APRA

Agricultural Policy Research in Africa

LIVELIHOOD OUTCOMES OF AGRICULTURAL COMMERCIALISATION, WOMEN'S EMPOWERMENT AND RURAL EMPLOYMENT

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Working Paper

WP | 92
April 2022

CONTENTS

List of tables

List of figures

ACKNOWLEDGEMENTS

The authors are grateful to the human subject (farmers, palm oil processors, community leaders, oil palm companies) whose willing participation has made this research successful by providing answers to our questions and providing vital insights into the issues discussed in this paper. We also thank all the field research assistants and APRA researchers; particularly Amrita Saha, Kofi Asante, Francis Dompae, and John Thompson. We thank Daniel Bruce Sarpong, Sarah Alobo Loison and Freda Asem for reviewing this paper and providing critical comments and useful suggestions, all of which have improved this paper.

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This working paper is funded with UK aid from the UK government (Foreign, Commonwealth & Development Office – FCDO, formerly DFID). The opinions are the authors and do not necessarily reflect the views or policies of IDS or the UK government.

ACRONYMS

APRA	Agricultural Policy Research in Africa
B-BOVID	Building Businesses on Values, Integrity and Dignity
BOPP	Benso Oil Palm Plantation
CCsh	cash crop share
CDF	Cumulative Density Function
FHH	female-headed household
HCI	household commercialisation index
NGL	Norpalm Ghana Ltd
OFE	off-farm employment
OPsh	oil palm share
OPMC	oil palm marketing channel
PPP	purchasing power parity
ROFE	rural off-farm employment
VCS	value of crop sales

EXECUTIVE SUMMARY

This paper has five research objectives: to identify which farmers engage with which oil palm marketing channels (OPMCs); to analyse the relationship between OPMCs, labour allocation to farm and off-farm employment and returns to labour; to analyse the association between employment and agricultural commercialisation; to test the associations between OPMCs, women's empowerment and household welfare; and to analyse the relationship between agricultural commercialisation and household welfare. These objectives are addressed using household level panel data collected in 2007 and 2019, covering a sample of 659 households or 1,318 observations. The study is sited in 21 communities of the Ahanta West and Mpohor districts in the Western region of Ghana. The following are the salient results.

First, we identified four main channels through which oil palm-producing households engage with the market for palm fruits and related output: (i) selling directly to industrial oil palm companies (33 per cent), (ii) selling indirectly to the companies through agents or middlemen (27 per cent), (iii) selling in the open market (27 per cent), and (iv) processing own palm fruits into palm oil (13 per cent). While the proportion of those using the agent channel dropped over time, the proportion processing their own fruits remained constant.

Second, we found high levels of commercialisation among the farm households in our sample, a result that challenges the general notion that rural African smallholders focus more on food self-sufficiently as a risk-mitigating strategy in the presence of factor and product market inefficiencies.

Third, we found that the level of education, gender and scale of production differentiate households that engage in the most remunerative OPMCs from those that do not. Male farmers who are better educated and operate medium- to large-scale farms are able to access the more remunerative OPMCs. This is because economies of scale allow them to overcome the initial transaction costs required to transport fruits to the industrial companies.

Fourth, although most economically-active household members work on-farm, farm work alone does not provide full employment, with members working only about 61 days a year on the farm, on average – even for highly commercialisation farm households. This suggests that other sources of rural employment would be important for reducing underemployment among the rural working population.

Fifth, although average annual returns to farm labour per worker are above the international poverty line of US$1.90/day, a nontrivial proportion (about one-third) of households achieved returns below the international poverty threshold. This shows that there are significant inequalities in the distribution of returns to farm labour.

Sixth, even among the highly-commercialised farm households in our sample, non-crop income constitutes more than half of total household income, with the highest non-crop income share (28 per cent) coming from rural off-farm employment. Annual returns to rural off-farm employment among participating households were higher than returns to farming, but only 55 per cent of households are involved.

Seventh, we show that the correlation between agricultural commercialisation and rural off-farm employment at the household level is negative, suggesting that rural off-farm employment is more important for households at lower levels of commercialisation than for those at higher levels of the commercialisation distribution. Thus, agricultural commercialisation and off-farm employment tend to be counterparts at low levels of commercialisation but competitors at high commercialisation levels.

Eighth, while household welfare differs significantly by OPMC, the welfare dimension being measured matters in the nature of the relationship. For example, households selling directly to companies and those processing their own fruits are significantly richer in income and asset dimensions of welfare, however, only processing households are better off food security wise. This is because processing allows income smoothening over a longer period due to the fact that processed products can be stored and sold for longer.

Ninth, we found a positive correlation between agricultural commercialisation and some dimensions of welfare (per capita income and productive asset accumulation) but not others (consumer asset accumulation and food security), after adjusting for omitted heterogeneity. This shows that choice of indicator and the use of panel data matters for the conclusions one might reach in analysing the relationship between agricultural commercialisation and household welfare.

1 INTRODUCTION

Although rural livelihoods are highly diversified, agriculture remains the dominant employment activity for most households in rural sub-Saharan Africa, including Ghana (Davis, Di Giuseppe and Zezza, 2017). As expected, the agricultural sector's share of employment has been declining, from about 61 per cent of the economically active population in the 1960s to 32 per cent in 2021 (Ghana Statistical Service, 2022). In spite of this decline, agricultural labour productivity growth has been slow, meaning, among other factors, that returns to agrarian livelihoods have been lower than in other sectors of the economy. Since the late 1980s, various living standard surveys have shown lower average welfare among farmers compared with the rest of the population (Ghana Statistical Service, 2018). However, there are important nuances that relate to crop choice, with poverty reduction being faster among farmers who engaged in export crop agriculture than among food crop farmers.

It is argued that some of the reasons for the lower-than-desired poverty reduction impact of agriculture include the nature of the farming system, whereby smallholders[1] with semi-subsistence – rather than commercial orientation – dominate the farmer population (MoFA, 2016). Also, production systems are still rudimentary with low levels of mechanisation. For example, the share of cultivated area under irrigation was about three per cent as of 2018 (MoFA, 2019).

Across Ghana, mixed-crop-livestock enterprises dominate the farming systems with most farmers producing both food staples and non-food cash crops. However, this paper focuses mainly on oil palm-producing farmers because, although cocoa has been the single most important non-food cash crop for Ghana since the late 19th century, oil palm was the first internationally traded cash crop with most of the country's export revenue accruing from the crop in the 1880s. Presently, oil palm is Ghana's second most important industrial crop (aside from cocoa) but has a more extensive local value chain that allows for artisanal processing and thus, has huge potential for rural employment generation and poverty reduction (Torvikey and Dzanku, 2022). Oil palm is currently one of the priority crops under Ghana's Food and Agriculture Sector Development Policy.

Danyo (2013), documents a variety of OPMCs. One could expect the characteristics of farmers that select into various OPMCs as well as the livelihood outcomes of such engagements to differ. Identifying the various OPMCs, the characteristics of those who participate in the various channels, and the poverty reduction impacts of the OPMCs could help identify opportunities and constraints for inclusive agricultural commercialisation. Such opportunities could then be promoted and constraints mitigated to make agricultural commercialisation more rewarding for rural households.

We also argue in this paper that it is important not to consider agricultural commercialisation in isolation, but consider how commercialisation interacts with other livelihoods in the rural economy in general, since rural farm households are known to straddle on-farm and off-farm activities. For instance, while commercialisation may lead to increased incomes, it is important to examine whether the benefits of commercialisation are inclusive – for instance, what are the implications of increased commercialisation for women's empowerment. Our main objective is therefore to identify farm household self-selection in OPMCs and the livelihood outcomes associated with such choices (or the lack of choices). Specifically, the objectives are as follows: to identify which farmers engage with which OPMCs; to analyse the relationship between OPMCs, labour allocation to farm and off-farm employment and returns to labour; to analyse the association between employment and agricultural commercialisation; to test the associations between OPMCs, women's empowerment and household welfare; and to analyse the relationship between agricultural commercialisation and household welfare.

The rest of the paper is structured as follows: the next section describes the study methods, including the sample and measurement of key indicators; section three presents the results and addresses all five research objectives; section four summarises the main results and provides lessons for policy and practice.

1 In Ghana, smallholders or small-scale farmers are those with cropland areas that are less than 0.8ha for arable crops and less than or equal to about 2ha for tree crops (Ghana Statistical Service, 2020)

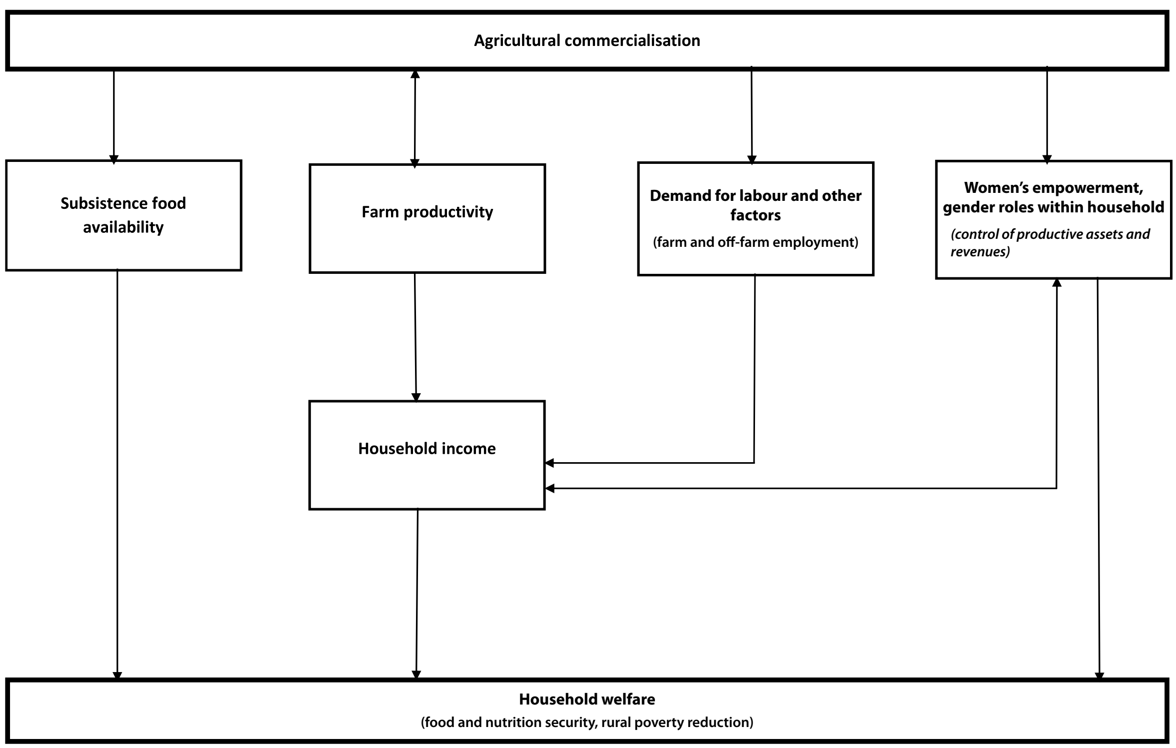
2 METHODS

2.1 Conceptual framework

Figure 2.1 provides a snapshot of the conceptual framework that guides our empirical analysis. Agricultural commercialisation potentially affects farm household welfare through various channels. First, increasing commercialisation implies increased market participation, which leads to increased demand for factors of production, including labour (Barrett, 2008). Increased employment (farm and off-farm) is expected to improve household incomes, resulting in better household welfare which manifests in poverty and food insecurity reduction. On the other hand, if increased commercialisation is achieved primarily though non-food cash crop production, as is the case in our present study areas, then this could result in reduced resource allocation toward food production, thus limiting food consumption though the subsistence pathway. Yet, households could avoid reductions in overall food consumption through food purchases using cash earnings from commercial agriculture (Ogutu, Gödecke and Qaim, 2020), depending on the efficiency of food markets (Dzanku, Tsikata and Ankrah, 2021).

