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Farmer empowerment in agriculture and its association with smallholder farm incomes in Kenya

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Abstract

Poverty in its various forms is widespread among smallholder farmers, including income poverty, rendering interventions that improve household income relevant. We employ a linear model on cross-sectional data collected from October to December 2015, with the preceding 12 months as the reference period. The data was from 835 smallholder farmers in Kenya to assess the effect of farmer empowerment in agriculture on farm income. This is a departure from numerous previous studies, which considered the intra-household empowerment of women relative to men on the assumption that men are empowered, which may not always be the case – as we show in this study. The results show that farmer empowerment in agriculture increases per capita farm incomes. Unlike male farmers, who benefit from the overall empowerment in agriculture, female farmers do not, possibly due to constraints in complementary drivers of farm income such as access to productive resources. Interestingly, improving the income domain for female farmers increases their farm incomes more than for their male counterparts. We conclude that farmer empowerment in agriculture is a necessary driver of farm incomes, with the production, leadership and income domains being the viable impact pathways. Thus, development interventions should target specific empowerment domains while controlling for sex differences among the target farmers.

Key words: dividends; empowerment; gender; heterogeneity; farm income

1. Introduction

A tenth of the global population lives on less than a dollar a day against the desired 1.95 dollars (World Bank 2016; Mahembe & Odhiambo 2018). Christiaensen *et al*. (2006) report that the majority of poor people living in Sub-Saharan Africa (SSA) earn their livelihood mainly from agriculture. Therefore, improving the agricultural sector is considered one of the most effective strategies to reduce poverty (Bezemer & Headey 2008; Dorosh & Thurlow 2018). Ending poverty is a global priority, as envisaged in the first Sustainable Development Goal [SDG] (United Nations Development Programme [UNDP] 2020), the aspiration of the African Union's 2063 agenda (African Union 2015). At the local level, the Kenya Vision 2030 promotes equity (Government of Kenya 2007).

Gender inequality exacerbates poverty, with the literature showing significant gender disparities in various aspects, including labour markets and decision-making. For instance, Folbre (2014) shows that unpaid work for women can be as high as 69% of their total work, compared to 28% for men.

Moreover, Murray *et al*. (2016) found that women worked for longer hours compared to men in Malawi. According to the UNDP (2020), women on average earn 23% less income than men. Kameri-Mbote (2005) and Shimeles *et al*. (2018) blame the patriarchal system in Africa, which prevents women from owning land, especially through inheritance.

The Food and Agriculture Organization of the United Nations ([FAO] 2011) argue that, if women would have similar access to productive assets as men, their agricultural yields would increase by up to 30%. This would reduce the number of hungry people by up to 150 million globally. Despite the existing gender biases against women, they contribute 47% of the farm labour force in SSA (Shimeles *et al*. 2018).

Gender disparities are the core of the fifth SDG on gender equality, which has prompted research on the topic (Heckert *et al*. 2019; Kassie *et al*. 2020). For example, Malapit and Quisumbing (2015) concluded that women's empowerment was strongly associated with the quality of feeding practices among infants and young children in Ghana, while Murugani and Thamaga-Chitja (2019) found that women's empowerment was associated with improved household food and nutritional security in South Africa. Diiro *et al*. (2018) used maize yields in Kenya to demonstrate that women's empowerment has a positive association with technology adoption and farm productivity. Sraboni *et al*. (2014) demonstrated that women's empowerment was positively associated with household calorie intake and dietary diversity in Bangladesh.

Empowerment is one's capacity to make choices and transform them into desired actions and outcomes (Alsop *et al*. 2006). The pathways to empowerment are referred to as domains, which are areas of influence that allow people to organise and mobilise themselves toward the desired social and political change (Laverack 2006). Alkire *et al*. (2013), Malapit *et al*. (2015) and Garbero and Perge (2017) define five empowerment domains to compute empowerment in agriculture (EIA), namely 1) decisions on agricultural production; 2) access to productive resources; 3) decisions on income use; 4) leadership and 5) time allocation. Empowerment domains are the areas of influence that allow individuals or groups of people to organise and mobilise themselves better toward the desired social and political change (Laverack 2006).

A common approach in the literature in analysing the effect of empowerment on household welfare has been the use of the women's empowerment in agriculture index (WEAI), or its abridged version (A-WEAI) (Alkire *et al*. 2013; Malapit *et al*. 2015; Garbero & Perge 2017). The index has three strengths that make it analytically appealing. First, it measures gender inclusion in agricultural decisions. Second, it can be adapted to measure empowerment in both the agricultural and non-agricultural sectors (Alkire *et al*. 2013). Lastly, the index deliberately excludes variables such as education and wealth, which are often considered as proxies for empowerment, and rather considers decision-making capacity, which is an outcome factors including education and social networks. Excluding such proxy variables makes it possible to analyse the association of empowerment and education, as well as social networks, among other variables.

