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Supermarket contracts and smallholder farmers: Implications for income and multidimensional poverty

Sylvester O. Ogutu*, Dennis O. Ochieng, and Matin Qaim

Sylvester O. Ogutu

Department of Agricultural Economics and Rural Development, University of Goettingen, Platz der Goettinger Sieben 5, 37073 Goettingen, Germany.

* Corresponding author e-mail: sylvester.ogutu@agr.uni-goettingen.de

Dennis O. Ochieng

Development Strategy and Governance Division (DSGD), Malawi Strategy Support Program, International Food Policy Research Institute, Malawi.

E-mail: D.Ochieng@cgiar.org

Matin Qaim

Department of Agricultural Economics and Rural Development, University of Goettingen, Platz der Goettinger Sieben 5, 37073 Goettingen, Germany.

E-mail: mqaim@uni-goettingen.de

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The modernization of retail food systems has induced a rapid growth of supermarkets with far-reaching implications for household welfare and rural transformation. While previous studies analyzed the impacts of supermarket contracts on various farm household welfare indicators, the effects on multidimensional poverty have rarely been examined. Furthermore, previous studies on the impacts of supermarkets on income poverty used cross-section data that limit causal inference. We assess the impacts of supermarkets on income poverty and multidimensional poverty using panel data from a sample of smallholder farmers in Kenya. We examine average treatment effects, impact dynamics, and heterogeneous treatment effects of supermarkets contracts on poverty using various panel data regression techniques. On average, supermarket participation significantly decreases both income poverty and multidimensional poverty. Supermarket stayers and dropouts have sustained income gains and poverty reductions, but newcomers do not immediately benefit, perhaps due to their huge initial capital investment. Heterogeneous impact analysis shows that income effects are larger for the richest households, but the poorest households also have significantly stronger reductions in poverty deprivations. Overall, supermarkets play an important role in reduction of income poverty, but also contribute to the achievement of broader welfare goals.

Keywords: supermarkets, commercialization, multidimensional poverty, welfare, Kenya

1. Introduction

Global agri-food systems transformation has occasioned the restructuring of food retailing. In many developing countries, this has manifested through the rapid growth of food retail outlets, such as supermarkets. Supermarket growth has been remarkable in many developing countries including sub-Saharan African countries, such as South Africa and Kenya (Planet Retail 2017). The growth has been attributed to rising population, urbanization, increased incomes and rise of middle class, and changes in tastes and preferences for foods, and points of purchase (Tschirley et al. 2015; Qaim 2017). This rapid growth of supermarkets has far-reaching supply and demand-side implications.

From the demand-side (supermarket purchases-side), supermarkets offer convenience and variety of foods to consumers at affordable prices. Previous studies have shown mixed results on the effects of supermarket purchases on nutrition. While some studies associate supermarket purchases with improved household nutrition, such as higher dietary quality and micronutrient intake (Asfaw 2008; Tessier et al. 2008; Rischke et al. 2015; Chege et al. 2015), others associate it with undesirable nutrition effects, such as increased adult body mass index (BMI) and higher odds of being overweight and obese due to consumption of energy dense yet micronutrient poor processed foods (Demmler et al. 2017; Demmler et al. 2018).

From the supply-side (farm production-side), supermarkets procure fresh fruits and vegetables from smallholder farmers through marketing contracts. This has the following benefits. First, supermarket contracting facilitates the modernization of the small farm sector through adoption of productivity-increasing technologies to meet the stringent quality and quantity requirements by supermarkets (Neven et al. 2009; Reardon et al. 2012). Increased productivity contributes significantly to food availability and poverty reduction (Christiaensen et al. 2011). Second, supermarket contracts for labor-intensive crops increase on-farm labor employment, which increases rural employment (Rao & Qaim 2013).

Third, in the broader context of contract farming, supermarket contracts have spill-over effects on off-farm activities that facilitate rural transformation through increased labor movements in and outside agriculture (Otsuka et al. 2016; Bellemare 2018). Finally, supermarket contracts increase farm household income and asset accumulation (Michelson 2013; Anderson et al. 2015). Given that two in every five Africans live in absolute poverty – on less than 1.90 US dollars (USD) a day – and majority of the world's population reside in rural areas with agriculture as their major source of livelihood (IFPRI 2018), supermarket contracts can contribute to the achievement of Sustainable Development Goals 1 and 2 of reducing poverty and hunger.

While previous studies examined the effects of supermarket contracting on various farm household welfare indicators, the implications of supermarkets for multidimensional poverty have rarely been analyzed. Previous studies analyzed effects on income poverty, but used cross-section data that limit causal inference (Rao & Qaim 2011). To address these research gaps, we employ panel data regression models on three rounds of panel data from a sample of small-scale farmers in Kenya to examine the impacts of supermarket participation on income poverty and multidimensional poverty. We also examine the impact dynamics of supermarket contracts in an attempt to understand: whether there are any income gains and poverty-decreasing effects to newcomers (latecomers), supermarket stayers or supermarket drop-outs; whether early participants (stayers) gain more than newcomers; and whether the income gains and the decreasing poverty levels of supermarket suppliers can be sustained when they return to traditional markets. Finally, besides average treatment effects, we estimate heterogeneous treatment effects of supermarket participation on the poverty indicators since some households may gain more than others based on their socioeconomic characteristics. Yet relying on average treatment effects alone may not provide these additional insights, as they assume that treatment effects are homogeneous across households.

The remainder of this paper is structured as follows. The next section describes the farm survey and the main poverty indicators used. Section 3 describes the econometric strategy used to evaluate the average, heterogeneous treatment effects, and impact dynamics of supermarket participation on income and poverty indicators. Section 4 presents the descriptive statistics, estimation results, and discussion. Section 5 concludes.

