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

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Abstract

The food retail sector in many developing countries is transforming with a rapid growth of modern supermarkets. Supermarkets are not only influencing how food is sold to consumers, but also how agricultural products are sourced from farmers. Especially for the procurement of fresh fruits and vegetables, supermarkets often contract farmers directly to ensure consistent, high-quality supply. Previous studies analyzed the effects of supermarket contracts on smallholder farmers' income. However, most existing studies relied on cross-section data and focused on the estimation of average income effects. Possible implications for other dimensions of household welfare were hardly examined. We add to this literature by using panel data from smallholder vegetable farmers in Kenya and econometric models with household fixed effects to estimate average and heterogeneous treatment effects of supermarket contracts on income and multidimensional poverty. On average, supermarket contracts increase per capita income in smallholder farm households by 60%. We also find significant reductions in income poverty and multidimensional poverty. Quantile regressions show that farmers in all income groups benefit, but richer households benefit more than poorer ones in absolute terms. On the other hand, supermarket contracts cause the strongest reductions in multidimensional deprivations among the poorest households.

Keywords: supermarkets, contract farming, income, multidimensional poverty, panel data, Kenya

JEL codes: O13, Q12, Q13, Q18

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1. Introduction

The global agri-food system transformation is characterized by a modernization of the food retail sector in many developing countries. Modern supermarkets are rapidly gaining ground. While the share of supermarkets in food retailing is already high in many parts of Asia and Latin America, developments in Africa are still at earlier stages but catching up (Reardon et al., 2003; Reardon et al. 2012; Qaim, 2017). Besides South Africa, Kenya and Zambia are other countries where the share of supermarkets in urban food retailing is already above 20% (Rischke et al., 2015; Tschirley et al., 2015). Supermarkets are changing the way food is sold to consumers with possible implications for food security and nutrition (Demmler et al., 2018; Popkin and Reardon, 2018). However, supermarkets can also influence how agricultural produce is sourced from farmers. Especially for the procurement of fresh fruits and vegetables, supermarkets often contract farmers directly to ensure consistent, high-quality supply (Hernandez et al., 2007; Neven et al., 2009; Reardon et al., 2012). One important question is how such contracts with supermarkets affect farmers' livelihoods. This is particularly relevant in the small farm sector, as smallholders are typically most affected by various basic need deprivations (Stokke, 2009; Christiaensen et al., 2011; Beegle et al., 2016).

Various studies analyzed the effects of supermarket contracts on agricultural performance and income in the small farm sector (Minten et al., 2009; Neven et al., 2009; Rao and Qaim, 2011; Michelson, 2013; Rao and Qaim, 2013; Andersson et al., 2015; Otsuka et al., 2016; Bellemare, 2018; Sutradhar et al., 2019). Most studies show that farmers benefit when they have access to a supermarket contract, because of higher and more stable output prices, and sometimes better access to inputs and technologies.

However, the existing literature on the effects of supermarket contracts has several shortcomings that we try to address in this article. First, most existing studies used cross-section data for the evaluation of impacts, which makes robust causal inference difficult. Moreover, with cross-section data one can only analyze short-term effects. Effects may change, especially when contract participation rates increase or decrease over time (Ochieng et al., 2017). We are only aware of one study that used panel data collected in two survey rounds to evaluate supermarket impacts (Andersson et al., 2015). Here, we use panel data collected in three rounds covering a time period of seven years. Second, most existing studies looked at smallholder livelihoods only in terms of income. While income is an important indicator of household welfare, it does not perfectly reflect the satisfaction of basic needs, such as food, shelter, sanitation, and education. We are aware of only one study that analyzed the effects of supermarket contracts on farm household nutrition with cross-section data (Chege et al., 2015). Here, we analyze effects on income but also on various other facets of human welfare using the multidimensional poverty index developed by Alkire and Santos (2014). Third, existing studies estimated average impacts without looking at possible impact heterogeneity. Understanding differential effects between various groups of farmers may help to design policies to avoid undesirable distributional outcomes. Here, we analyze average effects and heterogeneous effects for farmers in different income groups with quantile regressions.