The literature on gender empowerment in agriculture exhibits several gaps, however. First, the WEAI measures women's empowerment using men in the same households as the benchmark. This leaves out households in which the head is single, separated, divorced or widowed (Osanya *et al*. 2020). The number of women-headed farming households in developing countries can be too significantly high to ignore. In this study, female-headed households comprised 23% of the sample. Moreover, the fact that households are social units that are linked to extended family ties implies that the head being single may not translate into empowerment. Second, closing the empowerment in agriculture gap between men and women is a good starting point, and closing such a gap is a welcome outcome. However, this may not be adequate in cases where the men used as benchmark are not empowered, based on the 80% empowerment threshold suggested by Alkire *et al*. (2013). Lastly, the available studies analyse the association between the WEAI and food and nutrition security (Murugani & Thamaga-Chitja 2019), farm productivity (Diiro *et al*. 2018) and child health (Malapit & Quisumbing 2015), but none analyse the effect of empowerment in agriculture on per capita farm income, which we do in this paper. The SSA has the highest income inequality statistics in the world, in addition to a low per capita income.

Kassie *et al*. (2020) highlight farm income as one of the main pathways through which agriculture influences household welfare. Moreover, income is a desirable outcome, since it is a source of livelihood. Farm income enables households to access other basic needs, such as health care, clothing and shelter. Furthermore, as capital, farm income can influence farm production and commercialisation decisions.

To bridge the foregoing gaps, we compute an empowerment in agriculture (EIA) index for male- and female-headed households. We further also use per capita farm income as the dependent variable in order to add new insights to the existing literature on empowerment in agriculture. Disaggregating the index to the respective empowerment domains and by the sex of the farmers is imperative, because male- and female-headed households may benefit differently even from the same empowerment interventions. Moreover, the magnitude of the effect of various domains on per capita farm income may vary.

We find that involvement in household decisions regarding farm production, income utilisation and leadership are the important domains for enhancing farmer empowerment in agriculture in Kenya, even though the results show a high level of heterogeneity in empowerment dividends between male and female farmers. The rest of this paper is structured as follows. Section 2 describes the study methods. Section 3 presents the estimated results, while Section 4 discusses them. Section 5 concludes and makes recommendations for policy and practice.

2. Study methods

2.1 Data source

We surveyed smallholder farmers in Kisii and Nyamira Counties over the October to December 2015 season using the preceding 12 months as the reference period. The two counties receive rainfall of between 1 500 and 2 100 mm on average throughout the year, making farming the main economic activity. The choice of the two counties was justified by the observation that 42% and 32.7% of the population in Kisii and Nyamira counties respectively is poor, compared to a national average of 36.1% (Kenya National Bureau of Statistics [KNBS] 2018).

The survey utilised a list of registered farmer groups provided by the county department of cooperatives. A two-stage sampling technique was used to select the households to interview. In the first stage, we selected 48 groups (32 from Kisii and 16 from Nyamira) from a list of 94 groups (71 from Kisii and 23 from Nyamira), using the Research Randomizer online tool (https://www.randomizer.org/). Groups sampled in each county were proportional to the total number of groups on the list per county. In the second stage, the simple random technique was used to select 20 farmers from each of the groups selected in stage one. In cases where a group had 20 or fewer members, a group census was conducted. Based on the above stages, the target sample size was 960 farmers, but 835 farmers were surveyed, representing a non-response rate of 13%. This was because some of the target respondents were not available for the interviews.

2.2 Measurement of variables

2.2.1 Dependent variable

Per capita farm income in Kenyan shillings (KES) is the dependent variable in this study. Annual farm income was calculated following Datta and Meerman (1980) and Ogutu and Qaim (2019) as the value of all farm produce (sold and unsold) less the production costs. The valued produce included edible parts, such as grain and leaves, as well as non-edible products like manure from crop and livestock enterprises. The production costs considered included cost of seed, labour, fertiliser and pesticides for crops, and veterinary services, supplements and drugs for livestock. In the case of livestock, only the value of sold or consumed animals within the reference year was included in the computation because it contributed to farm income. The resulting income was divided by the number of members per household to derive per capita farm income.

Datta and Meerman (1980) argue that per capita income is a superior proxy compared to household income because a household with a higher income can be worse off if it has a higher number of members, especially dependants. The per capita farm income approach also has an advantage over gross margin analysis because researchers using gross margin analysis at times omit important products. For instance, in the case of pulses like cowpeas, the grain is often valued while the leaves, which are a valuable vegetable, are omitted. In addition, most studies report gross margin per unit of land for crops and tropical livestock units (TLU) for livestock. This makes it difficult to aggregate farm income in mixed farming systems due to the difference in the denominator, perhaps explaining why many farm analysis studies omit livestock (Kankwamba *et al*. 2012; McCord *et al*. 2015; Makate *et al*. 2016).