Enhanced market participation empowers farmers to better harness comparative advantages through higher levels of specialisation. Commercial orientation also exposes farmers to modern technology, and because commercially-oriented households are more willing to adopt yield-enhancing technology than subsistence farmers, this results in further increases in commercial activity (Ogutu, Gödecke and Qaim, 2020). Thus, higher levels of output commercialisation and improved yields generate employment, raise rural incomes, reduce the incidence of poverty, and contribute to enhanced food and nutrition security (Fafchamps, 1992; Govereth, Jayne and Nyoro, 1999; Dzanku and Sarpong, 2011;

Figure 2.1: Agricultural commercialisation and household livelihood outcomes



Source: Authors' own construct based on modifications from von Braun and Kennedy (1994) and Chege, Andersson, and Qaim (2015)

Wiggins et al., 2014). Yet, there are fears that as poor rural households focus on non-food cash crops and reduce own-food production, their food and nutrition security could be compromised (Ogutu, Gödecke and Qaim, 2020; Dzanku, Tsikata and Ankrah, 2021).

Since level of commercialisation, types of crops grown, technology adoption and the allocation of productive and reproductive labour are gendered within the household (Haddad et al., 1998; Tsikata, 2016; Hillesland, 2019; Dzanku, Tsikata and Ankrah, 2021), one would expect that increasing commercialisation will have implications for women's empowerment. Most often, subsistence crops are produced and controlled by women, while men produce and control cash crops (von Braun J. and Kennedy, 1994). While female-controlled income is particularly beneficial for enhanced household food and nutrition security – because women are more likely to spend their incomes on food and dietary quality than men (Haddad et al., 1998) – increased agricultural commercialisation may benefit women less than men due to women's weak control over the productive resources required to participate effectively in the commercialisation process. Thus, commercialisation may reduce women's empowerment by further concentrating resources in the hands of men. On another hand, the positive employment effects of commercialisation and increased incomes could result in higher household food and nutrition security outcomes. Hence, the total effect of commercialisation on household food and nutrition security via the gender pathway is unambiguous, it could be positive or negative, and must be determined within a particular empirical context.

2.2 Sample

Our study sites are in the Ahanta West and Mpohor districts. Our choice was guided by the following: since we wanted to study oil palm market participation arrangements, we purposively chose two districts located in Ghana's oil palm belt where two of the 'big four' oil palm plantations – Norpalm Ghana Ltd (NGL) and Benso Oil Palm Plantation (BOPP) – operate. The two districts were chosen also based on varying levels of oil palm production, with Ahanta West being the high oil palm concentration area and Mpohor the relatively lower concentration area. Twenty-one communities were randomly selected from a list of communities provided by oil palm companies. At the community level, we undertook a census to generate a sampling frame, from which, 10–60 households were randomly drawn depending on number of households per community. The baseline total sample is 725 households. However, 14 households (approximately two per cent of the sample) did not report any agricultural activity, which leaves us with a baseline sample of 711 households for the present analysis. At endline, 52 out of the 711 households could not be interviewed for various reasons (death, refusal, unavailability during the survey period or moved from the community), which gives an attrition rate of seven per cent. For this paper, we use the balanced sample of 659 households or 1,318 household-level observations. We did not test for attrition bias in this paper given that most of the analysis is descriptive.

2.3 Indicators

OPMCs: We first address the indicator variable that identifies the channels through which oil palm producers engage with oil palm markets. The survey identified six groups into which households self-select: (i) NGL, (ii) BOPP, (iii) B-BOVID (a medium-scale oil palm company called Building Businesses on Values, Integrity and Dignity in full), (iv) selling to NGL, BOPP or B-BOVID through middlemen called agents, (v) selling in the open market mainly to market women and small-scale processors, and (vi) processing own palm fruits. Because the six groups are too large for the statistical analysis given the sample size, we let the data speak for itself by applying cluster analysis, a statistical data reduction technique. This approach allows the identification of different OPMCs based on maximum intra-group similarity and inter-group heterogeneity.[2] This exercise resulted in four main channels: (1) Company – made up of NGL, BOPP and B-BOVID, (2) Agent, (3) Market (selling mainly in the open market), and (4) Processing (or simply Process). These are the OPMCs that form the basis of the statistical analyses.

Agricultural commercialisation: Although the focus of the surveys was oil palm, the farm households produced a variety of other crops. On this basis, we construct agricultural commercialisation indicators that consider all crops produced by households. The first indicator is the household commercialisation index (HCI), which is measured as:

$$HCI = \frac{gross\ value\ of\ crop\ sales}{gross\ value\ of\ crops\ produced} \times 100$$

2 We use k-means and k-median cluster analysis with Jaccard coefficient as the binary similarity measure for the grouping of households based on the ex-ante and ex post categories as well as district location. The k-means and k-median results are very similar for our sample

HCI lies between zero (full subsistence) and on (fully commercialised). We also use gross value of all crop output sold as a measure of commercialisation at the household level, since the main commercial crops (oil palm and cocoa) in the study areas can be considered non-food cash crops. Finally, we use the shares – cash crop share (CCsh) and oil palm share (OPsh) – of land devoted to all non-food cash crops as well as to oil palm in particular:

$$HCI = \frac{gross\ value\ of\ crop\ sales}{gross\ value\ of\ crops\ produced} \times 100$$

$$OPsh = \frac{oil\ palm\ culivated\ area}{total\ cultivated\ area} \times 100$$

Employment: Rural households make a living from both the farm and non-farm sectors. We use the shares of total income from off-farm activities to measure the level of income and livelihood diversification in the rural economy, and how this varies across the OPMCs.

Women's empowerment: We use two categories of variables to construct a women's empowerment indicator. The first is women's participation in decision-making, and the second is the burden of unpaid care work. For decision-making, we use four questions about women's participation in decision making about (i) farm production (i.e., plot management), (ii) allocation of gains (revenue/income) from commercial agriculture, and (iii) own wage or salary employment. For the burden of unpaid care work, we use total number of hours spent on all household care work.

Household welfare: Since welfare is a multidimensional concept, we use four measures. First, we use household per capita income based on household total net cash income from all sources (crops, livestock and off-farm income). Second, we use the value of household productive[3] and consumer assets.[4] Third, because how people feel about their living conditions is important – irrespective of what 'objective' poverty indicators might suggest (Posel and Rogan, 2016) – we follow Ravallion and Lokshin (2001) and asked households to place themselves on a nine-step ladder of life circumstances. In this system, step one represents the perception of being unable to change their life and nine represents the perception of having full control over household life circumstances. We then constructed a subjective poverty headcount ratio as the proportion of households that self-report being on the third ladder and below. Fourth, we used a measure of household food insecurity constructed using eight yes/no questions[5] about household food insecurity experiences (Ballard, Kepple and Cafiero, 2013; FAO, 2016). The questions were administered to one female adult household member. Answering yes to a question gives a score of one, answering no, a score of zero. A binary food insecurity indicator was constructed, which takes on the value of one if a household experienced moderate or severe food insecurity (i.e., a score of two–eight); a score of zero is given otherwise (Smith, Rabbitt and Coleman-Jensen, 2017).

3 The productive assets are hoes, spades, axes, sickles, shears, knives, sprayers and water pumps.

4 The consumer assets are mattresses, cooking stoves, radios, televisions, mobile phones, fridges, bicycles, motorcycles and car/trucks.

5 The questions are: (i) were you or others in your household worried about not having enough food to eat because of a lack of money or other resources? (ii) were you or others in your household unable to eat healthy and nutritious food because of a lack of money or other resources? (iii) did you or others in your household eat only a few kinds of foods because of a lack of money or other resources? (iv) did you or others in your household have to skip a meal because there was not enough money or other resources to get food? (v) did you or others in your household eat less than you thought you should because of a lack of money or other resources? (vi) did your household run out of food because of a lack of money or other resources? (vii) were you or others in your household hungry but did not eat because there was not enough money or other resources? (viii) did you or others in your household go without eating for a whole day because of a lack of money or other resources?

3 RESULTS

Figure 3.1 shows the distribution of households across the OPMCs at baseline (2017) and follow-up (2019). At both baseline and follow-up, about a third of households sold their palm fruits directly to oil palm companies; 29 per cent sold to companies through agents at baseline but that dropped by three percentage points at follow-up. Most of those who dropped out from the agent arrangement sold their palm fruits in the open market, perhaps due to dissatisfaction with the arrangement (Dzanku et al., 2020). The proportion of households that processed their own palm fruits (mostly into palm oil) remained constant at 13 per cent of the balanced panel sample.

In the next sub-sections, we show characteristics of the households that select into the four OPMCs and test for statistically significant differences across the baseline and endline groups.