Specifically, we use panel data collected from vegetable farmers in Kenya between 2008 and 2015 and econometric models with household fixed effects to evaluate impacts of supermarket contracts on household income, income poverty, and multidimensional poverty. The remainder of this article is structured as follows. The next section describes the farm survey data and the different outcome variables of interest. Section 3 describes the estimation strategy used to evaluate average and heterogeneous effects. Section 4 presents and discusses the estimation results, while section 5 concludes.

2. Survey data and definition of outcome variables

2.1 Farm household survey

This study uses three rounds of panel data from smallholder vegetable farmers in Kiambu County, Central Kenya. Kiambu is relatively near to Nairobi and was traditionally a vegetable-growing area before supermarkets entered the scene. Most of the vegetables from farmers in Kiambu are sold in domestic markets. Production of vegetables for export markets takes place mostly in other parts of Kenya (Rao and Qaim, 2013). Supermarkets started sourcing green leafy vegetables from farmers in Kiambu in the mid-2000s through simple marketing contracts. In these contracts, quantities, prices, and delivery dates are fixed. Furthermore, farmers have to meet certain quality standards. If farmers are unable to deliver according to the requirements, they lose their contracts and have to sell their vegetables in traditional markets, where prices are lower and more volatile. Hence, contract participation is characterized by dynamics, with some farmers dropping out and others newly entering the supermarket channel over time (Andersson et al., 2015; Ochieng et al., 2017).

The first round of the farm household survey was conducted in 2008. At that time, a multistage random sampling procedure was used to select 402 vegetable farmers in 31 locations. Of the 402 farmers, one-third had a supermarket contract, while the others were supplying traditional markets (Rao and Qaim, 2011). Two additional survey rounds were conducted in 2012 and 2015, with 384 and 409 farmers, respectively (Chege et al., 2015; Ochieng et al., 2017). Most of the farm households were observed in all three survey rounds. Drop-outs were replaced with other randomly selected households from the same locations whenever possible. The proportion of farmers with a supermarket contract decreased to 15% of the sample in 2012 and then increased to 22% in 2015.

In all three survey rounds, data on vegetable production, marketing, other agricultural enterprises, off-farm income sources, and broader socioeconomic and institutional characteristics were collected through face-to-face interviews with the vegetable farmer. Details on food consumption were not collected in 2008, but were added to the questionnaire in 2012 and 2015, using a 7-day recall period at the household level (Chege et al., 2015). As the food consumption data are needed for the construction of the multidimensional poverty index (see details below), we only use the 2012 and 2015 survey rounds for the respective parts of the analysis. All other parts of the analysis, namely those referring to income and income poverty, use all three survey rounds from 2008, 2012, and 2015.

2.2 Indicators of income and income poverty

We want to analyze the effects of supermarket contracts on household income and income poverty. Based on the survey data, household income is calculated as the sum of net farm income and off-farm income per annum. Farm income includes the total value of sold and home-consumed farm output minus production costs for all agricultural enterprises. Off-farm income includes income from employment, self-employment, remittances, pensions, as well as other revenues such as capital and land rents, considering all members living in the household. Annual household income is expressed in thousand Kenyan shillings (Ksh). The incomes calculated for the three survey rounds are adjusted for inflation using the consumer price index. Per capita income is calculated by dividing total annual household income by the number of household members.

To calculate the income poverty indicators we compute daily per capita income and convert it to US dollars using the purchasing power parity (PPP) exchange rate.[1] We use the international poverty line of $ 1.90 a day to differentiate between poor and non-poor households. The poverty status is expressed in the form of a poverty dummy variable. In addition, we calculate the income poverty gap, which measures the extent to which per capita

[1] In 2015, the PPP exchange rate was $1 = Ksh 43.89 (World Bank, 2015).

income falls below the poverty line (Foster et al., 1984). The income poverty gap is computed as follows:

$$G_{it} = \frac{P - I_{it}}{P} \quad (1)$$

where P is the poverty line and I_{it} is per capita income of household i at time t. Households with incomes above the poverty line are automatically assigned a zero value for the income poverty gap.