Two main constraints affect our approach of computing per capita farm income. The first constraint is missing data on price because smallholder farmers keep most of their produce for home consumption (Ogutu & Qaim 2019). The second constraint is that prices are not entirely random but rather depend on the market type (farm gate prices are often lower) and quantity of produce sold (large volumes benefit from economies of scale). To overcome these two constraints, we computed sample mean prices of the marketed produce and applied it as the valuation factor for all the farm produce, following Ogutu and Qaim (2019).

2.2.2 Independent variables

The independent variable of interest in this study is empowerment in agriculture, which was measured as an index. We used the five empowerment domains described by Alkire *et al*. (2013), namely time, production, leadership, income and resources, to compute the EIA index. Although Alkire *et al*. (2013) suggest the use of 10 indicators, Malapit *et al*. (2015) reduced them to six, resulting in the A-WEAI. This study adopted the latter because it is robust and leads to similar conclusions, yet it is less time and money consuming in the collection of data (Malapit *et al*. 2015). However, we dropped the word ‘women’ from the index, ending up with A-EAI, since we considered male- and female-headed households separately. We also adapted the indicators in the various domains, as follows:

For the time domain, we asked farmers whether they contributed labour to their farm operations on a full-time or a part-time basis. This was a departure from Alkire *et al*. (2013) and Malapit *et al*. (2015), who suggest asking farmers the number of hours they spent on their farm in the previous 24 hours. This departure is logical because some of the farmers had not spent time on their farm in the previous 24 hours for various reasons, such as heavy rain, and attending burials and other social functions, among others. Part-time farming gives farmers some time to seek leisure and complementary income-generating off-farm and non-farm activities.

The production domain was split into two indicators, namely participation in decisions regarding the crops grown and livestock kept. In the African cultural setting, enterprises belong to men or women depending on the enterprise type (Doss 2016). For example, large stock such as cattle belong to men, while poultry is a woman's enterprise. Given that all the farmers belonged to a farmer group by design of the study, we asked whether a farmer was an official in a social group. Often, the perception that a group member is empowered relative to other members is an important criterion in becoming a group official in Kenya, including the position they hold in the group, such as chair, secretary or treasurer – the three most important group positions.

For the resource domain, we asked whether the household head had a title deed. This is important because a title deed is a requirement in transactions involving land, such as sale and collateral to access credit. Furthermore, we asked whether the household head could have accessed credit during the reference period if they needed it. This was a departure from the norm of asking farmers whether they accessed credit, given that it was possible that some creditworthy farmers did not apply for it. Table 1 presents the six indicators used and their respective cut-off threshold for adequacy (whether one meets the criterion or otherwise). Each domain contributed 20 percentage points to the A-EIA index. The weights were adopted from Malapit *et al*. (2015).

Table 1: Domains and indicators of empowerment in agriculture

Domain	Indicators	Adequacy threshold	Weight
Production	Technology use	Household head decided on the crops to grow, either solely or jointly	0.1
		Household head decided on the livestock to keep, either solely or jointly	0.1
Leadership	Group official	Household head was an official in the farmer group	0.2
Income	Control over use of farm income	Household head decided on how to use farm income, either solely or jointly	0.2
Resources	Title deed	Household head had a title deed	0.1
	Access to credit	Household head could have accessed credit if it was needed	0.1
Time	Labour contribution to the farm	Household head contributed farm labour on a part-time basis	0.2

To compute the A-EIA index, the indicators that met the adequacy criteria in Table 1 were coded one, and zero otherwise. To derive the indicator score, we multiplied the indicator code by its weight for all the indicators. Using the technology-use indicator in the production domain as an example to demonstrate how adequacy or lack of it was arrived at, farmers were asked: "who makes decisions on the crops to grow?' The possible responses were (1) head, (2) spouse, (3) both, and (4) others. A respondent was to choose a single option and a response was adequate if the 'head' or the 'both' option was chosen. The third option (both) was considered to contribute zero points to empowerment and therefore to be inadequate. The final empowerment index was computed as an aggregate of the individual indicator scores for each household, as specified in Equation (1).

$$I_i = \sum_1^n X_s, \tag{1}$$

where, for the ith household, I_i is the A-EIA index and ranges from 0 to 1, and $\sum_1^n X_s$ is the sum of all individual indicator scores.

Table 2 presents the rest of the independent variables after testing for multicollinearity. The average annual per capita farm income was 23 384 Kenyan shillings (KES), and male-headed households had 5% higher per capita farm income compared to female-headed households. Male farmers were more empowered and educated relative to the female farmers, by 17% and three years respectively. Moreover, male-headed households had assets valued at 2 735 KES more and their farms were larger relative to the female-headed households (Table 2). Likewise, male-headed households were more diversified and used more labour compared to female-headed households.

