preferred. DID designs compare changes over time in treatment and control outcomes. Under these circumstances, there often exist plausible assumptions that we can control for time-invariant differences in the treatment and control/comparison groups and estimate the causal effects of the intervention (Fredriksson & Oliveira, 2019; Wing et al., 2018). The DID estimate of the impact of contract farming on the outcome variables (farm productivity and farm income) can be written as follows:

$$\mathrm{DID} = \left(\bar{Y}_{s=\mathrm{Treatment};\ t=\mathrm{After}} - \bar{Y}_{s=\mathrm{Treatment};\ t=\mathrm{Before}}\right) - \left(\bar{Y}_{s=\mathrm{Control};\ t=\mathrm{After}} - \bar{Y}_{s=\mathrm{Control};\ t=\mathrm{Before}}\right) \quad (1)$$

where Y is the outcome variable (farm productivity or farm income), the bar represents the average value (averaged over individuals in the group), the group is indexed by s and t is time. With before and after data for the treatment and control groups, the data is thus divided into the four groups and the double difference – Equation (1) – is calculated. The equation, however, says nothing about the significance level of the DID; therefore, regression analysis, modelled using the following equation, is needed.

$$Y_{ist} = A_s + B_t + \beta I_{st} + \varepsilon_{ist} \quad (2)$$

where A_s are treatment/control group fixed effects; B_t are the before/after fixed effects; I_{st} is an indicator variable for treatment (=1) or control (=0) groups; ε_{ist} is the error term while the DID estimate is obtained as the β-coefficient. To verify that the estimate of β will recover the DID estimate in (1), (2) is used to get:

$$\mathrm{E}\left(Y_{ist} | s = \mathrm{Control},\ t = \mathrm{Before}\right) = A_{\mathrm{Control}} + B_{\mathrm{Before}} \quad (3)$$

$$\mathrm{E}\left(Y_{ist} | s = \mathrm{Control},\ t = \mathrm{After}\right) = A_{\mathrm{Control}} + B_{\mathrm{After}} \quad (4)$$

$$\mathrm{E}\left(Y_{ist} | s = \mathrm{Treatment},\ t = \mathrm{Before}\right) = A_{\mathrm{Treatment}} + B_{\mathrm{Before}} \quad (5)$$

$$E\ (Y_{ist}|s\ =\ \text{Treatment},\ t = \text{After})\ =\ A_{Treatment} +\ B_{After} + \beta \tag{6}$$

In the expressions (3) to (6), E $(Y_{ist}|s)$ is the expected value of Y_{ist} in population subgroup (s, t), which is estimated by the sample average $\overline{Y}$ st. Estimating (2) and plugging in the sample counterpart of the above expressions into (1), with the hat notation representing coefficient estimates, gives DID $= \hat{\beta}$. Individual-level control variables X_{ist} can be added to make the regression more robust. Thus (2) becomes:

$$Y_{ist} = A_s + B_t + cX_{ist} + \beta I_{st} + \varepsilon_{ist} \tag{7}$$

Empirical model

Based on Equation (2), the DID regression model to be used in estimating the impact of participating in banana contract farming on banana farm productivity and income was defined as:

$$Y_{ist} = A_s + B_t + \beta I_{st} + \varepsilon_{ist} \tag{8}$$

where Y_{ist} is the outcome variable (banana farm productivity or income), A_s are treatment/control group fixed effects, B_t are the before/after fixed effects, I_{st} is an indicator variable for treatment (=1) or control (=0) groups, $?_{ist}$ is the error term while the DID estimate is obtained as the β-coefficient. To make the model more robust, individual-level control variables Xist are added (Vlachopoulou et al., 2013):

$$Y_{ist} = A_s + B_t + cX_{ist} + \beta I_{st} + \varepsilon_{ist}$$

Empirical results and discussion

The descriptive statistics were as follows:

As indicated in Table 1, the study used a total sample of 2,231 households engaged in banana farming. Among these households, 35 percent participated in banana contract farming, while the remaining 65 percent did not. Despite ongoing efforts by governmental and non-governmental organizations to promote contract farming as a viable strategy for revitalizing the banana industry and improving farmer welfare, the adoption rate remains relatively low. This is primarily due to factors such as the limited awareness among smallholder farmers about the existence and benefits of contract farming schemes, as well as the constrained capacity of food-marketing companies to enroll farmers into such schemes (Republic of Kenya, 2023).