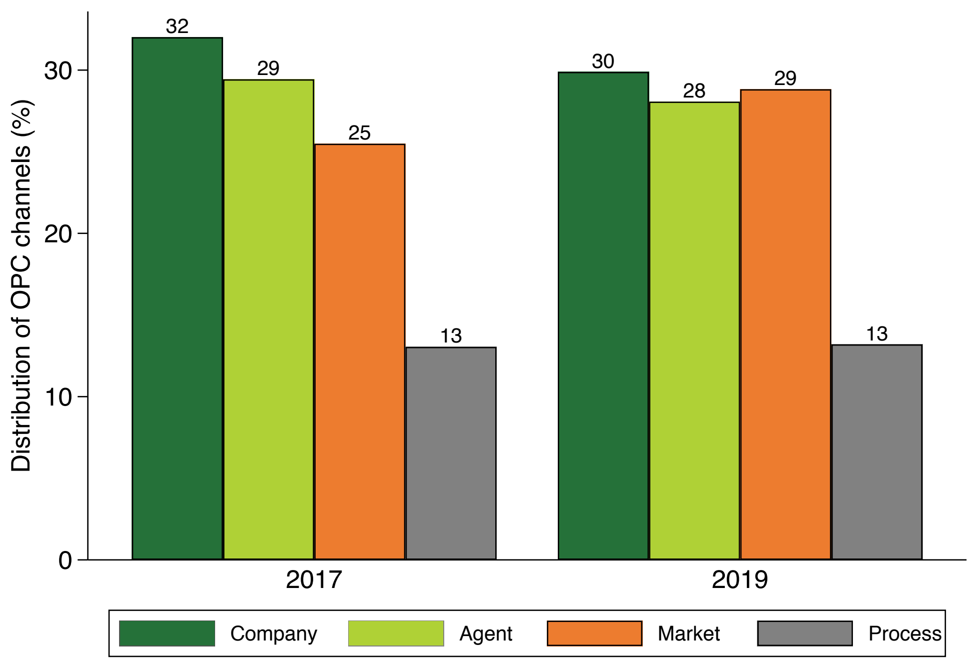
3.1 Household characteristics

Table 3.1 presents averages of various household and farm characteristics across the four OPMCs. Table 3.2 reports *p*-values for testing significant differences in means of the variables between the various groups. These tests are based on the following estimation equation:[6]

$$y_{ki} = \alpha + \varphi_1 Agent + \varphi_2 Market + \varphi_3 Process + u_i \quad (1)$$

where y_{ki} is the kth household or farm characteristic for the ith household, *Agent*, *Market*, and *Process* are dummies for the respective OPMCs, meaning that *Company* is the reference category, α is the intercept,

Figure 3.1 Distribution of households across the OPMCs over time



Source: Authors' own, based on APRA panel data

6 We account for within-village dependence when making inference by reporting p-values from clustering at the village level.

φ_1, φ_2 and φ_3 are the respective coefficients associated with each OPMC, and u_i is the random error term.

There are varying levels of difference in household characteristics between the OPMCs. The main source of difference between those who sell to companies directly and those who do so through agents is level of education (column 1 of Table 3.2) – those who sell directly are significantly more educated. *Company* households also differ from open *Market* households on education and gender-related variables. Female-headed households (FHHs) are significantly underrepresented in the *Company* channel compared with the open *Market* channel. About 20 per cent of the sample are FHHs but approximately 29 per cent of those who use the *Market* channel are FHHs; only about 16 per cent of those who use the other channels are FHHs. The reason FHHs are more likely to use the *Market* channel is that they produce smaller quantities and sell piecemeal, which is not desirable for the other channels.

We provide results from a joint test of the null hypothesis – that household characteristics are the same across the channels. The null is rejected for all comparisons except the *Company* and *Process* channels, showing that those who sell directly to companies and those that process their own fruits have similar household characteristics.

Table 3.1 also shows average farm characteristics of the entire sample and across the OPMCs. It must be noted that although oil palm is the dominant crop, the farm households also produce a variety of crops; the median number of crops produced is two. Figure 3.2 shows participation in the production of the top 10 crops at baseline and follow-up. Only four crops show statistically significant changes in participation over time: coconut (down by four percentage points),[7] maize (up by seven percentage points), okra (down by three percentage points), and pepper (down by three percentage points).

Table 3.1 Mean summary characteristics of the pooled sample, by OPC channel

	Total n = 1,318	Company n = 429	Agents n = 362	Market n = 354	Process n = 173
Household characteristics					
% FHH	19.7	16.5	16.0	28.8	16.2
Age of household head	52.3	51.9	52.1	52.3	53.7
Mean age of adult household members	43.5	42.9	43.9	43.9	43.6
Household size	4.3	4.3	4.2	4.2	4.7
Number of dependants	1.7	1.6	1.6	1.6	1.8
Number of working-age members	2.7	2.7	2.6	2.6	2.9
Dependency ratio (%)	74.5	68.0	78.3	77.9	75.1
Ratio of female to male adults	1.2	1.2	1.1	1.4	1.2
Head's years of schooling	7.6	8.3	7.2	7.0	7.9
Female adults' mean years of schooling	5.9	6.6	5.3	5.8	5.6
Male adults' mean years of schooling	8.8	9.3	8.2	8.7	9.2
Farm characteristics					
Farmland (ha)	3.3	3.7	2.9	2.7	4.0
Per cent small-scale farmers	39.5	29.8	44.8	49.3	31.8
Per cent medium-scale farmers	34.4	38.6	36.2	31.8	25.4
Per cent large-scale farmers	26.2	31.6	19.1	18.9	42.8
Number of crops cultivated	2.1	2.2	2.0	2.0	2.2
Oil palm farmland (ha)	2.2	2.4	2.0	1.9	2.7
Per cent cocoa producer	26.1	31.3	18.6	29.0	23.0
Cocoa farmland conditional on production (ha)	2.4	2.5	2.3	2.5	2.3
Per cent staple crop producer	54.5	50.0	55.2	58.4	56.1
Staple crop farmland conditional on production (ha)	0.7	0.8	0.6	0.8	0.8

Source: Authors' own, based on APRA Ghana survey data

7 We observed the cutting down of coconut tress due to diseases.

Table 3.1 shows that, on average, the farm households in our sample cultivated about 3ha of cropland which is above the small-scale threshold of 2ha for tree crops (Ghana Statistical Service, 2020). In fact, less than half (about 40 per cent) of the sample are smallholder farm households by this definition; 34 per cent are medium scale (cropland greater than 2ha but less than 4ha); and 26 per cent are large scale (4ha and above). If we use the threshold of less than 5ha as definition for small-scale (Muyanga and Jayne, 2019), however, 83 per cent of cropland holdings are small. There are significant scale differences across the OPMCs with *Company* and *Process* households holding significantly larger (about 26–50 per cent more) land than the other two groups. Transaction costs involved in engaging with companies make economies of scale an important factor. Also, investing in own-processing is more profitable in an environment of vertical integration, which requires large quantities of palm fruits (Torvikey and Dzanku, 2022).

Participation in the production of cocoa, the second most important non-food cash crop, is similar across the groups except that *Agent* households participate significantly less relative to the *Market* group (19 versus 29 per cent). It is remarkable that only about one half of households (55 per cent) in our sample produce any food staples (mainly cassava and plantains), showing heavy reliance on the market for food. Participation in staple food production is similar across the groups, except that *Market* households participate significantly more (58 per cent participation) than *Company* households (about 50 per cent participation). Joint test of the hypothesis – that all farm characteristics are the same between the groups – is rejected for all group pairs except the comparison between *Company* and *Process* households, just as we found for household characteristics.

From Figure 3.2, household participation in the production of non-food cash crops (oil palm, cocoa,

Table 3.2. p-values from the test for difference in means

	(1) C vs A	(2) C vs M	(3) C vs P	(4) A vs M	(5) A vs P	(6) M vs P
Household characteristics						
Female head	0.848	0.000	0.940	0.001	0.973	0.018
Age of head	0.834	0.736	0.196	0.827	0.168	0.098
Adult's mean age	0.426	0.442	0.652	0.973	0.760	0.761
Household size	0.399	0.673	0.129	0.699	0.054	0.119
Dependants	0.742	0.651	0.047	0.942	0.257	0.252
Working-age members	0.101	0.266	0.513	0.647	0.161	0.264
Dependency ratio	0.213	0.082	0.446	0.956	0.792	0.820
Female to male ratio	0.345	0.002	0.832	0.001	0.329	0.044
Head's education	0.009	0.007	0.403	0.486	0.136	0.069
Female education	0.003	0.045	0.127	0.061	0.558	0.677
Male education	0.002	0.028	0.795	0.096	0.010	0.157
Joint test of all coefficients	*0.007*	*0.000*	*0.321*	*0.000*	*0.000*	*0.000*
Farm characteristics						
Farmland (ha)	0.008	0.001	0.486	0.590	0.011	0.002
Small-scale farmers	0.000	0.000	0.654	0.151	0.039	0.002
Medium-scale farmers	0.520	0.084	0.027	0.303	0.058	0.266
Large-scale farmers	0.002	0.002	0.137	0.967	0.007	0.003
Number of crops	0.285	0.189	0.991	0.851	0.287	0.169
Oil palm farmland	0.004	0.007	0.257	0.238	0.026	0.005
Cocoa producer	0.078	0.560	0.313	0.017	0.496	0.334
Cocoa farmland	0.093	0.968	0.349	0.026	0.706	0.127
Staple producer	0.230	0.006	0.283	0.489	0.887	0.674
Staple farmland	0.014	0.522	0.880	0.045	0.076	0.445
Joint test of all coefficients	*0.000*	*0.000*	*0.088*	*0.000*	*0.000*	*0.000*

Note: C=Company, A=Agent, M=Market, and P=Process

Source: Authors' own, based on Table 3.1

and rubber) experienced marginal increases between 2017 and 2019. However, except for maize, households' engagement in the production of food crops (cassava, coconut, okra, pepper, plantain and tomato) generally declined over the period.

3.2 Level of commercialisation

First, gross value of sales increased by about eight per cent in real terms between 2017 and 2019 (from about US$2,400 purchasing power parity (PPP) in 2017 to about US$2,600 PPP in 2019). In 2017, *Company* households recorded between 43 and 89 per cent higher gross value of sales than the other groups; the gap increased in 2019 to between 69 and 143 per cent. Table 3.4 shows that the differences in gross value of sales between *Company* households and the other groups are all statistically significant at the 0.01 level. *Process* households have the lowest gross value of sales in both years, which is because their own-produced oil palm output that is processed is not accounted for in the calculation of gross value of crop sales (VCS). Evidence from Figure 3.3 shows that the mean quantities of palm fruit harvested were similar between *Company* and *Process* households, and lowest among *Market* households.

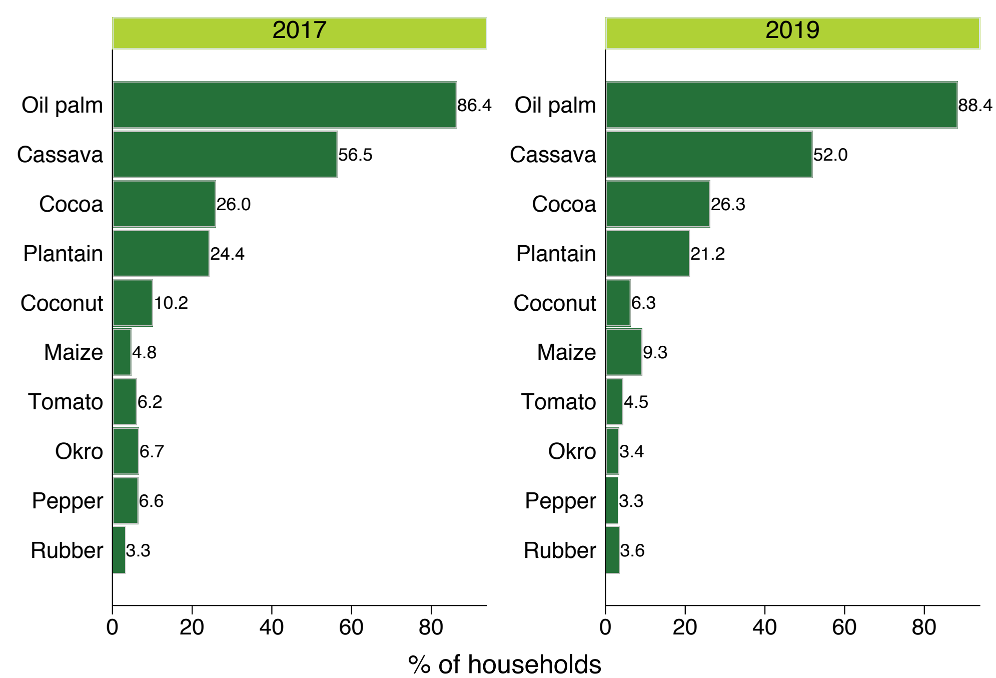
Second, our results challenge the perception that input and output market failures in rural Africa force farm households to devote most of their resources (land and labour) to self-provisioning, leading to low levels of agricultural commercialisation (Fafchamps, 1992; Govereth, Jayne and Nyoro, 1999; Dzanku and Sarpong, 2011; Wiggins et al., 2014). We observe very high levels of commercialisation among households in our sample, with average HCI of about 81 per cent in the pooled sample, meaning that approximately 81 per cent of the value of all crops produced were sold (Table 3.3). HCI increased by about four percentage points or about six per cent over the two periods (from 79 per cent in 2017 to 83 per cent in 2019). The observed high commercialisation level in the sample could be attributed to the high levels of specialisation in non-food cash crops, particularly oil palm in southwestern Ghana.