Table 2: Descriptive statistics of the variables used in the regression models

Variables	Full sample	Men	Women	Mean difference
Per capita income (KES/year)	23 383.66 (15 948.41)	24 438.78 (16 051.80)	19 752.49 (15 072.32)	1 312.17***
Empowerment in agriculture index (0 – 1)	0.41 (0.23)	0.45 (0.22)	0.28 (0.19)	-0.16***
Accessed government extension (yes = 1)	0.67 (0.47)	0.69 (0.46)	0.63 (0.48)	-0.06
Years of formal education	9.00 (3.74)	9.73 (3.25)	6.53 (4.22)	-3.19***
Had off-farm income (yes = 1)	0.85 (0.36)	0.85 (0.35)	0.83 (0.38)	-0.02
Value of assets (KES)	6 322.50 (4 617.66)	6 938.29 (4 607.11)	4 203.28 (3 993.24)	-2 735.01***
Farm size (acres)	2.08 (1.06)	2.18 (1.06)	1.72 (1.01)	-0.46***
Farm diversity (crop + livestock species)	11.93 (3.55)	12.18 (3.51)	11.05 (3.55)	-1.13***
Labour (man hours/acre/ year)	336.79 (9.47)	326.07 (10.37)	373.66 (22.08)	47.59**
Observations	835	647	188	

Notes: Values are sample means. Standard errors are in parentheses. 1 US$ = 100 KES in 2015. *** Difference is significant at the 1% level; Statistical differences determined using t-test.

2.3 Estimation strategy

Since the dependent variable is continuous, ordinary least squares (OLS) would be an ideal estimator. However, the A-EIA is potentially endogenous to income, possibly due to reverse causality, measurement error or both. As a result, the OLS estimator would result in biased estimates. We used an instrumental variable (IV) in a control function (CF) to test and control for endogeneity (Smith & Blundell 1986; Rivers & Vuong 1988; Wooldridge 2015).

The first stage in applying the CF method involves the estimation of the determinants of the A-EIA index using an appropriate technique and including a valid instrument (Wooldridge 2015). In the first stage, we used a Tobit model, following McDonald and Moffitt (1980), because the A-EIA index is bounded between zero and one. The Tobit model was specified as shown in Equation (2).

$$I_i = \alpha_0 + \alpha_{\boldsymbol{n}} X_{\boldsymbol{n}} + \varepsilon_i, \quad (2)$$

where, for the i^{th} household, I_i is the A-EIA index, $X_{\boldsymbol{n}}$ is the set of determinants of empowerment in agriculture, including the instrument (number of groups of which one is a member), $\alpha_{\boldsymbol{n}}$ is the set of parameter estimates, and ε_i is the error term.

After estimating Equation (2), we generated residuals and included them in Equation (3), which uses OLS to estimate the effect of the A-EIA index on per capita farm income.

$$\gamma_i = \beta_0 + \beta_1 I_i + \beta_n X_i + \varepsilon_i, \quad (3)$$

where, for the i^{th} household, γ_i is the annual per capita farm income, I_i is the A-EIA index, X_i is a set of the other control variables as defined in Table 2, ε_i is the error term, and $\beta_{0\text{-}n}$ are the estimated parameters. The estimate of interest is β_1, and we hypothesised a positive effect.

The statistical significance of the residual estimate in Equation (3) influences the choice of the results to interpret between the OLS and CF estimates. According to Wooldridge (2015), if the estimate of the residual term is statistically significant, we reject the exogeneity hypothesis of the A-EIA index, and the estimates of the CF model, which corrects the endogeneity bias, are interpreted. However, if the residual term estimate is not statistically significant, the results of the OLS model are deemed efficient and are interpreted. The validity of the instrument used in the CF models is judged using the conditions of relevance and exogeneity (Imbens & Wooldridge 2009). An instrument is relevant if it is highly correlated with the independent variable of interest (A-EIA index in this study), and it is exogenous if it is uncorrelated with the dependent variable, such as per capita farm income in this study. The number of groups a farmer belonged to, other than the farmer group sampled for this study, was used as an instrument, considering the important role of groups in empowering farmers.

Since the estimate of the instrument was positive and significant ($p = 0.00$) in the first-stage regression (Equation 2), the relevance condition was met (Table 3). In the second-stage estimation (Equation 3), the estimate of the residual was insignificant, implying that the exogeneity requirement was met. Since only one instrument was used, over-identification did not arise.

Table 3: Relevance test of the instrument, Tobit estimates

Variable	**Marginal effects**	**Standard error**
Number of groups (total groups minus one), instrument	0.056***	0.015
Accessed government extension (yes = 1)	0.019	0.017
Years of formal education	0.002	0.002
Had off-farm income (yes = 1)	0.014	0.021
Value of farm assets (log of Kenyan shillings)	0.055***	0.010
Farm size (acres)	-0.002	0.010
Farm diversity (number)	0.000	0.003
Sex (male = 1)	0.120***	0.023
Labour (man hours/acre/year)	-0.006	0.015
Observations	835	
F statistic (103, 825)	23.27***	
Pseudo R^2	-1.379	

3. Results

3.1 Contribution of various domains to empowerment in agriculture

The results in Figure 1 show significant differences in the mean empowerment scores for men and women. Men were more empowered than women in the production, leadership and income domains. The most limiting domains for men were leadership, income and resources (Figure 1). The trend was the same for women, with the addition of the production domain.