2. Farm survey and poverty indicators

2.1 Farm survey

This analysis is based on data from a sample of farm households drawn from the central Kenya. Sample households were interviewed in three survey rounds: 2008, 2012, and 2015. In 2008, multistage sampling procedure was employed to sample 402 smallholder vegetable farmers in 31 locations in Kiambu County. This comprised 133 supermarket contracted and 269 non-contracted vegetables and fresh fruit farmers. Besides fruits and vegetables, farm households produce staple and non-staple crops. Kiambu is the closest County to Nairobi, the capital city of Kenya, where many supermarkets have stores that procure fresh fruits and vegetables from smallholder farmers through marketing contracts. In 2012 and 2015 follow-up surveys, a total of 384 and 409 farmers were sampled, respectively with few replacements (see Chege et al. (2015) and Ochieng et al. (2017) for further details on the sampling).

Actual data were collected using semi-structured interviews with farm household heads, their spouses or adult household members well-informed about vegetable production, marketing and other socio-economic activities of the household. The data also included details of household demography, farm and off-farm income activities, crop and livestock production and marketing, and food consumption. In this paper, we rely on a sample with 1184 observations for income and income poverty analysis, where three rounds of panel data are used. But in the case of multidimensional poverty analysis, complete data for constructing multidimensional poverty indicators are only available for two survey rounds (year 2012 and 2015), hence 782 observations are used.

2.2 Income poverty indicators

To evaluate the effect of supermarket participation on income, and income poverty, we first compute household income, as the sum total of net farm and off-farm income per annum. Farm income includes the total value of farm output less all production costs, while off-farm income comprises income from employment, self-employment, remittances, pension, and capital and land rents. From the household income, which is adjusted for inflation using consumer price index, we compute three income poverty indicators following Foster, Greer, & Thorbeke (1984) poverty indicators.

The first indicator is per capita income, which is a continuous variable computed by dividing a household's annual income by the number of household members. We adjust per capita income in Kenyan shillings (Ksh) using purchasing power parity (PPP) exchange rate provided by World Bank (2015)[1]. The second indicator is income poverty dummy, which is assigned a value of one if per capita income of a household is less than 1.90 USD per day, and zero otherwise. The last income poverty indicator is income poverty gap, a share that ranges between zero and

[1] PPP for Kenya in 2015, 1 US dollar = Ksh 43.89

one. It measures the extent to which per capita income falls below the poverty line, expressed as ratio of poverty line. We compute poverty gap as follows:

$$y_{it} = \frac{s - p_{it}}{s} \quad (1)$$

where s is the poverty line and p_{it} is per capita income of household i at time t. Zero values are automatically assigned to households whose per capita incomes exceed the poverty line.

2.3 Multidimensional poverty indicators

Income poverty indicators comprise the indirect method of poverty measurement, which examines a household's ability to meet its basic needs by determining individuals that fall below the poverty line (1.90 USD a day). In contrast, multidimensional poverty indicators are a class of poverty indicators which measure directly whether or not a household's set of various basic needs are actually satisfied. Multidimensional poverty index measures acute poverty. It provides details of the share of households in a given population with manifold deprivations and the depth or intensity of their deprivations compared to the basic internationally accepted standards of well-being. Multidimensional poverty can be measured through different approaches, such as the ordinal approach, factor analysis, cluster analysis, and weighting procedures. Each of these approaches has its own advantages and disadvantages (see Ogutu *et al.* 2019; Alkaire & Santos 2014; Kakwani & Silber 2008 for further details).

Following Alkaire & Santos (2014), we compute multidimensional poverty indicators using a weighting procedure. The procedure used is more suitable for quantitative impact assessment as it yields an MPI index that: is reliable with cardinal or ordinal indicators; satisfies the dimensional monotonicity condition, which implies that if a poor person becomes deprived in an additional indicator, MPI automatically increases; can be decomposed by population subgroups to allow poverty comparisons across subgroups; can be decomposed by indicator to allow computation of share contributions of indicators used; and estimates poverty intensity, making it possible for poverty comparisons in different contexts.

Table 1. Dimensions (*italicized*) and indicators of the multidimensional poverty index

Dimension and Indicator	Deprivation cutoffs	Relative Weight
Education		
Years of schooling	Household's average education is less than 8 years	1/6
Child schooling	Household has a school-aged child not attending school up to class 8	1/6
Health		
Nutrition 1	Household consumes less than 625 µg of retinol equivalents/day/AE	1/6
Nutrition 2	Household consumes less than 2400 kcal/day/AE	1/6
Living standard		
Electricity	Household has no access to electricity	1/18
Sanitation	Household's toilet facility is not improved	1/18
Drinking water	Household does not have access to safe drinking water	1/18
Floor material	Household has dirt, sand, or dung floor	1/18
Cooking fuel	Household cooks with dung, wood, or charcoal	1/18
Asset ownership	Household does not own more than one radio, TV, telephone, bike, motorbike, or refrigerator and does not own a car or truck	1/18

Source: Adapted from Alkaire & Santos (2014). Notes: The indicators are similar to those in Alkaire & Santos (2014), except for small modifications in three indicators (years of schooling, nutrition 1, nutrition 2) as explained in the text.

Table 1 provides details of the three core dimensions of multidimensional poverty, namely education, health, and living standard, and the ten indicators that we use to compute the MPI at household level. All the indicators are identical to those used by Alkaire & Santos (2014), except for three adjustments. Notably, instead of using "all household members have less than

5 years of schooling" as an indicator for years of schooling, we use "average household education is less than 8 years", since less than 1% of the sample satisfies the unmodified threshold. Further, instead of using "any household member is malnourished" and "a child has died in the family" as indicators for health dimension, we use household calorie and vitamin A consumption as alternatives due to data limitation. Modifications in the MPI indicators are acceptable in the literature (Ogutu et al. 2019; OPHI 2017; Alkaire & Santos 2014).

We compute MPI for each household level as follows. First, we assign corresponding relative weights (Table 1) to each of the ten indicators if a household satisfies the set deprivation cut-off for each indicator, and zero otherwise. We then sum-up the relative weights across the ten indicators for each household. This produces the "total household deprivation score", which is a share ranging between zero and one. From the total household deprivation score, we compute "multidimensional poverty dummy", which is equal to one if the total deprivation score of a household is at least 0.33 – a standard threshold for determining if a household is multidimensionally poor or not – and zero otherwise. Finally, we compute "multidimensional poverty intensity" which is equal to a household's total deprivation score if multidimensional poverty dummy is equal to one, and zero otherwise. Hence, the MPI intensity is a fractional response or censored variable, with zero values and values that range from 0.33 to 1.