Average HCI is highest for *Company* households and lowest for *Process* households but as has been explained earlier, the lower HCI among the latter group is simply due to how the HCI indicator is calculated. Figure 3.4 shows clearly that the Cumulative Density Function (CDF) of *Company* households is strongly shifted to the right of that of the *Process* and *Market* households when HCI is less than 100, which shows that throughout the distribution of HCI, *Company* households are at higher levels of commercialisation.

Remarkably, approximately one-fifth of households in our sample have HCI of unity, meaning they are purely commercial farm households. These households produce mainly cocoa, coconut and oil palm.

Third, using the share of land devoted to oil palm and other non-food cash crops, we observe high levels of crop specialisation in our sample. The mean

Figure 3.2 Participation in the production of top 10 crops



Source: Authors' own, based on APRA panel data

share of land devoted to oil palm was about 60 and 61 per cent in 2017 and 2019 respectively. *Agent* and *Process* households had higher shares of land under oil palm than the sample mean in 2017; in 2019, *Company* households increased their share of land under oil palm significantly, while the share for *Market* households dropped.

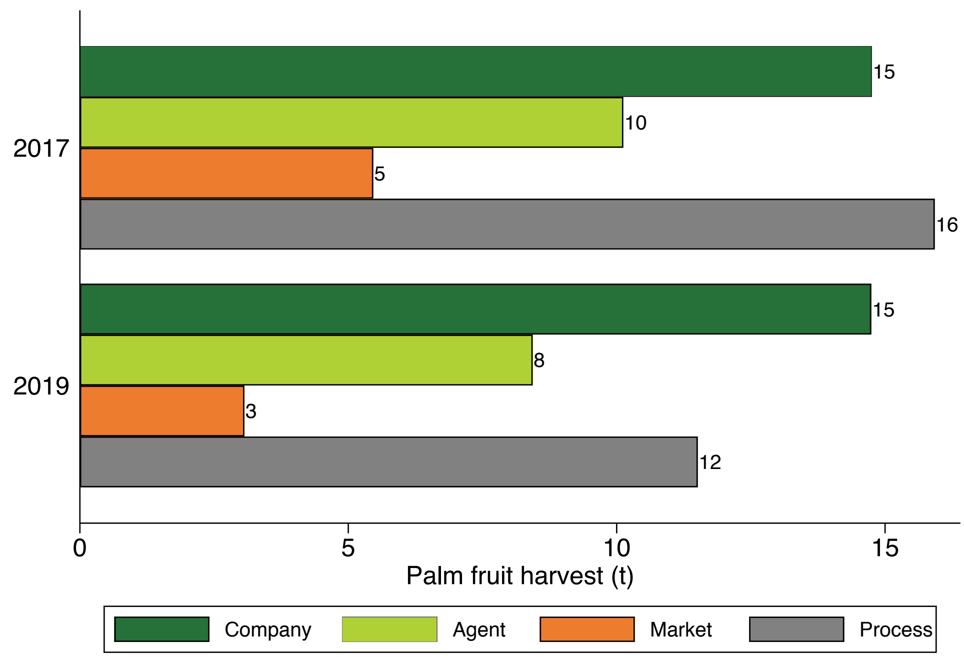
The share of land devoted to non-food cash crops was about 77 and 82 per cent in 2017 and 2019 respectively, indicating high concentration on production of crops for the market. Table 3.4 shows no statistically significant difference in non-food cash crop share of cropland across the OPMCs in 2017, but in 2019, *Market* households had significantly less non-food cash crop share of land compared with *Company* and *Process* households.

3.3 Labour allocation to farm and off-farm employment and returns to labour

3.3.1 Farm labour

Tables 3.5 and 3.6 show the mean summary statistics of farm employment and input use indicators across the commercialisation channels. The farm households in our sample are predominantly family farms, owned and operated using household labour, although the contribution of hired labour to farm operations is nontrivial. First, the majority (80 per cent or more) of working-age adult household members (15 years and above) are involved in farm work, and they work about 61 days in a year, on average. This means that on-farm

Figure 3.3 Level of oil palm output by commercialisation channels



Source: Authors' own, based on APRA panel data

Table 3.3 Mean summary statistics of commercialisation indicators by OPC channel

Variables	(1) Total	(2) Company	(3) Agents	(4) Market	(5) Process
Gross VCS in 2017 (PPP US$1,000)	2.4	3.2	2.1	2.1	1.8
Gross VCS in 2019 (PPP US$1,000)	2.6	3.5	2.4	2.3	1.5
Crop commercialisation index in 2017	78.9	82.7	81.9	79.5	60.7
Crop commercialisation index in 2019	83.4	88.4	83.3	80.6	76.7
Oil palm cropland share in 2017 (%)	60.0	59.6	65.2	52.8	64.3
Oil palm cropland share in 2019 (%)	61.4	66.4	65.5	48.5	66.7
Non-food cash cropland share in 2017 (%)	77.0	77.4	78.1	73.7	80.2
Non-food cash cropland share in 2019 (%)	81.6	86.3	81.1	73.7	87.6

Source: Authors' own

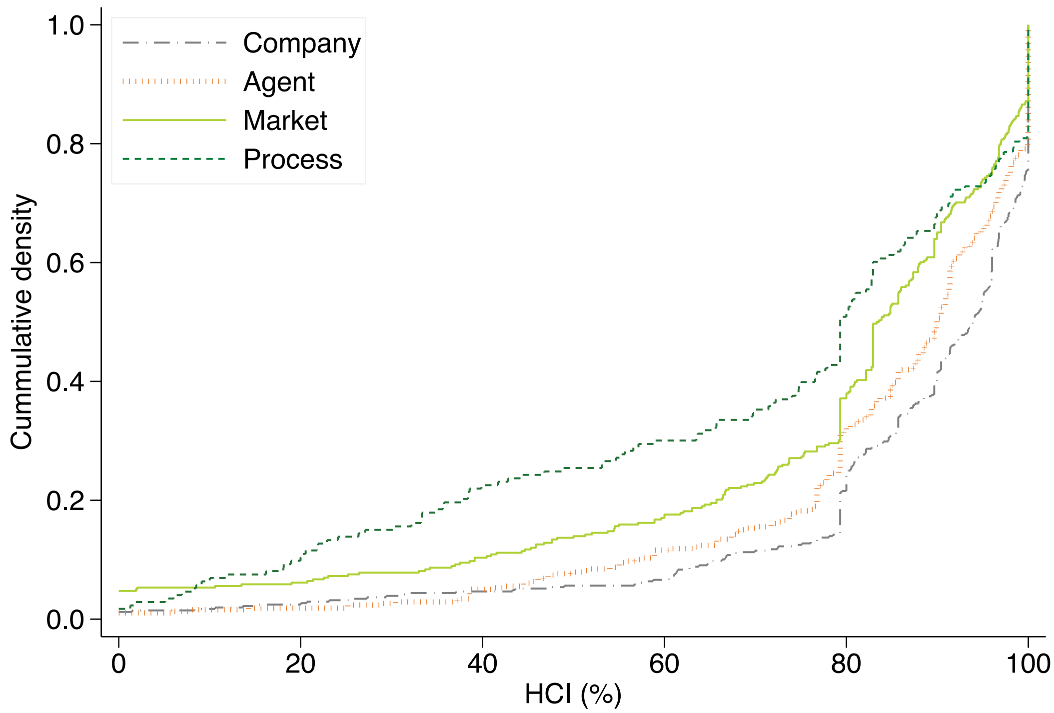
Table 3.4 *p*-values from the test for difference between means of commercialisation indicators

Variables	(1) C vs A	(2) C vs M	(3) C vs P	(4) A vs M	(5) A vs P	(6) M vs P
VCS in 2017 (US$PPP)	0.004	0.001	0.001	0.797	0.363	0.409
VCS in 2019 (US$PPP)	0.001	0.000	0.000	0.617	0.033	0.047
HCI in 2017	0.719	0.084	0.000	0.218	0.000	0.000
HCI in 2019	0.033	0.009	0.002	0.276	0.101	0.077
OPsh in 2017 (%)	0.329	0.063	0.535	0.009	0.893	0.065
OPsh in 2019 (%)	0.806	0.000	0.967	0.003	0.814	0.008
CCsh in 2017 (%)	0.880	0.219	0.546	0.269	0.627	0.163
CCsh in 2019 (%)	0.078	0.000	0.670	0.095	0.071	0.007

Note: C=Company, A=Agent, M=Market, and P=Process

Source: Authors' own, based on Table 3.3

Figure 3.4 CDF of HCI across the four OPMCs



Source: Authors' own, based on APRA panel data

work does not provide full employment throughout the year and is indicative of underemployment, unless the rest of working time is spent working off-farm.[8] Across the OPMCs, there are no statistically significant differences in the proportion of household members working on-farm or the number of days worked, except in 2017 where *Agent* households had a larger share of members working on-farm than *Process* households. This means that, in general, the OPMCs do not generate differential demand for household farm labour.

Second, it is important not to consider farm labour in isolation but in conjunction with other purchased farm inputs (mainly hired labour and chemical fertilisers). Considering these two main external inputs, we found that hired labour use is quite widespread among farm households, but fertiliser use is not. About 62 and 61 per cent of the sample hired some labour in 2017 and 2019, respectively, although hired labour constituted only 14 per cent of total farm labour used. Hired labour use differs significantly between the OPMCs; relative to the other groups, *Company* and *Process* households had the highest incidence of labour hiring as well as share of hired labour employed. This is not surprising given that *Company* and *Process* households

8 Although the association between working off-farm work (measured as the share of income from off-farm employment) and on-farm work days is negative, it is not statistically significant.

produced much higher quantities of oil palm than the other groups and are thus more commercialised, on average, than the rest.