It was surprising that there were no statistically significant differences between men and women in terms of the time and resource domains, as reported by Murray *et al*. (2016) and Shimeles *et al.* (2018). Perhaps, as women take the household headship due to the permanent absence of a spouse, they have more control over their time and resources. It is also possible that women's possession of the family's land title deed improved their creditworthiness, enabling them to use it as collateral to access credit. They also have control over the use of the credit, just like men.

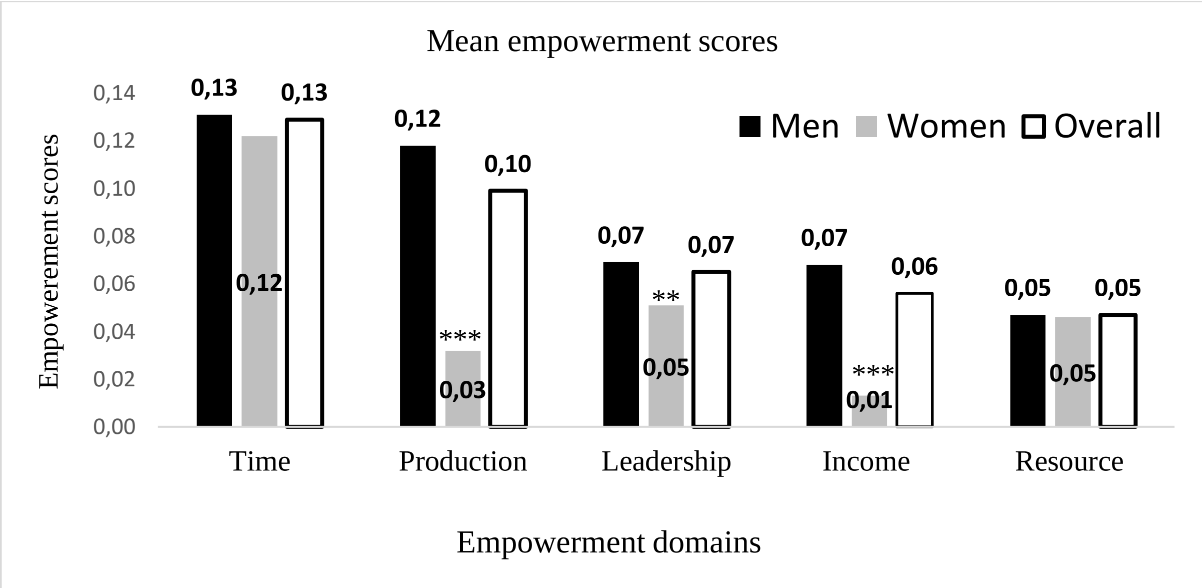

Figure 1: Contribution of various domains to men's and women's empowerment
** and *** – t-test returned significant differences between men and women at the 5% and 1% levels respectively

3.2 Effect of empowerment in agriculture on farm income

The econometric results are presented in Table 4. Since residuals from the Tobit regression in the first stage are insignificant when included in the CF models (Table 4), we failed to reject the null hypothesis that A-EIA is exogenous to per capita farm income and conclude that OLS estimates are efficient in the absence of endogeneity. Therefore, we discuss the OLS estimates for model [1], which uses log-transformed per capita income as the dependent variable to minimise the dispersion of the standard errors.

Interpreting OLS estimates when the dependent variable is log-transformed is not straightforward, and therefore the resulting percentage change in per capita farm income due to a unit change in the independent variables (other than value of assets and labour) was computed using Excel as (= exp (coefficient) – 1) *100). For the value of assets and labour that were also log-transformed, we computed the change in the independent variable due to X percent change as 1.X to the power of the coefficient, minus 1, and multiplied by 100.

All the CF model estimates and OLS estimates for model [3] were used for the robustness check (Table 4). The results for all the models are consistent, and the signs, magnitudes and significance levels of the estimated coefficients are comparable, indicating that the results are robust. Table 4 provides the changes in per capita farm income due to a 100% change in the A-EIA index. However, achieving an average unit change of the A-EIA score is unrealistic. Therefore, we interpret a 10% increase in A-EIA index, which we consider realistic.