3. Econometric strategy

3.1 Average treatment effects

We aim to evaluate the impact of supermarket participation on income poverty and multidimensional poverty. Since we rely on observational data, this is not straight forward as farm households may self-select into supermarket supply chains based on their observable and unobservable characteristics, making identification of causal effects difficult. However, we try to the extent possible to reduce self-selection problems and disentangle the effects of supermarkets on income and multidimensional poverty. Our econometric strategy involves estimating the following panel data regression model:

$$y_{it} = \alpha + \beta_1 SM_{it} + \delta' \boldsymbol{X}_{it} + c_i + v_{it}\,, \qquad (2)$$

where y_{it} is the poverty indicator for household i in year t, SM is the treatment dummy, which takes a value of one if a household supplies a supermarket and zero otherwise, $\boldsymbol{X}_{it}$ is a vector of time-varying and time-constant control variables, c_i captures the unobserved individual-specific effects or unobserved heterogeneity and v_{it} are the usual idiosyncratic shocks. β_1 is the parameter of interest, which represents the average treatment effects. We estimate separate regression models for all the poverty indicators (e.g. household income and per capita income, income poverty and multidimensional poverty indicators) discussed in the previous section. We expect supermarkets to have an income-increasing effect or positive coefficient on household income and per capita income, but have poverty-reducing effect or negative coefficient on the income poverty and multidimensional poverty indicators.

We estimate equation (2) using random effects (RE) and fixed effects (FE) panel data estimators. RE estimators assume that unobserved individual-specific effects are uncorrelated with observed explanatory variables, while FE estimators assume that an arbitrary correlation exists. Consequently, FE estimators are intuitively more appealing in the literature, as they account for unobserved time-invariant heterogeneity, which RE estimators do not account for (Wooldridge 2010; Cameron & Trivedi 2005). However, we estimate RE models in addition to FE models to account for the effects of time-constant explanatory variables, and for comparison of results.

While FE estimators are suitable for estimating linear models in the presence of unobserved heterogeneity that is correlated with the regressors, they yield inconsistent estimates in non-linear models (Cameron & Trivedi 2005). Since our outcome variables include a mix of continuous, dummy and fractional variables, we only apply linear RE and FE estimators on continuous outcomes – household income and per capita income – to avoid inconsistent estimates. To account for omitted variables in non-linear models, we use correlated random effects (CRE) estimators proposed by Mundlak (1978) and Chamberlain (1984). The CRE framework accounts for omitted variables by allowing the unobservable individual-specific effects (unobserved time-invariant heterogeneity) c_i to be determined by time-averages of observed explanatory variables. This relationship is modeled as follows:

$$c_i = \alpha + \gamma \overline{\boldsymbol{X}}_i + \omega_i \,, \tag{3}$$

where α is a constant, $\overline{\boldsymbol{X}}_i$ is a vector of the time-averaged explanatory variables $(\boldsymbol{X}_{it})$ across time, γ is a vector of parameter estimates of the time-averaged variables, ω_{it} is the error term. Hence, the estimated CRE model can be expressed as follows:

$$y_{it} = \alpha + \beta_1 SM_{it} + \delta' \boldsymbol{X}_{it} + \gamma \overline{\boldsymbol{X}}_i + \omega_i + \upsilon_{it} \,, \tag{4}$$

where β_1 is the parameter of interest. Equation (4) includes the explanatory variables for each household, time-averages of time-varying variables, year dummies, and time-constant observed variables (Wooldridge 2010). In the case of binary outcome indicators (income poverty dummy and multidimensional poverty dummy), we estimate CRE probit models and compare them with RE probit models, while for fractional outcome variables or censored indicators (income poverty gap and multidimensional poverty intensity) we use CRE Tobit and compare them with RE Tobit models.

3.2 Impact dynamics

As mentioned, we also examine the impact dynamics of supermarket contracts to determine whether there are income gains and poverty-decreasing effects to supermarket newcomers (latecomers), supermarket stayers or supermarket drop-outs; whether early participants gain more or less than newcomers; and whether the income gains and the decreasing poverty levels of supermarket suppliers can be sustained when they return to traditional markets. For this analysis, we rely on two rounds of balanced panel data, since multidimensional poverty data is available for two rounds, and since using two rounds allows for computational ease of the treatment variables capturing the supermarket participation dynamics. Fixed effects estimators would be unsuitable for this analysis as the time-constant treatment variables would be dropped due to collinearity, thus we rely on CRE models discussed in equation (4).

3.3 Heterogeneous treatment effects

While the models specified in equations (2) and (4) are appropriate for estimating the average treatment effects of supermarket participation, they are unsuitable for estimating impact heterogeneity. As mentioned, estimating heterogeneous treatment effects is important since supermarket participating households may have dissimilar benefits from supermarket sales, depending on their socioeconomic characteristics. Hence, estimating heterogeneous effects may provide important additional insights on which households benefit more or less than others for policy targeting, if treatment effects are not homogeneous.

We employ quantile regression for panel data (QRPD) to estimate the heterogeneous treatment effects of supermarkets. The QRPD model allows us to account for unobserved heterogeneity, and heterogeneous effects of covariates. The model also yields consistent estimates in the presence of small sample size (Powell 2016). Quantile regressions in general allow the study of the effects of explanatory variables over the distribution of dependent variables, rather than only examining the average effect of explanatory variables (Koenker & Hallock 2001). We estimate a quantile regression model of the poverty indicators y_{it}, conditional on a vector of explanatory variables $\boldsymbol{X}_{it}$ as follows (Powell 2016; Koenker 2004):

$$Qy_{it}(\tau|\boldsymbol{X}_{it}) = \boldsymbol{X}'_{it}\beta(\tau) + \varepsilon_{it\tau}, \tag{5}$$