The descriptive statistics also highlighted that the average size of farm households in the sample was three members. This aligned favourably with the 2019 Kenya Population and Housing Census, which reported a national average household size of 3.9 members and Kirinyaga County's average of 3 members (Kenya National Bureau of Statistics, 2020). The average age of a farm household head at baseline was 52 years, and there was no significant difference in the average age between enrolled/participating households and non-enrolled/participating households, as indicated by the associated probability of the t-value (0.446). The total agricultural land owned by a farm household averaged 1.5 acres, with land under banana cultivation averaging 0.2 acres. This underscores that banana cultivation is predominantly carried out on smallholder farms, typically measuring under 5 acres (Kenya Agricultural and Livestock Research Organization (KALRO), 2019).

Regarding banana farm productivity within the study sample, the average was 2613 kilogrammes per acre at baseline. For enrolled farm households, productivity was slightly higher at 2633 kilograms of banana per acre compared to 2576 kilogrammes for non-enrolled farm households. The difference of approximately 57, however, was statistically insignificant, as evidenced by the associated probability of the t-value (0.660). At the endline, the average farm productivity for participating farmers had increased to 3827 kilogrammes per acre compared to 2636 kilogrammes per acre for the non-participating farmers, a difference of 1,191, which was statistically significant at one percent level.

The surveyed farm households earned an average amount of Kenya shillings 12,406 from banana farming at baseline. The average amount earned by the enrolled farm households was 10,475, while the average earnings for the farm households not enrolled was 15,649, thus a difference of about 5,173,

Table 1. Descriptive statistics at baseline and end-line.

Descriptive statistics at baseline					
Variable	Total sample Mean (S.D)	Participants Mean (S.D)	Non-participants Mean (S.D)	Difference	*p* value
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)	1.47 (1.266)	1.49 (1.35)	1.45 (1.09)	0.04	0.161
Land under banana (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
Descriptive statistics at end-line					
Variable	Total sample Mean (S.D)	Participants Mean (S.D)	Non-participants Mean (S.D)	Difference	*p* value
Household head age (years)	54.83 (14.49)	54.61 (14.45)	55.24 (14.56)	−0.63	0.385
Household size	3.00 (1.36)	3 (1)	3 (1)	0.00	0.640
Total land size (acre)	1.46 (1.09)	1.46 (1.14)	1.46 (0.99)	0.00	0.111
Land under banana (acre)	0.23 (0.18)	0.24 (0.18)	0.21 (0.18)	0.03	0.279
Banana farm income	18576.35 (19311.83)	25490.85 (26598.77)	16477.6 (17104.51)	9013.25**	0.001
Banana farm-gate price	23.11 (3.98)	25.92 (3.42)	21.6 (3.40)	4.32***	0.000
Off-farm income	101933.69 (107373.63)	107041.84 (106748.47)	99761.09 (108040.77)	7280.75	0.431
Banana farm productivity	3052.27 (2418.35)	3826.9 (2843.38)	2635.86 (2038.31)	1191.04***	0.000
n	**2231**	**780**	**1451**		

n = Number of observations, asterisks *** and ** denote levels of statistical significance at 1% and 5%, respectively and P. value is probability value associated with differences in proportions between the enrolled/participants and non-enrolled/non-participants.
Source: University of Sydney (2023). *An impact assessment of EAMDA's banana initiative to increase technology adoption by smallholder farmers in Kenya*. AEA RCT registry.

which was not statistically significant. At the endline, the average banana farm income for the participating farmers had grown to 25,491 shillings compared to 16, 478 shillings for the non-participating farmers, a difference of 9,013 which was statistically significant at five percent level.

Following Nolan and Da Silva Santos (2019), stochastic dominance graphs were also used to compare banana farm productivity and income between participants and non-participants, at baseline.

Figure 1 shows that the distribution of banana farm productivity for the participants and non-participants was nearly similar for most values at baseline. This is because banana growing conditions before the roll-out of contract farming were essentially the same, and so were the productivity levels. Also, the distribution of banana income for the participants and non-participants was largely similar, with neither group dominating the other at baseline. As all the banana farmers then sold their banana through the same marketing channels, in open markets, the average price of a kilo of bananas was roughly the same at Kenya shillings 19, and so was their income. Notably, the study sample was balanced at baseline in relation to the outcome variables of interest: banana farm productivity and farm income.