Chemical fertiliser use is very low in the sample, with only 23 per cent of households using any fertilisers in 2017, and although this went up by about five percentage points in 2019, this increase is only significant at the 10 per cent level (*p*-value = 0.057). This low use of fertiliser is worrying due to the general decline in soil quality in the region and a large yield gap for oil palm (Rhebergen et al., 2020). Chemical fertiliser use incidence varies significantly across the OPMCs, with *Company* households being the group that uses the input most (31–33 per cent). The proportion of households using fertilisers increased among the other groups relative to *Company* households over the period of the panel, such that there was no statistically significant difference at follow-up except between the *Company* and the Market groups. The level of oil palm yields across the OPMCs (Figure 3.5) reflects the level of fertiliser use, with *Company* households recording the highest yields, 6.9t/ha compared to the sample mean of 6.1t/ha. The reason for this is that the industrial companies offer training in good agronomic practices to farmers who engage with them, including the importance of using fertilisers to boost yields.

Third, and most important for poverty reduction, we consider returns to farm labour measured as the value of farm output per worker. Average returns to farm labour were about US$1,951 and US$2190 per worker

Table 3.5 Mean summary statistics of agricultural employment and input indicators

Variables	Total	Company	Agents	Market	Process
Per cent of adult on-farm workers in 2017	82.9	81.9	86.0	82.7	78.8
Per cent of adult on-farm workers in 2019	80.2	77.8	83.2	81.3	77.0
On-farm work days per family worker in 2017	64.8	62.4	63.2	67.3	69.2
On-farm work days per family worker in 2019	60.9	58.9	64.5	61.3	56.8
Per cent using hired labour in 2017 (%)	61.8	68.6	54.0	56.8	72.7
Per cent using hired labour in 2019 (%)	60.9	71.3	52.8	53.2	69.2
Hired labour share of farm labour in 2017 (%)	13.7	17.2	10.7	12.5	14.0
Hired labour share of farm labour in 2019 (%)	13.9	16.9	11.4	11.4	17.1
Per cent using fertiliser in 2017 (%)	23.1	31.4	17.8	20.9	18.2
Per cent using fertiliser in 2019 (%)	28.0	32.5	29.1	23.3	23.8
Returns to farm labour in 2017 (US$PPP/worker)	1,951	2,482	1,501	1,451	2,669
Returns to farm labour in 2019 (US$PPP/ worker)	2,190	2,920	1,833	1,702	2,162

Source: Authors' own

Table 3.6 *p*-values from testing difference between means of farm employment and input indicators

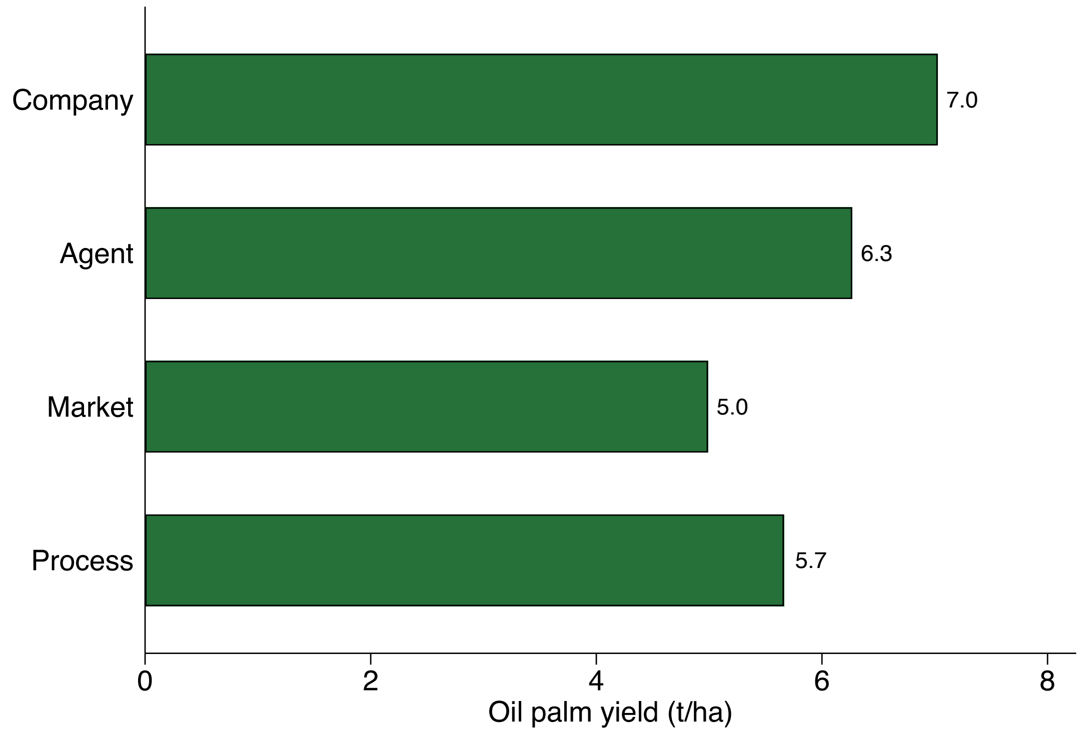
Variables	(1) C vs A	(2) C vs M	(3) C vs P	(4) A vs M	(5) A vs P	(6) M vs P
On-farm workers in 2017	0.139	0.691	0.369	0.275	0.017	0.280
On-farm workers in 2019	0.079	0.233	0.859	0.509	0.104	0.342
Days per worker in 2017	0.878	0.313	0.253	0.421	0.304	0.781
Days per worker in 2019	0.222	0.739	0.808	0.518	0.237	0.440
Hired labour use in 2017	0.006	0.009	0.588	0.518	0.036	0.074
Hired labour use in 2019	0.000	0.000	0.741	0.937	0.038	0.012
Hired labour share in 2017	0.000	0.011	0.311	0.266	0.247	0.576
Hired labour share in 2019	0.013	0.013	0.927	0.998	0.044	0.027
Fertiliser use in 2017	0.000	0.014	0.031	0.207	0.936	0.533
Fertiliser use in 2019	0.383	0.023	0.083	0.172	0.332	0.916
Returns to farm labour in 2017	0.001	0.000	0.641	0.742	0.009	0.005
Returns to farm labour in 2019	0.001	0.000	0.019	0.525	0.255	0.030

Note: C=Company, A=Agent, M=Market, and P=Process

Source: Authors' own, based on Table 3.3

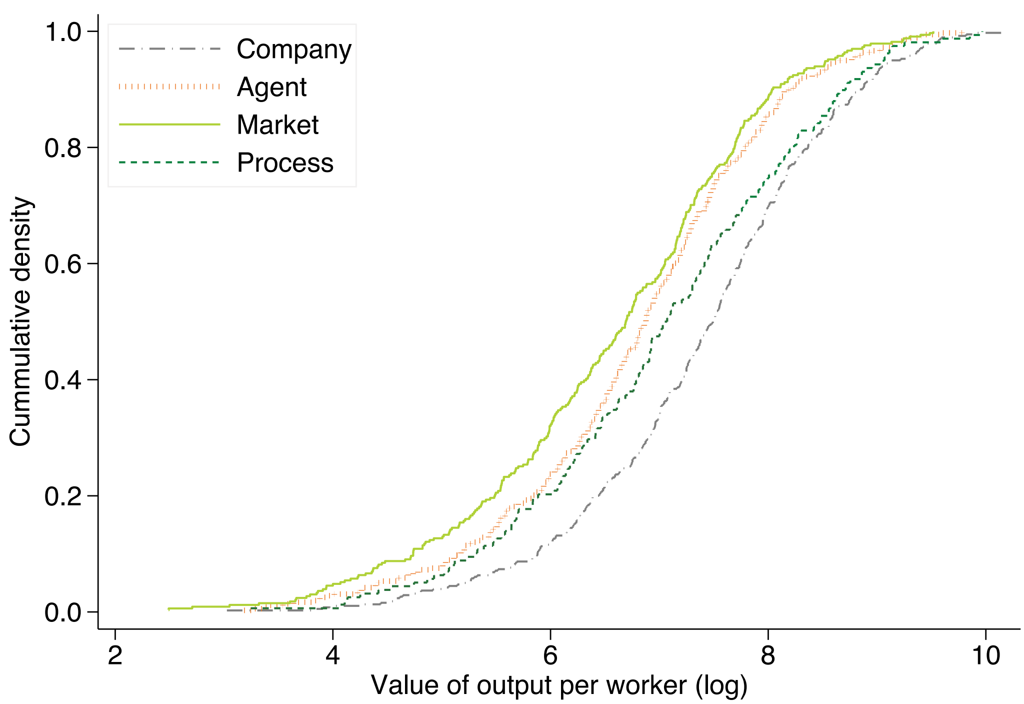
in 2017 and 2019 respectively, an increase of about 12 per cent over the period. Tables 3.5 and 3.6 show that returns differ significantly by the OPMCs. For instance, in the pooled sample, returns to labour for *Agent* and *Market* households were only 58 and 53 per cent respectively of the returns that *Company* households achieved; returns to labour for *Process* households were 86 per cent of that of *Company* households. Returns to output increased for all groups (by between 17 per cent for the *Market* group and 22 per cent for *Agent* households) except *Process* households whose returns dropped by 19 per cent. The CDFs of returns

Figure 3.5 Oil palm yields by the four OPMCs



Source: Authors' own, based on APRA panel data

Figure 3.6 CDFs of returns to farm labour per worker, by the four OPMCs



Source: Authors' own, based on APRA panel data

to farm labour are plotted in Figure 3.6 and show that when we consider the entire distribution, returns for the *Company* channel are distinctly shifted to the right of the other groups, particularly the *Agent* and *Market* channel households.

One could contextualise the average returns to farm labour by comparing them with the international poverty line of US$1.90 (PPP). Clearly, the average returns per worker are well above the poverty line, but about 35 per cent of the total sample have returns below the chosen poverty threshold. The proportion of households with returns below the poverty threshold varies significantly across the OPMCs – from 22 per cent for *Company* households to about 46 per cent for *Market* households (Figure 3.7).