where $Qy_{it}(\tau|\boldsymbol{X}_{it})$ is the conditional quantile of y_{it} at quantile τ, with 0< $\tau < 1$. $\beta(\tau)$ is the vector of coefficients to be estimated. The coefficients of interest are estimated using the generalized method of moments (GMM) with $\hat{\beta}(\tau)$ expressed as:

$$\hat{\beta}(\tau) = arg \min_{b \in B} \hat{g}\,(\boldsymbol{b})'\hat{A}\hat{g}(\boldsymbol{b}), \tag{6}$$

where **b** is equivalent to a vector of parameters of the explanatory variables ($\boldsymbol{X}_{it}$) , B is a set of all estimated parameters, $\hat{g}(\boldsymbol{b})$ are the sample moments, and $\hat{A}$ is a weighting matrix for the sample moments. We estimate $\hat{\beta}(\tau)$ at five different quantiles (τ = 0.10, 0.25, 0.50, 0.75, 0.90) for three of the previously defined poverty indicators. The three indicators are household income, per capita income and total household deprivation scores, selected due to their suitability for use with quantile regressions. Excluded indicators are either binary or censored, which means that obtaining estimates at all five different quantiles of the indicators is impossible due to many zeros.

4. Results and discussion

4.1 Descriptive statistics

This subsection presents the descriptive comparisons between supermarket (SM) and traditional market channel (TC) suppliers in terms of farm and household characteristics, including incomes, income poverty and multidimensional poverty indicators.

Table 2. Summary statistics by supermarket participation.

Variables	Full sample	SM	TC	Mean difference
Age of household head (years)	51.742	49.600	52.436	-2.836***
	(14.068)	(12.852)	(14.379)	
Male household head (dummy)	0.880	0.938	0.861	0.077***
	(0.325)	(0.242)	(0.346)	
Post-primary education of head (dummy)	0.716	0.807	0.687	0.120***
	(0.451)	(0.395)	(0.464)	
Household size (number)	4.039	4.159	4.000	0.159
	(1.788)	(1.887)	(1.754)	
Farm size (acres)	1.982	2.617	1.776	0.842***
	(3.106)	(4.688)	(2.344)	
Off-farm income (dummy)	0.653	0.728	0.629	0.099***
	(0.476)	(0.446)	(0.483)	
Group membership (dummy)	0.722	0.679	0.736	-0.057*
	(0.448)	(0.468)	(0.441)	
Public transport available (dummy)	0.734	0.814	0.708	0.106***
	(0.442)	(0.390)	(0.455)	
Observations	1184	290	894	

Source: Authors' computation. Notes: SM, Supermarket supplying households, TC, Traditional channel supplying households. Standard deviations are shown in parentheses. * Significant at the 10% level; *** significant at the 1% level.

Table 2 presents summary statistics of the main explanatory variables, by full sample and supermarket participation. Sample households are typically smallholder farmers, with average farm sizes of about 2 acres. Some significant differences in the socio-economic characteristics can be observed. For instance, SM suppliers are more likely to be male, better educated, with relatively larger farms and more off-farm income compared to TC farmers. Furthermore, SM suppliers are less likely to be organized in marketing groups. This is plausible since SM suppliers with relatively less resource-constraints and sizeable quantities to deliver usually prefer individual to collective marketing because of the poor-quality enforcement mechanism that results in rejections of consignments with losses distributed among members regardless of quality delivered (Chege *et al.* 2015; Ochieng *et al*. 2017).

Table 3 presents the descriptive statistics of poverty indicators by full sample and supermarket participation. In panel A, sample households have average household income and per capita income of Ksh 309,000 and 91,000, respectively. About one-third of the households are income poor – live on less than 1.90 USD per day –, while the income poverty gap is 0.21. Overall, SM suppliers are significantly better-off in terms of household income and per capita income, with their incomes being more than double those of TC suppliers. SM suppliers are also less likely to be income poor, and have a significantly lower poverty gap than TC suppliers.

As regards multidimensional poverty indicators, the average household deprivation score is 0.28 (Panel B of Table 3), implying that the average household is deprived in 28% of the total possible deprivations. About 39% of the households are multidimensionally poor, implying that their total deprivation scores are less than 0.33, which is the multidimensional poverty threshold. Multidimensional poverty intensity (MPI intensity) is 0.17 on average. Again, SM suppliers are significantly better-off in terms all three multidimensional poverty indicators.

Table 3. Poverty indicators by supermarket participation

Variables	Full sample	SM	TC	Mean difference
Panel A: Income poverty indicators				
Household income (1000 Ksh)	309.177	536.379	235.476	-300.9***
	(441.010)	(679.957)	(292.953)	
Per capita income (1000 Ksh)	90.817	156.169	69.618	-86.55***
	(145.268)	(221.817)	(100.973)	
Income poverty (dummy)	0.330	0.197	0.374	0.177***
	(0.470)	(0.398)	(0.484)	
Income poverty gap (0–1)	0.207	0.108	0.239	0.132***
	(0.401)	(0.305)	(0.422)	
Observations	1184	290	894	
Panel B: Multidimensional poverty indicators				
Total household deprivation score (0–1)	0.276	0.223	0.289	-0.066***
	(0.157)	(0.135)	(0.159)	
Multidimensional poverty (dummy)	0.389	0.236	0.427	-0.192***
	(0.488)	(0.426)	(0.495)	
Multidimensional poverty intensity (0–1)	0.168	0.098	0.186	-0.088***
	(0.223)	(0.181)	(0.229)	
Observations	782	157	625	

Source: Authors' computation. Notes: SM, Supermarket supplying households, TC, Traditional channel supplying households; Ksh, Kenyan shillings. Standard deviations are shown in parentheses. *** Significant at the 1% level.

Table 4 shows comparisons between SM and TC suppliers in terms of the (ranked) share of households deprived in multidimensional poverty index (MPI) indicators. The results show that the farm households are least deprived in child schooling – perhaps due to free primary schooling policy in Kenya –, but are most deprived in sanitation. More than one-half of the households are deprived in terms of access to safe drinking water, cooking fuel, and sanitation. The results also show that supermarket supplying households are better-off in terms of access to electricity, assets ownership, floor material, years of schooling, safe drinking water, cooking fuel and sanitation. The last column of Table (4) shows significant associations between household income and the indicators, suggesting that income is one of the possible pathways to reduce deprivations in the MPI indicators.