Placebo test

Before performing the actual regression analysis on the impact of contract farming on farm productivity and income, a placebo test was conducted to confirm the credibility of the DID empirical research

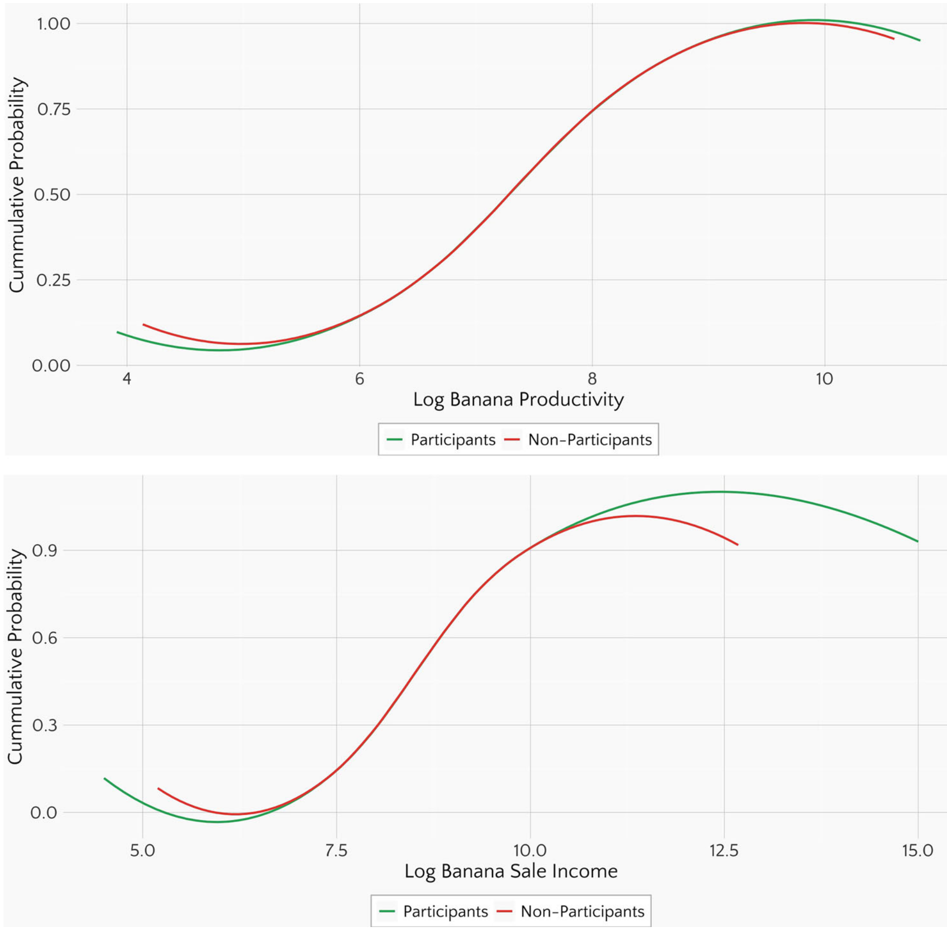

Figure 1. Stochastic dominance graphs on banana farm productivity and income at baseline.
Source: University of Sydney (2023).

Table 2. Placebo test using off-farm income and other agricultural income.

	Simple linear regression	Multivariate linear regression
Estimated impact on off-farm income	−0.032	−0.006
	(0.075)	(0.019)
Estimated impact on other agricultural income	0.201	0.160
	(0.082)	(0.022)

Standard errors are in parentheses; Asterisks ***, **, * denote levels of statistical significance at 1%, 5% and 10%, respectively.
Source: University of Sydney (2023).

design and especially of the 'Parallel trends' assumption (Cunningham, 2021). According to World Bank (2020), for a placebo test, you perform an additional DID estimation using a fake outcome – an outcome known not to be affected by the intervention. Two fake outcomes were identified for this test: off-farm income and other agricultural income. The two hypotheses considered for the test:

Null Hypothesis (H0): There is no statistically significant impact of contract farming on the fake outcomes (off-farm income and other agricultural income).

Alternative Hypothesis (H1): There is a statistically significant impact of contract farming on the fake outcomes (off-farm income and other agricultural income).

If the DID estimation reveals a significant impact on off–farm income and other agricultural income, leading to the rejection of the null hypothesis, this would indicate potential shortcomings in the study's design (World Bank, 2020).