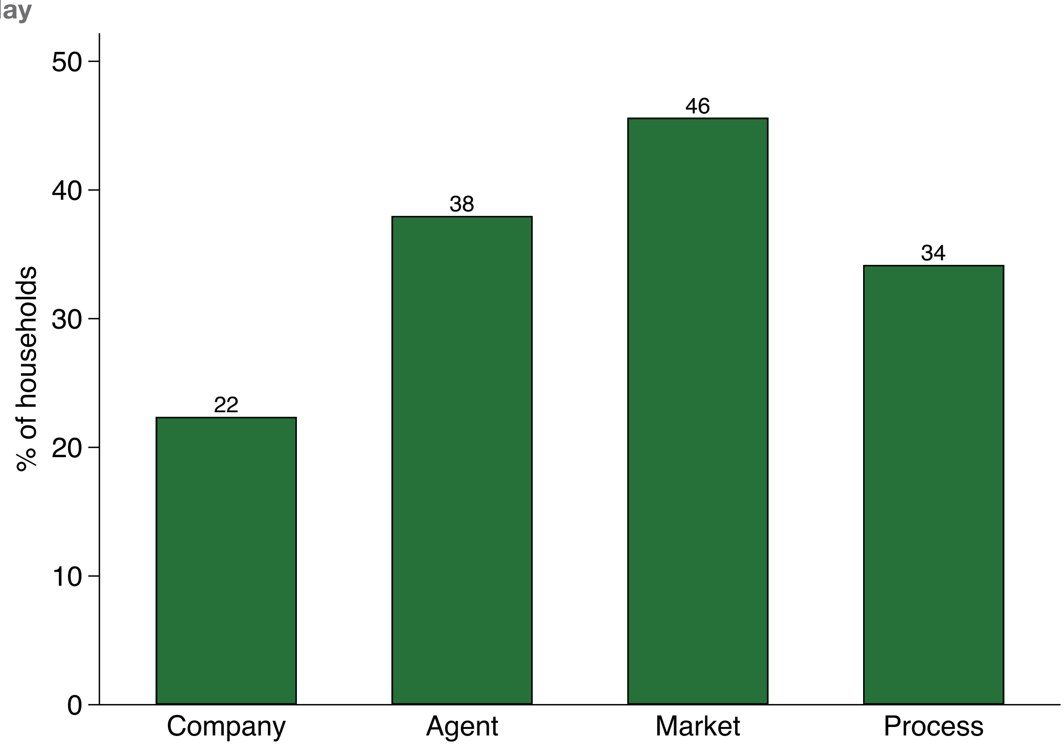
3.3.2 Off-farm participation, income shares and returns to off-farm labour

Pluriactivity is the norm among rural African households (Davis, Di Giuseppe and Zezza, 2017). Therefore, even among the highly-commercialised farm households in our sample, our analysis is concerned with the level of participation in off-farm income-generating activities. The previous section in this paper suggested that crop farming alone was not enough to provide full-time employment for some farm households. We categorise non-crop income into three broad groups: livestock income, off-farm employment income, and non-labour income. Table 3.7 presents mean summary statistics of non-crop income and returns to rural off-farm employment (ROFE). The following are the key results.

First, only about 13 per cent of households do not participate in any non-crop income-generating activity; they are full-time crop famers. About 53 per cent of households received some income from livestock sales, 55 per cent from the supply of labour to off-farm employment activities, and 28 per cent received non-labour income (remittances and other capital transfers). Participation in all three non-crop income activities increased slightly over time – but significantly so (p-value = 0) only for ROFE participation, which saw a 10 percentage point increase. *Process* households increased their participation in livestock income significantly in 2019 compared with the other groups of households, investing part of their profits from processing into livestock rearing (including chickens). Non-labour income participation behaviour does not differ significantly across the OPMCs.

Second, although highly commercialised, the households in our sample derive more than half (53 per cent) of their income from non-crop sources (livestock, ROFE and non-labour income) – about 28 per cent from ROFE, 16 per cent from livestock, and 9 per cent from non-labour income. Income shares differ significantly across the OPMCs, with the most significant source of difference being ROFE, from which *Process* households derive about 58 per cent of their income compared with the sample average (28 per cent).

Figure 3.7 Share of household with return to farm labour below the poverty line of US$1.9/day



Source: Authors' own, based on APRA panel data

Table 3.7 Mean summary statistics of non-crop income generating activities

Variables	Total	Company	Agents	Market	Process
Received livestock income in 2017 (%)	54.0	55.5	50.6	50.8	65.0
Received livestock income in 2019 (%)	56.2	56.3	52.8	52.2	72.0
Received OFE income in 2017 (%)	50.5	42.6	40.5	47.5	100.0
Received OFE income in 2019 (%)	59.2	54.1	49.7	56.1	100.0
Received non-labour income in 2017 (%)	24.1	21.3	24.5	28.6	21.0
Received non-labour income in 2019 (%)	28.9	27.6	29.4	32.2	23.8
Livestock income share in 2017 (%)	15.8	17.0	17.7	15.8	8.6
Livestock income share in 2019 (%)	14.1	14.1	13.2	14.8	14.3
OFE income share in 2017 (%)	23.7	16.1	20.2	22.2	54.5
OFE income share in 2019 (%)	28.9	23.4	23.9	27.1	58.1
Non-labour income share in 2017 (%)	7.9	7.6	8.3	10.6	2.5
Non-labour income share in 2019 (%)	7.6	6.8	8.3	10.0	3.2
Returns to OFE in 2017 (US$ PPP)	2,225	1,768	2,028	1,933	4,458
Returns to OFE in 2019 (US$ PPP)	2,756	2,947	2,018	2,101	5,331

Note: OFE – off-farm employment
Source: Authors' own

Table 3.8 *p*-values from testing difference between means

Variables	(1) C vs A	(2) C vs M	(3) C vs P	(4) A vs M	(5) A vs P	(6) M vs P
Livestock income in 2017	0.309	0.211	0.085	0.961	0.009	0.014
Livestock income in 2019	0.433	0.368	0.046	0.901	0.013	0.013
OFE income in 2017	0.606	0.313	0.000	0.136	0.000	0.000
OFE income in 2019	0.325	0.620	0.000	0.198	0.000	0.000
Non-labour income in 2017	0.387	0.056	0.943	0.397	0.435	0.237
Non-labour income in 2019	0.687	0.208	0.600	0.536	0.438	0.291
Livestock income share in 2017	0.822	0.568	0.028	0.481	0.004	0.012
Livestock income share in 2019	0.686	0.747	0.968	0.438	0.742	0.871
OFE income share in 2017	0.174	0.032	0.000	0.479	0.000	0.000
OFE income share in 2019	0.874	0.153	0.000	0.351	0.000	0.000
Non-labour income share in 2017	0.756	0.228	0.006	0.461	0.032	0.002
Non-labour income share in 2019	0.325	0.087	0.045	0.278	0.001	0.002
Returns to OFE in 2017	0.320	0.685	0.039	0.825	0.059	0.045
Returns to OFE in 2019	0.033	0.031	0.078	0.663	0.010	0.014

Note: OFE – off-farm employment; =Company, A=Agent, M=Market, and P=Process
Source: Authors' own, based on Table 3.7

How do returns to ROFE compare with on-farm employment? First, participation in ROFE is only 55 per cent so 45 per cent of households are not involved; as has long been reported in the literature (Reardon et al., 2000), there seem to be binding entry barriers to ROFE relative to on-farm employment. That said, yearly returns to ROFE among participating households was US$3,062 (PPP) compared with US$2,070 (PPP) for on-farm work. Returns to ROFE are much higher (about US$4,906 PPP) for the *Process* group of households, and is about 1.6 times the sample average for participating households – and more than double the return among *Agent* and *Market* households. We note that the most commercialised group (the *Company* group) is not the one with the lowest returns to ROFE, although they have significantly less returns than *Process* households, suggesting that agricultural commercialisation and ROFE could be counterparts, not necessarily competitors.

3.4 Association between agricultural commercialisation and employment

Beyond comparing employment indicators across the OPMCs, it is useful to examine their relationships with level of agricultural commercialisation. For example, does the use of hired labour expand with increasing rates of agricultural commercialisation? Is increasing commercialisation associated with intensive use of family labour? Is rising agricultural commercialisation associated with increasing or decreasing off-farm employment? We use the following employment indicators: (i) working adult family labour supply, measured as man-days of family labour used, (ii) hired labour demand, measured as hired labour expenses, and (iii) ROFE share of total income.

Since we seek to examine only correlations, we simply estimate the following equations using the fixed effects estimator if the dependent variable is continuous:

$$employment_{it,k} = \gamma com_{it} + \beta' X_{it} + \delta_t + c_i + u_{it} \qquad (2)$$

where $employment_{it}$ is the k_{th} employment indicator for the i_{th} household in year t, com_{it} is the commercialisation indicator, X_{it} is a set of controls for scale of production, δ_t is the time dummy, c_i is the household-specific time-constant unobserved *effect*. c_i is allowed to be correlated with commercialisation and thus helps minimise the impact of endogenous commercialisation on our results. The parameter of interest that defines the association between employment and agricultural commercialisation is γ, and u_{it} is the random error term. For the two non-continuous employment variables, we use the correlated random effects approach to model the unobserved household-specific heterogeneity:

$$employment_{it,k} = \gamma com_{it} + \pi' \overline{com_i} + \beta' X_{it} + \varphi' \bar{X}_i + u_{it} \qquad (3)$$

where $\overline{com_i} \equiv T^{-1} \sum_{t=1}^{T} com_{it}$

or the time average of the commercialisation indicator which allows correlation with the household-specific unobserved effect. We included district fixed effects when estimating equation 3.

Table 3.9 reports the results from estimating the regression equations. The following results are salient. First, the estimate of the crop commercialisation effect ($\hat{\gamma}$) is positive in both the family and hired labour equations, indicating that family labour supply and hired labour demand are both significantly increasing (p-value < 0.05) with the level of commercialisation, although the effect magnitudes are not so large. For instance, a one per cent increase in the level of agricultural commercialisation is predicted to increase family labour supply by only about 0.07 per cent, holding other variables fixed; the same per cent increase raises hired labour demand by approximately 0.08 per cent.

Second, the results show a significant negative correlation between agricultural commercialisation and ROFE at the household level. A 10 per cent increase in crop commercialisation is predicted to decrease the share of income from ROFE significantly (p-value = 0), by about 0.3 percentage points. Going beyond averages, we obtain partial effects at various percentiles of the crop commercialisation distribution. Table 3.10 displays the estimated average partial effects for the log crop commercialisation variable at the 10th, 25th, 50th, 75th, and 90th percentiles of the distribution at baseline (2017) and follow-up (2019). We see that the average partial effect of commercialisation decreases as we move from the lowest to the highest percentile. At baseline, the estimated effect on ROFE of a 10 per cent increase in commercialisation is three percentage points at the 10th percentile, compared with two percentage points at the 90th percentile; the p-value of the difference is zero to three decimal places. The difference in effect size is similar at follow-up (2019). These results mean that ROFE is more important for

Table 3.9 Association between agricultural commercialisation and employment

	Log family labour	Log hired labour	ROFE income share
Log VCS	0.07***	0.08**	–0.03***
	(0.02)	(0.03)	(0.00)
Log of cropland	0.23***	0.25	–0.00
	(0.07)	(0.18)	(0.02)
2019 vs 2017	–0.05	–0.12	0.06***
	(0.05)	(0.13)	(0.02)
High vs low oil palm zone		–0.72***	–0.02
		(0.15)	(0.02)
Observations	1136	1136	1136

Note: Standard errors in parentheses; * p<.10, ** p<.05, *** p<.01

Source: Authors' own

households at lower levels of commercialisation than for those at higher levels, as could be expected.