While the descriptive results are consistent with our hypotheses, they should not be interpreted as impact as they do not account for pre-existing heterogeneity between SM and TC suppliers. To disentangle the impacts of supplying supermarkets, we control for the any such differences using econometric models earlier discussed in the following subsections.

Table 4. Share of households deprived in terms of MPI indicators (indicators ranked by share of deprived households)

Indicator	Deprivation cutoffs	Full sample	SM households	TC households	Mean difference	Correlation with household income
Child schooling	Household has a school-aged child not attending school up to class 8 (dummy)	0.027	0.051	0.021	0.030**	0.021
		(0.162)	(0.221)	(0.143)		
Nutrition 1	Household consumes less than 625 μg of retinol equivalents/day/AE (dummy)	0.125	0.115	0.128	0.013	-0.029
		(0.331)	(0.320)	(0.334)		
Electricity	Household has no access to electricity (dummy)	0.129	0.057	0.147	-0.090***	-0.133***
		(0.336)	(0.233)	(0.355)		
Asset ownership	Household does not own more than one of specified assets (dummy)	0.130	0.045	0.152	-0.107***	-0.160***
		(0.337)	(0.207)	(0.359)		
Floor material	Household has dirt, sand, or dung floor (dummy)	0.151	0.064	0.173	-0.109***	-0.133***
		(0.358)	(0.245)	(0.378)		
Nutrition 2	Household consumes less than 2400 kcal/day/AE (dummy)	0.192	0.172	0.197	-0.025	-0.017
		(0.394)	(0.379)	(0.398)		
Years of schooling	Household's average education is less than 8 years (dummy)	0.451	0.357	0.475	-0.118***	-0.130***
		(0.498)	(0.481)	(0.500)		
Drinking water	Household does not have access to safe drinking water (dummy)	0.523	0.446	0.542	-0.096**	-0.101***
		(0.500)	(0.499)	(0.499)		
Cooking fuel	Household cooks with dung, wood, or charcoal (dummy)	0.753	0.541	0.806	-0.265***	-0.302***
		(0.431)	(0.500)	(0.395)		
Sanitation	Household's toilet facility is not improved (dummy)	0.895	0.777	0.925	-0.148***	-0.230***
		(0.307)	(0.418)	(0.264)		
	Observations [a]	782	157	625		

Source: Authors' computation. Notes: MPI, Multidimensional poverty index; SM, Supermarket supplying households, TC, Traditional channel supplying households, AE, adult male equivalent. Standard deviations are shown in parentheses. [a] Complete information for MPI computation only available for year 2012 and 2015, hence only two rounds of panel data are used in MPI analysis. * Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

4.2 Average treatment effects

4.2.1 Supermarket impacts on income and income poverty

Table 5 presents the estimation results of the models in equation (2), estimated with random effects (RE) and fixed effects (FE) estimators. Hausman test for equality of RE and FE estimators was rejected in per capita income models (but not household income) suggesting that FE estimator was more appropriate. The FE estimator accounts for unobserved time-invariant heterogeneity. Hence, the discussions of the findings are based on the FE estimation results.

Table 5. Effect of supermarket participation on household income and per capita income

	Household income (1000 Ksh)			Per capita income (1000 Ksh)	
Variables	(1) RE	(2)FE		(3)RE	(4)FE
SM participation (dummy)	223.775***	147.300***		64.800***	39.577**
	(43.779)	(52.075)		(13.296)	(18.590)
Age of household head (years)	-1.653*	-0.720		-0.599*	0.109
	(1.002)	(1.644)		(0.335)	(0.570)
Male household head (dummy)	57.330**	-22.215		7.275	-31.853
	(27.390)	(40.106)		(11.087)	(20.715)
Post-primary education of head (dummy)	54.241**	47.668		20.625***	20.408
	(24.187)	(43.044)		(7.442)	(19.243)
Household size (number)	15.069**	11.514		-21.583***	-25.653***
	(7.476)	(9.825)		(2.763)	(3.677)
Farm size (acres)	79.071***	43.832**		26.356***	7.396
	(10.589)	(17.759)		(2.880)	(6.172)
Farm size squared (acres)	-1.512***	-0.729**		-0.458***	-0.082
	(0.229)	(0.317)		(0.078)	(0.119)
Off-farm income (dummy)	101.711***	78.300**		34.062***	31.629***
	(22.712)	(31.540)		(7.202)	(9.446)
Group membership (dummy)	-18.383	-13.777		-8.682	-6.350
	(29.572)	(37.142)		(9.967)	(12.289)
Public transport available (dummy)	-1.484	-21.845		5.322	0.945
	(22.087)	(25.275)		(6.901)	(7.799)
Year 2012 (dummy)[a]	42.460	39.557		4.142	1.169
	(28.445)	(31.290)		(9.849)	(10.495)
Year 2015 (dummy)[a]	62.272**	50.021*		13.110	1.783
	(30.334)	(28.307)		(10.866)	(11.400)
Region dummies	Yes	No		Yes	No
Constant	-110.161	114.630		77.361***	160.927***
	(80.578)	(98.712)		(26.455)	(38.987)
Wald χ^2	140.93***			162.35***	
F-value		3.14***			5.49***
Hausman test χ^2		14.19			50.21***
Observations	1184	1184		1184	1184

Source: Authors' computation. Notes: Coefficient estimates are shown with robust standard errors in parentheses. SM, supermarket; RE, random effects estimator; FE, fixed effects estimator. [a] Year 2008 is the base category.* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

After accounting for confounding factors to the extent possible, Table 5 column (2) shows that supermarket participation significantly increases household income by Ksh 147,000. These are sizeable gains which translate to 63% income growth over-and-above the average income of TC suppliers. These results are consistent with those of earlier research which showed that supplying supermarkets increases household income (Rao & Qaim 2011; Chege *et al.* 2015; Andersson *et al.* 2015). Column (4) shows that supermarket participation significantly increases per capita income by Ksh 40,000. These are substantial gains, equivalent to 57% growth in per capita income over-and-above the average per capita income of TC suppliers. The impact estimates are also significant with RE estimators.