As shown in Table 2, the simple linear DID regression did not yield any significant impact of contract farming on off-farm income and other agricultural income. Following Vlachopoulou et al. (2013), incorporating some control variables identified through stepwise regression (access to hired labour, use of tissue-culture banana plantlets, access to credit, access to irrigation facilities, access to training, household

Table 3. Impact of contract farming on farm productivity and income: DID regression analysis.

Impact on farm productivity			
		Simple linear regression	Multivariate linear regression
Estimated impact on farm productivity		0.198*** (0.025)	0.261*** (0.030)
Banana farm size	Percentage of the sample	Estimated impact on farm productivity	Difference
0–0.2 acres	43.5%	0.222*** (0.034)	0.024 (0.047)
Above 0.2 acres	56.5%	0.246*** (0.028)	
Impact on farm income			
		Simple linear regression	Multivariate linear regression
Estimated impact on farm income		0.030 (0.030)	0.109** (0.037)
Banana farm size	Percentage of the sample	Estimated impact on farm income	Difference
0–0.2 acres	43.5%	0.076** (0.049)	0.077 (0.057)
Above 0.2 acres	56.5%	0.153** (0.088)	

Standard errors are in parentheses; Asterisks ***, **, * denote levels of statistical significance at 1%, 5% and 10%, respectively.
Source: University of Sydney (2023).

size, and age of the household head) in the multivariate regression also yielded a non-significant impact on off-farm income and other agricultural income. The absence of a significant effect on the fake outcomes indicated that there was no basis to reject the null hypothesis. This lent credence to the suitability of the DID methodology to determine the impact of contract farming on banana farm productivity and income (World Bank, 2020).

DID regression results

The results of the DID regression on the impact of contract farming on banana farm productivity and income are presented.

Table 3 shows that, for the impact of contract farming on banana farm productivity, simple linear regression yielded a positive coefficient of 0.198 which was statistically significant at one percent level implying that on average banana farmers that participated in contract farming produced 19.8 percent more per acre than their non-participating counterparts. Following Vlachopoulou et al. (2013), stepwise regression was used to identify the following individual control variables for incorporation in the multivariate linear regression to account for potential confounders and provide a more nuanced analysis of the treatment effect: Banana cooperative membership, access to credit, access to hired labour, access to banana training, access to market information, and total land size. The multivariate linear regression yielded a positive coefficient of 0.261, also statistically significant at one percent level, implying that the average increase in banana farm productivity due to participation in contract farming was 26.1 percent. These findings mirror those of Mpeta et al. (2018), who found that the impact of contract farming participation by sunflower farmers in Tanzania on land productivity averaged 24 percent. For the study based in India, Mishra et al. (2018) also found a positive impact of contract farming on land productivity in baby corn production. While they found a positive and significant impact of contract farming on potato productivity in Pakistan, Khan et al. (2019) found no significant impact on productivity in maize farming. Maganga-Nsimbila (2021) found that the impact of contract farming on productivity in small-holder cotton farming in Tanzania was insignificant.

These findings support the view that participation in contract farming increases farm productivity in small-holder banana farming. Contract farming bridges the information asymmetry prevalent in small-holder agriculture as contractors provide helpful information and training to farmers to produce to their required quantity and quality (Mugwagwa et al., 2020; World Bank, 2017). In the study case, banana farmers participating in the Twiga Foods' contract scheme received regular training on banana orchard management. Thus, they were more likely to produce more banana from a unit acre than non-participating farmers.

The findings also show that the estimated impact of contract farming was not statistically different for farms bigger than 0.2 acres and farms sized 0.2 acres and less. According to World Bank (2017), the impact of contract farming on productivity may not necessarily vary significantly based on farm size, as long as farmers receive equal access to inputs, technology, knowledge, risk mitigation, and market opportunities. Twiga Foods' contract farming scheme involved technical assistance and knowledge transfer to all the participating small-holder banana farmers, including agronomic advice and training on best practices, such that farm productivity would have improved regardless of farm sizes. Henningsen et al. (2015) also found that the impact of contract farming on productivity in smallholder sunflower production in Tanzania did not vary by farm size.