Empowerment in agriculture as measured by the A-EIA index had a positive and significant effect on annual per capita farm income (model 1 of Table 4). A 10% increase in the empowerment index increased annual per capita farm income by 11% (model 1 of Table 4). This corresponds to an increase of ≈ 2 572 KES in annual per capita farm income, relative to the sample mean of 23 383.66 KES, representing an empowerment in agriculture dividend that accrued to farming households, even after controlling for other drivers of farm income.

Table 4: Ordinary least squares estimates of the effect of empowerment in agriculture on per capita farm income

	Log per capita income		Per capita income	
Variables	**OLS [1]**	**CF [2]**	**OLS [3]**	**CF [4]**
Empowerment index (0 – 1)	0.744*** (0.18)	0.722*** (0.18)	11 374.249*** (4.64)	11 657.530*** (4.71)
Government extension (Accessed = 1)	-0.040 (0.08)	-0.047 (0.08)	-696.974 (-0.64)	-607.678 (-0.52)
Formal education (years)	0.034*** (0.01)	0.032*** (0.01)	411.302*** (2.80)	437.905*** (2.80)
Has off farm income (yes = 1)	-0.226** (0.11)	-0.230** (0.11)	-2605.663 (-1.73)	-2551.985 (-1.68)
Value of assets (log of KES)	0.181*** (0.06)	0.161** (0.07)	2 059.092*** (2.79)	2 311.228*** (2.58)
Farm size (acres)	0.157*** (0.04)	0.156*** (0.04)	2 567.892*** (4.05)	2 581.518*** (4.01)
Farm diversity (number)	0.026** (0.01)	0.025** (0.01)	169.434 (1.05)	172.702 (1.06)
Labour (log of man hours)	0.150** (0.07)	0.151** (0.07)	1103.793 (1.09)	1090.647 (1.06)
Residue from first stage		0.313 (0.73)		-14713.080 (-1.86)
Constant	6.177*** (0.58)	6.248*** (0.59)	-13 793.260* (-1.73)	-4 055.653* (-0.44)
Observations	835	835	835.00	835.00
Adjusted R^2	14.20%	14.10%	11.80%	11.70%
Wald chi^2	114.51***	111.11***	111.22***	115.37***

Notes: The dependent variable is annual per capita farm income. Standard errors are shown in parentheses for models [1] and [2] and t-statistics for models [3] and [4]. For robustness, standard errors are bootstrapped with 1 000 replications. OLS, ordinary least squares; CF, control function estimators. ***, ** and * show significance at the 1%, 5% and 10% levels respectively. 1 US$ = 100 KES in 2015. KES, Kenyan shillings

Besides empowerment in agriculture, education, the value of assets, farm size, farm diversity and labour had positive and significant effects on annual per capita farm income, whereas off-farm income returned a negative and significant effect. Off-farm income reduces the labour and time available for farm activities, explaining the negative association. This finding suggests that empowerment in agriculture is a necessary, but not sufficient, driver of farm incomes. Therefore, interventions aiming to increase farm incomes should identify complementary drivers of farm income, some of which we identify in this paper.

An extra year in school increased annual per capita farm income by 3.46%. Furthermore, an acre of land increased annual per capita farm income by 17%, while an extra crop and/or livestock species was associated with a 2.63% increase in annual per capita farm income. Moreover, a 10% increase in the value of assets and a 10% increase in the number of man hours invested in the farm increased annual per capita farm income by 1.74% and 1.44% respectively (Table 4). Off-farm income had a negative effect on annual per capita farm income, probably as time resources are channelled away from the farm (Noack & Larsen 2019).

Given the difference in empowerment between men and women in Table 2, we tested the effect of empowerment in agriculture on the farm incomes of male-headed and female-headed households separately (Table 5). Female-headed households did not benefit from the overall empowerment in agriculture, unlike their male-headed counterparts (models 1 and 3 of Table 5). This observation is of particular interest since it is against the expectations, especially considering that many empowerment interventions target women in the hope that they will improve their welfare, including income. The increase in annual per capita farm income due to a unit percentage increase in the women's empowerment index possibly was too small to be detected in our statistical model. However, access to government extension services, formal education and off-farm income were important drivers of the farm incomes of female-headed households.

Table 5: Sex-differentiated OLS estimates of the effect of empowerment in agriculture on per capita farm income