In terms of the control variables, education, farm size and off-farm income significantly increase household income and per capita income as expected. The findings are in line with those of previous studies that found that better educated farmers are most likely to engage in contract farming in general and supermarket contracting in particular. Farmers with larger farms are more likely to allocate more land to vegetable production and invest in irrigation technologies to ensure year-round supply of vegetables (Anderson *et al.* 2015). Off-farm income plays a significant role in the timely acquisition of material inputs such as fertilizers to increase productivity especially among resource-constrained farmers (Mathenge *et al.* 2015)

The significant effects of supermarkets on household income and per capita income are a first indication that supermarkets can reduce income poverty through income growth. In Table 6, we analyze the impact of supermarkets on income poverty more explicitly.

Table 6. Effect of supermarket participation on income poverty and poverty gap

	Income poverty (dummy)			Income poverty gap (0-1)	
Variables	(1) RE Probit	(2) CRE Probit		(3) RE Tobit	(4) CRE Tobit
SM participation (dummy)	-0.126***	-0.118***		-0.109***	-0.100***
	(0.036)	(0.036)		(0.029)	(0.029)
Age of household head (years)	0.003***	0.006*		0.003***	0.004
	(0.001)	(0.003)		(0.001)	(0.003)
Male household head (dummy)	-0.040**	0.100		-0.036	0.079
	(0.044)	(0.081)		(0.034)	(0.061)
Post-primary education of head (dummy)	-0.042	0.086		-0.018	0.070
	(0.034)	(0.072)		(0.026)	(0.055)
Household size (number)	-0.047***	0.053		-0.029***	-0.034
	(0.008)	(0.012)		(0.007)	(0.009)
Farm size (acres)	-0.068***	-0.046**		-0.039***	-0.021
	(0.010)	(0.019)		(0.008)	(0.014)
Farm size squared (acres)	0.001***	0.000		0.001	0.000
	(0.000)	(0.000)		(0.001)	(0.000)
Off-farm income (dummy)	-0.145***	-0.128***		-0.109***	-0.088***
	(0.029)	(0.037)		(0.023)	(0.029)
Group membership (dummy)	-0.055	-0.013		-0.053**	-0.029
	(0.034)	(0.043)		(0.025)	(0.032)
Public transport available (dummy)	0.017	-0.063		-0.009	0.021
	(0.025)	(0.041)		(0.024)	(0.032)
Year 2012 (dummy) [a]	0.103***	-0.088**		0.098***	0.081***
	(0.036)	(0.041)		(0.028)	(0.031)
Year 2015 (dummy) [a]	0.008	-0.020		0.026	0.002
	(0.037)	(0.044)		(0.028)	(0.034)
Region dummies	Yes	Yes		Yes	Yes
Wald χ^2	121.92***	126.97***		111.89***	127.58***
Log likelihood	-662.882	-653.019		-864.982	-853.879
Observations	1184	1184		1184	1184

Source: Authors' computation. Notes: Average partial effects are shown with standard errors in parentheses. SM, supermarket; RE, random effects; CRE, correlated random effects. CRE models include explanatory variables (time constant and time varying variables, and year dummies) and additional averages of time-varying variables (not shown for brevity), [a] Year 2008 is the base category.* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 6 presents the results of the effects of supermarkets on non-linear income poverty variables. RE estimators for non-linear models (RE probit and Tobit estimators) and correlated random effects (CRE) probit and Tobit estimators are used for the analysis. We also rely on the CRE estimators as they account for unobserved time-invariant heterogeneity. All the coefficients shown are average partial (marginal) effects. Table 6 column (2) shows that supermarket participation significantly reduces the probability of income poverty – living below 1.90 USD a day – by 12 percentage points. This is a sizeable effect, which compared to the 37% average income poverty prevalence rate among TC suppliers, translates to a 32% reduction in income poverty prevalence. Column (4) shows a 10 percentage point reduction in poverty gap, on average. Relative to the 24% average poverty gap among TC suppliers, this is a significant effect which translates to a 42% decrease in the average poverty gap.

The econometric results have so far shown that supermarket participation significantly reduces income poverty (poverty prevalence and poverty gap) among farm households. Income poverty falls immediately a household experiences an income increase large enough to lift it of poverty, but whether or not the income gain is actually used to reduce basic needs deprivation is a question that income poverty indicators alone cannot answer (Ogutu & Qaim 2019). Hence, to answer this question, we also examine the impact of supermarkets on multidimensional poverty.

4.2.2 Supermarket impacts on multidimensional poverty

Table 7. Effect of supermarket participation on multidimensional poverty

	MPI dummy			MPI intensity	
Variables	(1) RE Probit	(2) CRE Probit		(3) RE Tobit	(4)CRE Tobit
SM participation (dummy)	-0.200***	-0.180***		-0.078***	-0.072***
	(0.057)	(0.055)		(0.023)	(0.023)
Age of household head (years)	0.000	0.003		0.000	0.002
	(0.002)	(0.007)		(0.001)	(0.003)
Male household head (dummy)	-0.008	0.096		-0.000	0.039
	(0.068)	(0.131)		(0.026)	(0.049)
Post-primary education (dummy) [a]	-0.231***	0.217		-0.095***	0.083
	(0.053)	(0.163)		(0.022)	(0.066)
Household size (number)	0.046***	0.056***		0.020***	0.025***
	(0.012)	(0.018)		(0.005)	(0.007)
Farm size (acres)	-0.077***	-0.062**		-0.032***	-0.024**
	(0.017)	(0.026)		(0.007)	(0.010)
Farm size squared (acres)	0.003**	0.002**		0.001**	0.001**
	(0.001)	(0.001)		(0.000)	(0.001)
Off-farm income (dummy)	0.045	0.092		0.014	0.031
	(0.046)	(0.053)		(0.016)	(0.021)
Group membership (dummy)	-0.101*	-0.090		-0.038*	-0.033
	(0.057)	(0.069)		(0.022)	(0.026)
Public transport available (dummy)	-0.020	-0.022		-0.016	0.002
	(0.045)	(0.057)		(0.017)	(0.022)
Year 2015 (dummy) [b]	-0.099***	-0.120***		-0.045***	-0.055***
	(0.286)	(0.043)		(0.014)	(0.017)
Region dummies	Yes	Yes		Yes	Yes
Wald χ^2	61.46***	73.00***		90.99***	114.18***
Log likelihood	-455.287	-433.166		-430.851	-418.420
Observations	782	782		782	782