Regarding the impact on income, simple linear regression yielded a positive but statistically insignificant coefficient. However, incorporating control variables, viz. use of tissue-culture banana plantlets, access to credit, access to irrigation facilities, access to hired labour, access to training, household size, and household's head age, in the multivariate regression yielded a positive and statistically significant coefficient at five percent level. On average, banana farmers who participated in contract farming earned 10.9 percent more than non-participants. Mishra et al. (2016) and Mulatu et al. (2017) also found a positive and significant impact of contract farming participation in paddy seed production in Nepal and vegetable farming in Ethiopia, respectively. However, Soullier and Moustier (2018) found no impact of contract farming on farm incomes for the participating rice farmers in Senegal, while Olounlade et al. (2020) found a significant negative impact of contract farming on income from rice farming in Benin.

The study findings buttress the assertion that contract farming may increase farm incomes, provided the set contract price is above the prevailing market price at any given harvest season (World Bank, 2017). The prices in Twiga Foods' contract were set reasonably higher than those in the local markets to curb side-selling. With better prices for the contract farmers than non-contract farmers, participants were likely to earn more from their banana farming than non-participating farmers.

The difference in the estimated impact of contract farming on banana farm income between farms sized below 0.2 acres and farms sized above 0.2 acres was statistically non-significant. Contract farming provides farmers with assured market access and often includes predetermined prices or price guarantees. This benefit is not contingent on farm size but rather on the contractual agreement with the contracting company (World Bank, 2017). Whether small or large, farmers participating in the Twiga Foods' contractual arrangement could secure a stable market for their banana at predetermined prices, minimizing income volatility and ensuring a steady income stream. A study by Maertens and Vande Velde (2017) that looked at the impact of contract farming on the income of small and large farmers in Benin also found that contract farming had a similar impact on the income of both small and large farmers.

Conclusion and policy implications

In conclusion, this study employed the DID methodology to assess the impact of smallholder banana contract farming on farm productivity and income. The study revealed a positive impact on both aspects. Farmers engaged in contract farming demonstrated increased productivity per unit acre of land, likely attributed to the extension services provided by the contractor. Additionally, participating farmers earned higher incomes compared to non-participants, with the enhanced income being attributed not only to increased productivity but also to the guaranteed higher prices provided through the contract. Notably, the positive impact on both farm productivity and income did not vary by farm size.

Building on these findings, the study recommends targeted policy interventions to leverage the observed positive impacts of smallholder participation in banana contract farming in Kenya. These interventions encompass increased government support through financial assistance and capacity-building, reinforced institutional backing, and the establishment of regulatory frameworks to protect the interests of farmers and contracting entities. Additionally, the promotion of sustainable practices in banana farming is encouraged. Collectively, these measures aim to create an enabling environment, enhance farmer capacity, and address challenges in the banana industry, ultimately ensuring sustained benefits for both farmers and food marketing firms in Kenya.

Authors' 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. Michael Murigi involved in the conception and design of the research, analysis and interpretation of the data, drafting of the paper, revising it critically for intellectual content, final approval of the version to be published. Dianah Ngui involved in the conception and design of the research, analysis and interpretation of the data, drafting of the paper, revising it critically for intellectual content. Maurice Juma Ogada involved in the conception and design of the research, analysis and interpretation of the data, drafting of the paper, revising it critically for intellectual content, final approval of the version to be published.

Disclosure statement

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

About the authors

Michael Murigi is a Monitoring and Evaluation Specialist at the Partnership for Economic Policy (PEP) and a PhD candidate at Kenyatta University. His research interests include agricultural and rural development, climate change, renewable energy, youth, and women empowerment.

Dianah Ngui is a Research Manager at the African Economic Research Consortium (AERC). Previously, she was a senior Lecturer of Economics at Kenyatta University, a member of the Advisory Committee of the Environment for Development (EfD) Initiative in Kenya, and a senior researcher with various multinational organizations. She has over 15 years of experience conducting high-quality empirical research on issues related to industrial policies, enterprise performance, and natural resources in developing countries. She holds a PhD in Economics from Martin-Luther-Universität Halle-Wittenberg, Germany.

Maurice Juma Ogada is a Professor of Economics at Taita Taveta University in Kenya. Previously, he worked with the International Livestock Research Institute (ILRI) and the Kenya Institute for Public Policy Research and Analysis (KIPPRA) in the areas of Agriculture, Trade, and Environment and Natural Resource Management. His areas of interest in research include Randomized Control Trials, Impact Evaluation, Food and Nutrition Security, Climate change, and Natural Resource Management. He holds a PhD in Economics from Kenyatta University.

ORCID

Michael Murigi http://orcid.org/0000-0003-2035-6867
Maurice Juma Ogada http://orcid.org/0000-0003-1512-6370

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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Appendices

Table A1. Output of the DID regression for the impact of contract farming on log of farm productivity.