3.5 Oil palm commercialisation channels, women's empowerment and household welfare

3.5.1 Channels of market participation and women's empowerment

Here, we examine women's empowerment and its difference across the OPMCs. First, Table 3.11 shows that based on adequate achievements in four out of the five domains of empowerment (Malapit and Quisumbing, 2015), only about one-half of women in our sample are empowered. However, the level of empowerment varies with the dimension being measured, for instance, women are most empowered (86 per cent) in autonomy over decision-making for their own employment; whilst decision-making regarding revenue allocation from commercial agriculture is the area where women are least empowered (31 per cent). This is quite significant because women's direct contribution to household agricultural labour is not much lower than men's (Figure 3.8).

Does women's empowerment differ significantly across the OPMCs? Table 3.12 shows that women living in *Market* channel households are significantly (p-value < 0.05) more empowered than their counterparts in *Company* and *Agent* households. The source of this difference is with respect to decisions about farm production and revenue utilisation, but not employment autonomy and care work burden. Recall that the most commercialised households are the *Company* group so this result suggests that women's empowerment falls with increased commercialisation, which is consistent with the results of Dzanku (2022).

3.5.2 Market participation channels and household welfare

Table 3.13 shows the mean values of the welfare indicator for the overall sample and across the OPC models. The data shows that the sample mean income per capita of above US$1,600 is well above the US$1.90/day international poverty line value of US$694 per annum. Does per capita income differ significantly across the OPC models? The answer is in the affirmative – *Company* and *Process* households are significantly (*p*-value < 0.01) richer in income than *Agent* and *Market* households (Table 3.14).

It is striking that, despite the modest average per capita incomes in our sample, the income poverty headcount ratio is approximately 48 per cent, meaning that nearly one-half of the sample were below the US$1.9/day

Table 3.10 APE of log (commercialisation) at percentiles of the commercialisation distribution

Percentiles	2017	2019
10th	0.330	0.304
	(0.018)	(0.014)
25th	0.282	0.271
	(0.012)	(0.011)
50th	0.250	0.245
	(0.011)	(0.011)
75th	0.227	0.225
	(0.011)	(0.011)
90th	0.210	0.210
	(0.012)	(0.012)

Note: Standard errors in parentheses; * p<.10, ** p<.05, *** p<.01

Source: Authors' own

Table 3.11 Commercialisation models and women's empowerment

Variables	Total	Company	Agents	Market	Process
Per cent empowered across all dimensions	50.2	47.5	45.4	56.5	54.5
Per cent empowered: production decisions	68.7	64.5	65.6	74.4	74.1
Per cent empowered: revenue decisions	31.5	26.5	30.4	39.9	29.4
Per cent empowered: employment decisions	86.5	88.0	85.6	86.4	85.3
Per cent empowered: care workload	74.8	73.8	75.8	72.4	80.4

Source: Authors' own, based on APRA panel survey data poverty line. This result suggests that the distribution of income could be highly positively skewed. Indeed, Figure 3.9 is evidence that the distribution of income is indeed highly unequal, with a Gini index of 62 per cent, which is much higher than Ghana's Gini of around 44 per cent (World Bank, 2022). Although income inequality reduced slightly between baseline and endline (64 versus 60 per cent), it remained high. At baseline, the poorest 10 per cent of the sample earned only about two per cent of the per capita income of the richest 10 per cent, and this improved only slightly by 2019 – with the bottom 10 per cent earning four per cent of the per capita income of the top 10 per cent.

With respect to assets, Table 3.13 shows that households in our sample invest much more in consumer assets than they do in producer assets – the mean value of producer assets is only about 14 per cent of that of consumer assets. As with income, *Agent* and *Market* households are significantly poorer in assets than *Company* and *Process* households. This may be the case because, compared to selling through Agents and the Market, processing requires certain productive assets for oil palm processing, for instance.

The subjective poverty headcount ratio is 22 per cent in the overall sample, and is lowest for *Company* and *Process* households, which is consistent with the income and asset poverty examples. As mentioned previously, objective and subjective measures of poverty might not necessarily tell the same story; we see here that the subjective poverty headcount ratio is much lower than the income poverty headcount – meaning that a much lower proportion of the sampled households identified themselves as poor than the income poverty measure suggests. There are at least two reasons for this: income measurement error and the fact that poverty is also a subjective feeling. For our sample, only 57 per cent of households have the same objective and subjective poverty outcome; 35 per cent identified themselves as non-poor although the income measure identified them as poor; eight

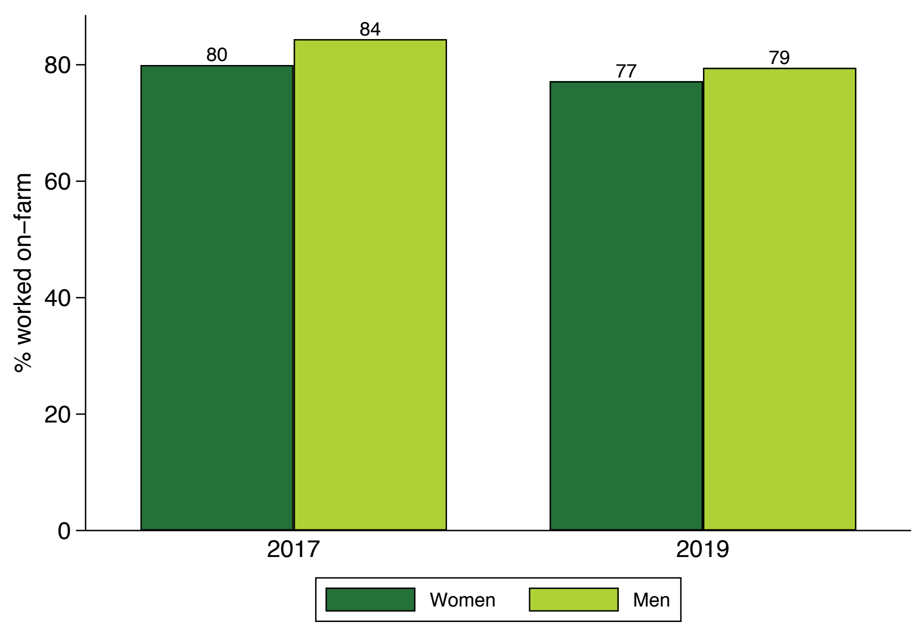
Table 3.12 *p*-values from testing women's empowerment differences across the OPC models

Variables	(1) C vs A	(2) C vs M	(3) C vs P	(4) A vs M	(5) A vs P	(6) M vs P
Empowered: all dimensions	0.675	0.007	0.335	0.019	0.182	0.759
Empowered: production	0.763	0.003	0.116	0.046	0.197	0.960
Empowered: revenue	0.445	0.000	0.628	0.018	0.839	0.044
Empowered: employment	0.461	0.694	0.492	0.813	0.951	0.765
Empowered: care work	0.712	0.687	0.187	0.533	0.428	0.113

Note: C=Company, A=Agent, M=Market, and P=Process

Source: Authors' own, based on Table 3.13

Figure 3.8 Proportion of female and male adults who worked regularly on-farm



Source: Authors' own, based on APRA panel data

Table 3.13 Commercialisation models and household welfare

Variables	Total	Company	Agents	Market	Process
Per capita income (US$PPP)	1633	1944	1381	1265	2189
Income poverty headcount ratio (%)	47.7	41.8	54.0	53.8	35.7
Real value of productive assets (US$)	52.5	63.8	37.7	40.3	83.0
Real value of consumer assets (US$)	369.3	546.7	179.4	303.0	487.9
Subjective poverty headcount ratio (%)	21.9	17.2	23.3	28.2	17.5
Per cent food insecure	34.7	31.7	40.2	38.9	21.0

Source: Authors' own, based on APRA panel survey data

Table 3.14 *p*-values for testing welfare differences across the OPC models

Variables	(1) C vs A	(2) C vs M	(3) C vs P	(4) A vs M	(5) A vs P	(6) M vs P
Per capita income	0.309	0.211	0.085	0.961	0.009	0.014
Income poverty headcount	0.433	0.368	0.046	0.901	0.013	0.013
Productive assets	0.606	0.313	0.000	0.136	0.000	0.000
Consumer assets	0.325	0.620	0.000	0.198	0.000	0.000
Subjective poverty headcount	0.387	0.056	0.943	0.397	0.435	0.237
Food insecurity	0.687	0.208	0.600	0.536	0.438	0.291

Note: C=Company, A=Agent, M=Market, and P=Process

Source: Authors' own, based on Table 3.13

per cent identified themselves as poor but the income measure classified them as non-poor. This means that households feel better about themselves than the absolute income poverty line suggests. This supports the argument that material well-being is not always strongly correlated with subjective well-being (Diener, Oishi and Tay, 2018).

When we regressed the subjective poverty headcount ratio against log per capita income with household fixed effects and the time dummy, we found a negative relationship. This indicates that households feel better-off, on average, as their incomes rise (p-value < 0.05), but the size of the correlation is small with an estimated average marginal effect of -0.035, meaning that the probability of feeling poor is only 0.3 percentage points lower for a 10 per cent increase in per capita income.

Finally, a critical household welfare indicator is food insecurity. This indicator is particularly important for our study because of longstanding debates about the association between non-food cash crop production and food and nutrition security (von Braun and Kennedy, 1986; Fafchamps, 1992). Table 3.13 shows that about 35 per cent of households experienced moderate to severe food insecurity. With a food insecurity incidence of about 17 per cent, *Process* households are significantly less food insecure than all other groups of households. At the 0.05 level of significance, *Company* households are only better off food security wise than *Agent* households. Our conjecture for the food insecurity-reducing effect of processing is that it allows the spread of income over a longer period of time, since palm oil can be stored and sold throughout the year, whereas oil palm fruit sales are seasonal (Torvikey and Dzanku, 2022).