Source: Authors' computation. Notes: Average partial effects are shown with standard errors in parentheses. SM, supermarket; RE, random effects; CRE, correlated random effects. CRE models include explanatory variables (time constant and time varying variables, and year dummies) and additional averages of time-varying variables (not shown for brevity), [b] Year 2012 is the base category.* Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 7 presents the results of the effects of supermarkets on multidimensional poverty indicators, estimated using RE estimators for non-linear models and correlated random effects (CRE). As mentioned, we only discuss the CRE estimation results. Column (2) shows that supermarket participation significantly reduces the prevalence of multidimensional poverty (MPI dummy) – likelihood of deprivation in multiple indicators of education, health, and living standards – by 18 percentage points. Compared to the 42.7% average multidimensional poverty prevalence among TC suppliers, this is equivalent to a 42% reduction in multidimensional poverty prevalence. Column (4) shows a 7.2 percentage point reduction in MPI intensity, on average. Relative to the 18.6% average MPI intensity among TC suppliers, this effect translates to a 39% reduction in the average MPI intensity.

Up till now the results have shown that supermarket participation significantly reduces poverty irrespective of whether income or multidimensional poverty indicators are used. However, we observe that the magnitude of the decrease in poverty prevalence and intensity differs across the two indicators. The reductions are much stronger with multidimensional poverty prevalence (-0.180) than with income poverty prevalence (-0.118), but are much larger for income poverty gap (-0.100) than for MPI intensity (-0.072). Larger effects are seemingly found with the indicator that has a higher prevalence rate or intensity (see Table 3).

4.2.3 Supermarket impact dynamics

Table 8 presents the results of the average effects of consistently supplying supermarkets, late entry, and dropping out of supermarket channels, on income and multidimensional poverty indicators. Relative to TC suppliers, SM stayers significantly gain from supermarket contracts in terms of both income growth and reductions income poverty and multidimensional poverty. However, newcomers (latecomers) do not immediately benefit from supermarket contracts (except in the case of MPI intensity), possibly due to huge initial capital investment (e.g. means of transport, irrigation technology, and material inputs) required to enter into the contracts and to maintain consistent supply. Interestingly, households returning to traditional channels enjoy sustained income growth and poverty reduction. Although the magnitudes of impacts for dropouts diminish in the case of income and income poverty, they do not reduce in the case of multidimensional poverty. This is possible since income poverty indicators are more volatile compared to multidimensional poverty indicators.

Table 8. Impacts of staying in supermarkets, late entry and dropping out of supermarkets on income and multidimensional poverty indicators

Variables	Household income (1000 Ksh)	Per capita income (1000 Ksh)	Income poverty (dummy)	Income poverty gap (1-0)	MPI poverty (dummy)	MPI intensity (1-0)
	(1) CRE	(2) CRE	(3) CRE probit	(4) CRE Tobit	(5) CRE probit	(6) CRE Tobit
SM stayers	405.723***	90.334***	-0.164***	-0.122***	-0.186***	-0.077***
	(103.051)	(26.498)	(0.059)	(0.042)	(0.070)	(0.026)
SM newcomers	-47.682	-13.009	0.113	0.132	-0.150	-0.065*
	(57.276)	(15.263)	(0.082)	(0.084)	(0.093)	(0.035)
SM dropouts	172.865***	43.089***	-0.158**	-0.135***	-0.218***	-0.089***
	(50.884)	(17.493)	(0.063)	(0.042)	(0.072)	(0.027)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Wald χ^2	143.01***	140.20***	72.54***	74.24***	64.69***	100.42***
Observations	712	712	712	712	712	712

Source: Authors' computation, Notes: Coefficient estimates are shown with standard errors in parentheses. SM, supermarket; CRE, correlated random effects estimator;. [a] Traditional channel farmers are the reference group. Similar controls as in table 6 included, but not shown for brevity. * Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

4.3 Heterogeneous treatment effects

The results discussed so far provide interesting insights on the average treatment effects of supermarkets on the poverty indicators. However, the results do not show whether some households benefit more or less from supermarket contracts based on their socioeconomic profiles. In the following, we examine possible impact heterogeneity using quantile regressions for panel data (QRPD).

Panels (A) and (B) of Table 9 present quantile regression results for household income and per capita income estimated at five different quantiles, alongside average treatment effects estimated with fixed effects (FE) estimators. In these panels, 0.10 quantile represents the poorest households, while 0.90 quantile represents the richest households. As shown, supermarket participation significantly increases household income and per capita income in all five income quantiles, which suggests that the results are robust. Strikingly, richer households gain significantly more income as shown by the larger household income and per capita income gains at higher income quantiles (0.90). At 0.90 quantile, the coefficients of Ksh 395,000 and 130,000 for household income and per capita incomes, respectively, are significantly different from the corresponding average treatment effects as they fall outside the confidence intervals (CI) of the FE estimators[2]. These findings suggest that the effects of supplying supermarkets on household income and per capita income are heterogeneous. Furthermore, the results imply that although supplying supermarkets improve incomes in farm households, it may contribute to growth in income inequality.

Supplying supermarkets involve risks of delayed payment and produce rejections. Richer households are able to take the risks and reap the benefits of stable prices offered by supermarkets, unlike the unpredictable prices offered in the TC channels where resource-constrained farmers sell (Ochieng *et al.* 2017). Richer farmers can possibly supply larger quantities to supermarkets, and also negotiate for better prices for higher quality supplies. These are possible mechanisms through which the finding of heterogeneous income effect could be explained.