	Men		Women	
	Log per capita income	**Per capita income**	**Log per capita income**	**Per capita income**
Variables	**[1]**	**[2]**	**[3]**	**[4]**
Empowerment index (0 – 1)	0.837*** (0.18)	12 710.900*** (4.87)	0.331 (0.52)	4 506.584 (0.73)
Government extension (accessed = 1)	0.041 (0.09)	889.60 (0.69)	-0.334 (0.20)	-5 564.843** (-2.31)
Formal education (years)	0.032** (0.01)	538.501*** (3.04)	0.049** (0.02)	423.825 (1.53)
Has off farm income (yes = 1)	-0.139 (0.12)	-2562.568 (-1.45)	-0.545** (0.25)	-3 798.050 (-1.27)
Value of assets (log of KES)	0.191*** (0.06)	2 899.046*** (3.60)	0.036 (0.14)	-755.701 (-0.54)
Farm size (acres)	0.174*** (0.04)	2 872.394*** (4.20)	0.080 (0.12)	1 336.849 (1.08)
Farm diversity (number)	0.021 (0.01)	257.549 (1.33)	0.044 (0.03)	111.789 (0.35)
Labour (log of man hours)	0.103 (0.08)	198.468 (0.18)	0.361 (0.21)	3 659.574 (1.74)
Constant	6.241*** (0.59)	-20 264.960** (-2.31)	6.475*** (1.40)	2 696.664 (0.17)
Observations	647	647	188	188
Adjusted R^2	14.78%	13.79%	6.34%	3.11%
Wald chi^2	88.32***	119.66***	26.79***	15.03*

Notes: The dependent variable is per capita farm income per year. Standard errors bootstrapped with 1 000 replications and shown in parentheses for models [1] and [3] and t-statistics for models [2] and [4]. OLS, ordinary least squares estimator. * Significant at the 10% level; ** Significant at the 5% level; *** Significant at the 1% level. 1 US$ = 100 in 2015. KES, Kenyan shillings

3.3 Empowerment pathways

Figure 1 shows that various domains do not contribute equally to empowerment in agriculture, implying that they may also influence farm incomes differently. From a development perspective, it is useful to identify the specific domains (pathways) to target for the greatest empowerment effect on farm income. We analysed the effect of each domain on annual per capita farm income (Table 6). Suitable instruments were not available for the individual domains to control for possible endogeneity, and therefore the estimated relationships in Table 4 are interpreted as associations rather than causal.

The production, income and leadership domains were the important drivers of per capita farm income depending on the sex of the household head (Table 6). These three domains were among the limiting ones, especially for women (Figure 1). The income domain was significant regardless of the sex of the household, perhaps presenting a low-hanging fruit for empowerment interventions. A one percent improvement in the income domain was associated with a 39.48% increase in annual per capita farm income for female-headed households – an impressive 13 times higher compared to the 3% increase in annual per capita farm incomes for male-headed households (models 5 and 10 of Table 6). Improving the production empowerment domain by one percent among male farmers was associated with a 1.5% and 3% increase in annual per capita farm income (columns 7 and 9 of Table 6).

Table 6: Sex-disaggregated OLS estimates of the effect of individual empowerment domains for women on per capita income

	Female-headed households					Male-headed households				
Domain	**[1]**	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**[8]**	**[9]**	**[10]**
Resource	-2.449 (1.32)					0.584 (0.40)				
Leadership		0.244 (1.16)					0.914** (0.39)			
Workload			0.767 (1.07)					0.264 (0.040)		
Production				1.720 (1.24)					1.479*** (0.40)	
Income					3.701*** (1.40)					1.428*** (0.39)
Constant	6.407*** (1.32)	6.501*** (1.34)	6.338*** (1.39)	6.716*** (1.37)	6.749*** (1.35)	6.108*** (0.61)	6.238*** (0.63)	6.057*** (0.59)	6.278*** (0.62)	6.217*** (0.62)
Observations	188	188	188	188	188	647	647	647	647	647
Adjusted R^2	8.40%	6.16%	6.43%	6.97%	7.81%	12.00%	12.44%	11.84%	13.67%	13.41%
Model significance	28.06***	23.74***	24.39***	28.43***	30.50***	66.31***	69.30***	73.52***	80.16***	92.99***

Notes: The dependent variable is per capita income per year in Kenyan shillings. Domains were codded 0 if domain was inadequate and 0.2 if adequate. Robust standard errors are shown in parentheses bootstrapped with 1 000 replications. OLS, ordinary least squares. ** Significant at the 5% level; *** Significant at the 1% level. 1 US$ = 100 KES in 2015. Covariate factors controlled for were access to government extension services, education, off-farm income, value of farm assets, farm size, farm diversity and labour

4. Discussion

The finding that empowerment in agriculture is a significant driver of annual per capita farm incomes underscores the significant contribution it can make to reducing income poverty, among other drivers of farm incomes. The implication is that farmer empowerment interventions are relevant. In turn, income security can enable farming households to secure basic needs, since it is a source of livelihood and thus will improve their general welfare.

Although the effect of empowerment in agriculture on farm income provides useful insights for informing development decisions, it is not obvious which domain to target due to the compound nature of the A-EIA index, especially when resources are insufficient. The latter is almost always the case in developing countries. Disaggregating the empowerment index into specific domains provides a more focused understanding of the various impact pathways for policy and practice. We found that male-headed households differed from female-headed households in various socio-economic characteristics and did not enjoy empowerment dividends to the same extent.