	Simple linear regression	Multiple linear regression
Intercept	3.125***	3.338***
	(0.023)	(0.041)
Contracts	−0.221***	−0.299***
	(0.039)	(0.042)
Survey round	0.097***	0.044**
	(0.014)	(0.022)
Contracts × survey round	0.198***	0.261***
	(0.025)	(0.030)
Banana cooperative membership		0.034
		(0.020)
Credit		0.118***
		(0.016)
Hired labour		−0.022*
		(0.012)
Banana training		0.003
		(0.257)
Market information		−0.088
		(0.258)
Total land size		−0.025***
		(0.005)
Number of observations	4282	4282
R2	0.066	0.114
R2 Adj.	0.066	0.112

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
Source: University of Sydney (2023).

Table A2. Output of the DID multiple linear regression with triple interactions for the impact of contract farming on log of farm productivity.

Independent variables	Marginal effects (dy/dx)	Std errors	Statistic	Probability value
Intercept	3.3782	0.0453	74.6339	0.0000
Contracts	−0.2788	0.0563	−4.9489	0.0000
Survey round	0.0583	0.0265	2.1984	0.0734
Banana group membership	0.0387	0.0194	1.9960	0.0858
Credit	0.1152	0.0158	7.2869	0.0000
Hired labour	−0.0099	0.0117	−0.8414	0.4002
Banana training	0.0639	0.2552	−0.2502	0.8024
Market information	−0.0207	0.2556	−0.0808	0.9356
Total land size acre	−0.0254	0.0051	−5.0150	0.0000
Land under banana above 0.2 acre	−0.2763	0.0447	−6.1749	0.0000
Contracts X Survey round	0.2215	0.0388	5.7029	0.0000
Survey round X Land under banana above 0.2 acre	0.0304	0.0283	1.0746	0.2826
Contracts X Land under banana above 0.2 acre	0.0981	0.0740	0.1891	0.8500
Contracts X Survey round X Land under banana above 0.2 acre	0.0239	0.0468	1.0923	0.2748

Source: University of Sydney (2023).

Table A3. Output of the DID regression for the impact of contract farming on farm income.

	Simple linear model	Multiple linear model
Intercept	3.688***	3.637***
	(0.027)	(0.055)
Contracts	−0.031	−0.111**
	(0.047)	(0.051)
Survey round	0.074***	0.003
	(0.017)	(0.024)
Contracts × survey round	0.030	0.109***
	(0.030)	(0.037)
Tissue culture banana		0.183***
		(0.017)
Credit		0.106***
		(0.020)
Irrigation		0.138***
		(0.020)
Hired labour		0.061***
		(0.014)
Household size		−0.003
		(0.005)
Age		0.002***
		(0.0005)
Banana training		−0.094***
		(0.023)
Number of observations	3729	3729
R2	0.010	0.079
R2 Adj.	0.010	0.076

**$p < 0.05$, ***$p < 0.01$.
Source: University of Sydney (2023).

Table A4. Output of the DID multiple linear regression with triple interactions for the impact of contract farming on log of farm income.

Independent variables	Marginal effects (dy/dx)	Std errors	Statistic	Probability value
Intercept	3.5964	0.0599	60.070	0.0000
Contracts	−0.0697	0.0697	−1.000	0.3174
Survey round	−0.0329	0.0307	−1.070	0.2848
Tissue culture banana (yes)	0.1439	0.0167	8.626	0.0000
Credit (yes)	0.1256	0.0186	6.739	0.0000
Irrigation (yes)	0.0984	0.0189	5.200	0.0000
Hired labour (yes)	0.0292	0.0135	2.168	0.0302
Household size	−0.0055	0.0048	−1.148	0.2512
Age years	0.0010	0.0005	2.176	0.0296
Banana training (yes)	−0.0808	0.0218	−3.706	0.0002
Land under banana above 0.2 acre	0.2451	0.0507	4.837	0.0000
Contracts X Survey round	0.0763	0.0489	1.559	0.0186
Contracts X Land under banana above 0.2 acre	−0.0932	0.0878	−1.061	0.2886
Survey round X Land under banana above 0.2 acre	0.0196	0.0321	0.612	0.0357
Contracts X Survey round X Land under banana above 0.2 acre	0.0771	0.0569	1.354	0.1759

Source: University of Sydney (2023).