Panel (C) of Table 9 presents quantile regression results for total household deprivation scores, with the corresponding average treatment effects estimated using CRE Tobit estimator. Here, 0.10 quantile represents the least deprived – better-off – households, while 0.90 quantile represents the most deprived – worse-off – households. As shown, supermarket participation significantly reduces total deprivation scores in all the five quantiles. But more importantly, the larger magnitudes of total household deprivation scores at higher quantiles (0.90) imply that the poorest households gain significantly more in terms of reduction in poverty deprivations. The coefficients at 0.75 and 0.90 quantiles (-0.073, -0.084) are significantly different from the average treatment effect (-0.045). Thus, the results suggest that the effects of supplying supermarkets on multidimensional poverty are heterogeneous[3].

[2] This is informal test for the Wald test of equality of slope parameters in quantile regressions (Koenker & Hallock 2001). The formal test is not fully developed for QRPD.

[3] Total household deprivation scores are used to represent multidimensional poverty as in Ogutu & Qaim (2019). MPI dummy and MPI intensity variables are unsuitable for quantile regression estimations, due to many zeros in the indicators.

Table 9. Panel data quantile regression results for household income, per capita income, and total household deprivation score

	FE/CRE results for comparison		Quantile				
Variables	FE	95% FE CI	0.10	0.25	0.50	0.75	0.90
Panel A: Effect on household income							
SM participation (dummy)	147.300***	44.96 – 249.635	32.329***	41.064***	111.595***	185.338***	394.798***†
	(52.075)		(9.559)	(7.362)	(4.932)	(20.949)	(70.324)
Control variables	Yes		Yes	Yes	Yes	Yes	Yes
F-value	3.14***						
Panel B: Effect on per capita income							
SM participation (dummy)	39.577**	3.044 – 76.110	8.220***	16.923***	25.673***	51.717***	129.693***†
	(18.590)		(1.570)	(1.215)	(1.768)	(2.300)	(5.062)
Control variables	Yes		Yes	Yes	Yes	Yes	Yes
F-value	5.49***						
Observations	1184		1184	1184	1184	1184	1184
	CRE Tobit	95% CRE CI					
Panel C: Effect on total deprivation score							
SM participation (dummy)	-0.045***	-0.072 - -0.019	-0.038***	-0.050**	-0.052***	-0.073***†	-0.084**†
	(0.013)		(0.011)	(0.023)	(0.011)	(0.015)	(0.041)
Control variables	Yes		Yes	Yes	Yes	Yes	Yes
Wald χ^2	201.97***						
Observations	782		782	782	782	782	782

Source: Authors' computation. Notes: FE, fixed effects; CI, confidence interval; SM, supermarket; CRE, correlated random effects. Standard errors level in parentheses. The same explanatory variables used in Tables 5-7 of the main paper were used for estimation but are not shown here for brevity. * Significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level. † Coefficient is significantly different from FE (CRE) estimates (coefficient falls outside FE CI).

5. Conclusion

The modernization of retail food systems has induced a rapid growth of supermarkets, with far-reaching implications on farm household welfare and rural transformation. Previous studies examined the effects of supermarkets on several indicators such as, productivity, asset accumulation, nutrition, and income poverty. But the possible effects of supermarkets on multidimensional poverty were hardly analyzed. Previous research on the impacts of supermarkets on income poverty also relied on cross-section analysis plagued with potential endogeneity problems. To address these research gaps, we have used panel data from a sample of small-scale farmers in Kenya to evaluate the average treatment effects, supermarket impact dynamics and heterogeneous treatment effects of supermarkets on both income poverty, and multidimensional poverty.

The results of the average treatment effects have shown that supermarket participation significantly increases household income by 63% and per capita income by 57% over-and-above the mean incomes of traditional market channel (TC) suppliers. Supermarket participation also reduces the prevalence of income poverty by 32% relative to the mean income poverty prevalence among TC suppliers. Moreover, supermarket participation significantly reduces poverty gap by 42%. In terms of multidimensional poverty, supermarket participation significantly reduces the prevalence of multidimensional poverty (MPI dummy) by 42% relative to the mean prevalence among TC suppliers. Similarly, supermarket participation significantly reduces multidimensional poverty intensity (MPI intensity) by 39%. Impact dynamics results show that supermarket stayers and dropouts have sustained income gains and poverty reductions, but newcomers do not immediately benefit, perhaps due to their huge initial capital investment.

As mentioned, we also examined impact heterogeneity using quantile regressions. The results show that supermarket participation significantly increases household income and per capita income across all income quantiles. The results also reveal that the richest households gain significantly more household income and per capita income, suggesting that although supermarkets improve incomes in farm households, they may also contribute to higher income inequality. Quantile regression results for total household deprivation scores show that supermarket participation significantly reduces total deprivation scores in all five quantiles. But more importantly, the results show that the poorest households gain significantly more in terms of reductions in multidimensional poverty deprivations. Hence, the impacts of supermarkets on income and multidimensional poverty are not homogeneous.

Based on our findings, we conclude that supermarkets significantly increases household income, per capita income, but reduce income and multidimensional poverty. However, these impacts are heterogeneous. We argue that supermarket participation among smallholder farm households should be encouraged to help them realize the benefits of participation. This could be done through improvement of market infrastructure and institutions such as, roads, and supermarket contract designs tailored to reduce transaction costs, ensure transparent quality grading, and encourage fairer risk sharing (Ochieng *et al.* 2017). We also argue that special market support may be provided to extremely poor households to reduce the potential rise in income inequality. Lastly, we argue that complementary interventions that enhance access to better education, healthcare, water and sanitation etc., must be provided since supermarket participation alone cannot alleviate all forms of multidimensional poverty.

The results discussed in this article were robust across different rigorously estimated panel data econometric specifications. However, we caution against over-interpreting the results as causal since some potential endogeneity problems may remain in the presence time-variant unobserved confounding factors which were not fully accounted for with our econometric techniques. Further, the results are context-specific and should not be generalized. While the study setting is typical of the small farm sector in sub-Saharan Africa, suggesting that some broader insights may be gained, the specific magnitude of effects of supermarket participation may differ geographically.

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