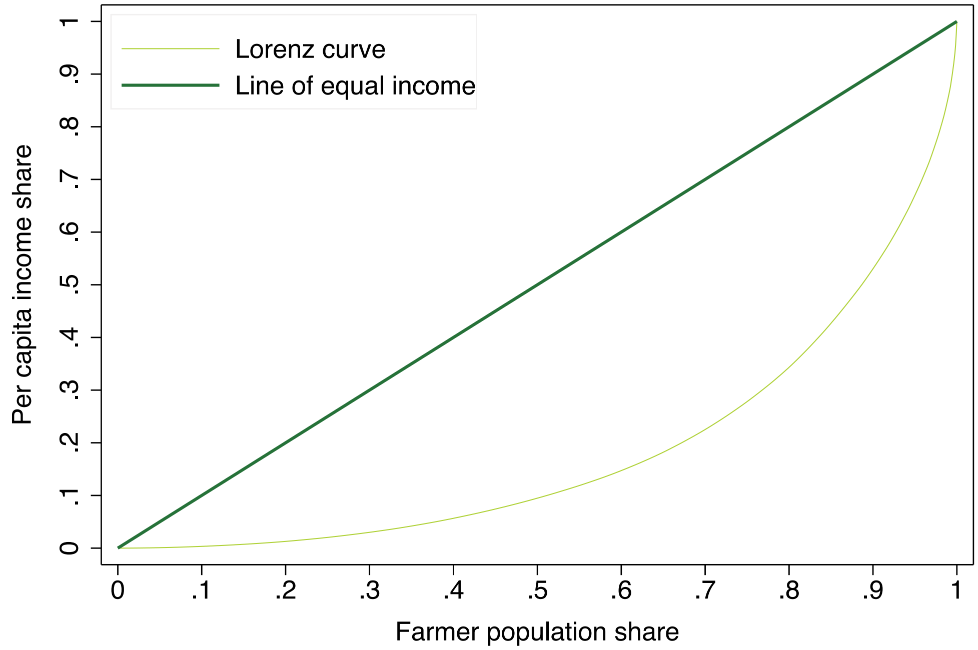
3.6 Association between agricultural commercialisation and household welfare

Here, we ask if the main basis for promoting agricultural commercialisation – the expectation that it is positively associated with welfare (Barrett, 2008) holds for our sample. Note that we only explore associations since we do not address endogeneity that may arise due to time-varying unobserved factors that jointly determine welfare and commercialisation. However, we account for endogeneity due to household-specific unobserved heterogeneity by using the fixed effects estimator:

$$welfare_{it\,k} = \beta com_{it} + \delta_t + c_i + u_{it} \tag{4}$$

Where $welfare_{it}$ is the kth welfare indicator for the ith household at time t, com_{it} is the agricultural commercialisation indicator, β is the parameter of interest that defines the association between welfare and agricultural commercialisation, δ_t is the time dummy, c_i is the time-constant household-specific

Figure 3.9 Per capita income Lorenz curve



Source: Authors' own

Table 3.15 Commercialisation and household welfare

		Explanatory variables	
	Dependent variable	Log VCS ($\hat{\beta}$)	2019 versus 2017 ($\hat{\delta}$)
	Random effects		
row 1	Log income	0.207***	0.358***
		(0.022)	(0.064)
row 2	Log productive assets	0.117***	0.034
		(0.015)	(0.056)
row 3	Log consumer assets	0.068***	0.045
		(0.025)	(0.081)
row 4	Subjective poverty headcount	–0.027***	0.051**
		(0.005)	(0.023)
row 5	Food insecurity incidence	–0.009	–0.076***
		(0.006)	(0.023)
	Fixed effects		
row 6	Log income	0.174***	0.367***
		(0.027)	(0.064)
row 7	Log productive assets	0.092***	0.046
		(0.020)	(0.055)
row 8	Log consumer assets	0.040	0.056
		(0.032)	(0.076)
row 9	Subjective poverty headcount	–0.013	0.047**
		(0.009)	(0.023)
row 10	Food insecurity incidence	0.013	–0.081***
		(0.008)	(0.023)

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; the random effects estimates also included district fixed effects.
Source: Authors' own, based on APRA panel survey data

unobserved effect or heterogeneity that is allowed to be correlated with commercialisation, and, u_{it} is the random error term. As comparison, we also estimate the random effects variant of equation 4, in which, we also include district fixed effects.

Table 3.15 reports the results from estimating equation 3, with the estimate of β $\hat{\beta}$ being of key interest. The results show that, firstly, without accounting for endogeneity due to omitted household-specific heterogeneity (random effects), welfare significantly (p-value < 0.01) increases with agricultural commercialisation (rows one–three); subjective poverty headcount ratio falls significantly (p-value < 0.01) with increasing commercialisation (row four); and increasing commercialisation has a negative but statistically insignificant effect of food insecurity (row five). This simply means that commercialisation does not have the same effect on all dimensions of welfare, showing that welfare measurement matters in assessing the association between agricultural commercialisation and household welfare.

Secondly, after allowing the time-constant household unobserved effect to be correlated with commercialisation, only two statistically significant effects remain: holding other variables fixed, a one per cent increase in agricultural commercialisation is estimated to increase per capita income and productive asset accumulation by approximately 0.17 and 0.09 per cent respectively (rows six and seven); we find no evidence that increasing agricultural commercialisation is significantly associated with consumer asset accumulation, subjective poverty reduction or improvements in food security. Therefore, commercialisation matters for income poverty reduction but less so for other dimensions of welfare. The reason for this could be found in the seasonal nature of cash from commercial agriculture – such income is modest but not large enough to smoothen consumption over the entire year and thus, does not make a significant impact on reducing food insecurity.

4 SUMMARY AND IMPLICATIONS

We have used household panel data for two time periods (2017 and 2019) covering 659 households (1,318 household-level observations) in two districts of the Western region of Ghana (Ahanta West and Mpohor districts) to: (i) identify which farmers engage with which OPMCs; (ii) analyse the relationship between OPMCs, labour allocation to farm and OFE and returns to labour; (iii) analyse the association between employment and agricultural commercialisation; (iv) test the associations between OPMCs, women's empowerment and household welfare; and (v) analyse the relationship between agricultural commercialisation and household welfare.

Our results show very high levels of commercialisation among the farm households and thus challenges the notion that rural African smallholders focus more on food self-sufficiently as a risk-mitigating strategy in the presence of factor and product market inefficiencies. It should be noted, however, that historically, the study area is a commercial zone for oil palm and its derivatives, and that the communities are home to the production of commercial crops such as oil palm, rubber and cocoa.

Which farmers engage with which OPMCs: we identified that the level of education, gender and scale of production impacts on which farmers sell directly to companies on the one hand, and which sell through agents and on the open market on the other hand. Farmers who are male, better educated, and are operating medium to large-scale farms are more able to access the company channel. The scale of production effect is relevant because farmers need larger fruit quantities to make gains from taking their harvests to the companies – when taking into account transaction costs. It is thus not surprising that the level of crop commercialisation is highest for those who sell directly to industrial companies.

For labour allocation to farm and OFE and returns to labour, our results showed that the majority of economically-active household members are involved in farm work, but that on-farm work does not provide full employment for household members – even in spite of high levels of commercialisation. Mean annual returns to farm labour were slightly above US$2,000 per worker, which is clearly above the international poverty line of US$1.90/day. Yet, approximately one-third of the sample had returns below the poverty threshold, showing significant inequality in the distribution of returns; returns were highest for those who sold to the industrial companies and for those who processed their own fruits.

It is striking that even among the highly-commercialised farm households in our sample, 53 per cent of income comes from non-crop sources: 16 per cent from livestock, 28 per cent from ROFE, and 9 per cent from non-labour income. Income shares differ significantly across the OPMCs, with ROFE being the most significant source of difference. Annual returns to ROFE among participating households were above US$3,000, with returns much higher among artisanal oil palm processing households – by between 30 and 41 per cent relative to the other household groups.

On the association between agricultural commercialisation and employment, firstly, we found that family labour supply and hired labour demand are both increasing with level of commercialisation, but the magnitude effect are not meaningful. Secondly, we show a statistically significant and economically meaningful negative correlation between agricultural commercialisation and ROFE at the household level, suggesting that ROFE is more important for households at lower levels of commercialisation than for those at higher levels. This result also suggests that agricultural commercialisation and OFE tend to be counterparts at low levels of commercialisation but competitors at high levels of commercialisation.

On the associations between OPMCs, women's empowerment and household welfare, our results show that women are most empowered in the dimension of autonomy over own employment decision-making, and least empowered regarding decisions about the utilisation of returns from agricultural commercialisation. This, in spite of the fact that women contribute directly to the household's commercial agriculture enterprise. Women who live in OPMC households with the highest commercialisation level (the *Company* group) are the least empowered, suggesting that women's empowerment falls with increased commercialisation. Second, while household welfare differs significantly by OPC channel, welfare measurement matters in the nature of the relationship. For instance, households selling directly to companies and those processing their own fruits are significantly richer in income and asset dimensions of welfare, and feel better about themselves based on the measure of subjective wellbeing; however, selling directly to companies does not offer better food security but own processing does. This may be the case because processing allows income smoothening over longer periods of the year – since palm oil can be stored but oil palm fruit cannot.

On the relationship between agricultural commercialisation and household welfare, our results show that using panel data, which allows time-constant heterogeneity to be correlated with commercialisation, is important for the conclusions one might reach on the relationship. Once omitted heterogeneity is controlled for, a significantly positive association between commercialisation and welfare holds up only for per capita income and productive asset dimensions of welfare, but not consumer asset accumulation, subjective poverty reduction and improvements in food security.

Based on these findings, the following messages stand out for policy and practice. First, in high agricultural commercialisation zones, focus should be on increasing the inclusivity of remunerative pathways of commercialisation by improving rural transportation infrastructure that allows even small-scale farmers to transact business with industrial companies, or be able to process their own palm fruits. Current policy is too focused on providing handouts, such as purchase input subsidies to farmers. Paying more attention to women in particular could lead to more inclusive welfare outcomes, given that women are less represented in the group that is able to deal directly with the industrial companies. This can be done by providing gender-inclusive starter packs and soft loans tied to equipment acquisition, which would allow women to invest in artisanal processing of palm oil, for instance. The budget statement and economic policy of the Government of Ghana for the 2022 financial year already contains facilities that could be harnessed for such an initiative.

Second, given the evidence that farming does not provide full-time employment for even the highly-commercialised farm households, it is quite clear that development policies and practices aimed at rural transformation need not focus exclusively on agriculture. More attention should also be paid to addressing entry barriers to ROFE.

Third, the fact that women living in households with the highest average agricultural commercialisation rates are also the most disempowered, calls for more educational campaigns that address structural gender norms that disempower women as commercialisation levels rise. Beyond education, however, attention could also be paid to increasing women's bargaining power by facilitating efficiency in rural markets, since those engaged in such markets are more empowered.

Finally, the fact that rising agricultural commercialisation does not necessarily guarantee household food security means that food market shocks could have negative impacts on risk-taking smallholders, such as those devoting most of their resources to non-food cash crop production. Campaigns that advocate for some resources to be allocated to food crops may be needed in such highly-commercialised areas until food markets become more efficient.

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ISBN: 978-1-78118-986-3 DOI: 10.19088/APRA.2022.033

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The APRA Directorate is based at the Institute of Development Studies (IDS), UK (www.ids.ac.uk), with regional hubs at the Centre for African Bio-Entrepreneurship (CABE), Kenya, the Institute for Poverty, Land and Agrarian Studies (PLAAS), South Africa, and the University of Ghana, Legon. It builds on more than a decade of research and policy engagement work by the Future Agricultures Consortium (www.future-agricultures.org) and involves more than 100 researchers and communications professionals in Africa, UK, Sweden and USA.

Funded by

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This report is funded with UK aid from the UK government (Foreign, Commonwealth & Development Office – FCDO, formerly DFID). The opinions are the authors' and do not necessarily reflect the views or policies of IDS or the UK government.

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