Although male-headed households realised an increase in annual per capita farm income from the overall farmer empowerment index, female-headed households did not. This unusual finding may suggest that women are constrained in other key drivers of farm incomes besides empowerment. For female-headed households, the value of their assets and farm size (two of the most important drivers of farm income) were 39% and 21% lower respectively compared to male-headed households. This underscores the need for comprehensive interventions in the smallholder farm sector. It was not surprising that improving the income empowerment domain was a significant driver of farm income among female-headed households, given that it was the most limiting domain, contributing 1% to their A-EIA index. Moreover, involvement in decisions on income use can enable farmers to invest in high-yielding and cost-saving technologies, hence the positive association with farm income.

Farmers maximise farm profitability (Doss 2016), which can also be used as a proxy for farm income. Farmers' involvement in production decisions can have important bearing on their farm incomes.

This is plausible because farmers are able to adopt and utilise technologies and practices that enhance yield or save costs, or both, which translates into higher profitability. Diiro *et al*. (2018) found a positive and significant effect of the production domain on maize productivity in Kenya. Empowerment in the leadership domain is also an important driver of per capita farm income. Groups are a key component of social networks and have been shown to contribute significantly to other spheres of agriculture, such as improving household food security (Kelemu *et al*. 2017; Mbugua & Nzuma 2020). Group members have access to information about existing and new technologies, and further can receive new technologies from fellow group members, thereby enhancing adoption and thus income (Matuschke & Qaim 2009).

The results show a highly significant effect of formal education on farm income. Education enhances farmers' entrepreneurial skills, enabling them to allocate scarce factors of production optimally (Mwololo *et al*. 2019). This, in turn, increases productivity, and thus farm income. Similar findings were reported by Paltasingh and Goyar (2018) in India, where education increased paddy productivity, while Korgitet (2019) found that higher education contributed to higher productivity among maize farmers in Ethiopia.

Off-farm income had a negative effect on farm income. This is plausible because farmers with off-farm income, such as formal employment, have less time left to invest in their farms. However, Anang *et al*. (2020) found a positive effect of off-farm income on farm income in Ghana, as farmers invest some of the off-farm income in improved technologies and farm managers. The value of farm assets and land is important as capital in explaining the positive effect on farm incomes. Richer farmers may be able to afford improved technologies, such as inputs that are a requisite to catapult farm income by increasing yields. The observation that farm size had the largest effect on annual per capita farm income was expected, since it is a fundamental factor of production. This finding corroborates Noack and Larsen (2019), who found a positive effect of farm size on farm income in Uganda.

Labour returned a positive and significant effect on per capita farm income. For most smallholders in Kenya, farming is manual, making it labour intensive due to the numerous activities involved, such as land preparation, weeding, fertiliser application and spraying, harvesting and loading/off-loading. Family labour is common relative to hired labour because it is affordable, but it is becoming scarcer with declining household size and government policies on free and mandatory access to basic education, which is keeping children of working age in school. Similar results were reported by Achonga *et al*. (2015) and Harkness *et al*. (2021).

5. Conclusions and recommendations

The finding that male farmers were 16 percentage points more empowered than their female counterparts underscores the importance of eliminating gender disparities among smallholder farmers. The numerous gender empowerment policies in Kenya, such as the National Policy on Gender and Development, therefore should be sustained. Given that the mean A-EIA index for male farmers was 35% lower than the 80% frontier suggested by Alkire *et al*. (2013), we conclude that male farmers are not as empowered as is often thought. While eliminating the gender empowerment disparity between male and female farmers may lead to an improvement in empowerment amongst the female farmers relative to the males, it does not lead to the absolute empowerment of either sex, which should be the development outcome of interest. Instead, policies and programmes need to improve farmers' empowerment in absolute terms, using an agreed-upon threshold.

Since the contribution of various domains to farm incomes differs by the sex of the farmer in question, interventions targeting the empowerment of farmers should prioritise the production, income and leadership domains, amidst scarce resources. Involvement in decisions regarding the use of household income is paramount for both sexes, owing to its linkages with other drivers of farm incomes.

Empowered farmers can optimally allocate family income to acquiring assets such as modern technologies for agriculture, leasing land for farming in case the family farm is small, hiring labour in the case of deficit, diversifying to high-value enterprises and educating children who are the farmers of tomorrow. Such linkages can easily result in a compounded effect of the income domain, underlining its importance.

Interventions should enhance the production knowledge of male farmers through the provision of inclusive extension services. In this way, farmers' opinions in agricultural production are more likely to matter. Group formation and management should be part of farmer training for men. Specifically, interventions should build their capacity for leadership, as this would have a positive and significant bearing on farm incomes. Extension services can also complement formal education, as most farmers may be beyond school-going age or may not prioritise formal education, given competing needs such as their children who are attending school.

In spite of the robustness of the results of this study, one limitation remains relevant. The EIA may change even within small geographic areas, thus weakening the external validity of the findings. This calls for similar studies in other geographical contexts.

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