2.3 Indicators of multidimensional poverty

Calculating poverty based on income is an indirect way of assessing a household's ability to satisfy basic needs. A more direct way is to assess whether a household actually satisfies key basic needs, such as food, shelter, sanitation, and education. The multidimensional poverty index (MPI) developed by Alkire and Santos (2014) attempts to do so by defining a set of basic needs and using survey data to evaluate whether or not these basic needs are satisfied. The MPI indicates the proportion of households in a given population suffering from multiple deprivations.

For the calculation of multidimensional poverty and the combined evaluation of the various basic needs, different methodological approaches can be used, including ordinal ranking, factor analysis, cluster analysis, and weighting procedures (Kakwani and Silber, 2008; Alkire and Santos, 2014; Ogutu et al., 2019). All of these approaches have their advantages and drawbacks depending on context of use. Following Alkire and Santos (2014), we compute the MPI using a weighting procedure as explained below. This procedure is particularly useful for quantitative impact assessment, as it produces an MPI index that satisfies the dimensional monotonicity condition, which implies that if a poor person becomes deprived in an additional dimension, MPI always increases. The weighting procedure also ensures that the MPI is decomposable by population subgroups to allow for poverty comparisons.

Table 1 provides details of the three core dimensions of multidimensional poverty, namely education, health, and living standard (including various indicators of housing and sanitation), and the ten indicators that we use to compute the MPI at the household level. The indicators are the same as those proposed by Alkire and Santos (2014), except for three adjustments. Adjustments of individual indicators are recommended to properly reflect conditions in the local context (Alkire and Santos, 2014; OPHI, 2017; Ogutu et al., 2019). Instead of "all household members have less than 5 years of schooling", as proposed by Alkire and Santos (2014), we use "average household education is less than 8 years", because eight years is the minimum number of schooling years to complete primary education in Kenya. Further, instead of "any household member is malnourished" and "a child has died in the family" as indicators of the health dimension, we use "inadequate household calorie consumption" (nutrition 1) and "inadequate household vitamin A consumption" (nutrition 2) as alternatives due to data limitations. Our survey data contain household-level but not individual-level nutrition and health information.

(Insert Table 1 here)

We compute three different MPI variables for each household. First, we calculate the total household deprivation score by using dummy variables for each of the ten MPI indicators (each dummy takes a value of one if the household is below the deprivation cutoff) and then assigning relative weights, as shown in Table 1. The sum of the weighted values across all ten indicators results in the total deprivation score, which ranges between zero and one. Larger score values indicate higher levels of deprivation. Second, we calculate an MPI dummy, which takes a value of one if the total deprivation score of a household is 0.33 or higher, and zero otherwise. The 0.33 threshold is a standard value used in the literature to determine whether or not a household is multidimensionally poor (Alkire and Santos, 2014). Third, we compute the MPI intensity, which is equal to a household's total deprivation score if the MPI dummy is equal to one, and zero otherwise. Thus, the MPI intensity is a fractional variable, with a number of zero observations (for households that are not multidimensionally poor) and continuous values ranging from 0.33 to 1 (for MPI poor households).

3. Estimation strategy

3.1 Estimating average treatment effects

We aim to evaluate the impact of supermarket contracts on household income, income poverty, and multidimensional poverty, using the outcome variables described in the previous section. As we rely on observational data with households self-selecting into supermarket contracts, endogeneity is likely an issue, especially endogeneity resulting from unobserved heterogeneity. Fortunately, we have panel data that allow us to estimate panel regression models with household fixed effects that control for time-invariant unobserved heterogeneity (Cameron and Trivedi, 2005; Wooldridge, 2010). In particular, we estimate panel data regression models of the following type:

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

where y_{it} is the income or poverty indicator for household i in year t, SM_{it} is our treatment dummy variable that takes a value of one if household i had a supermarket contract in year t and zero otherwise, $\boldsymbol{X}_{it}$ is a vector of control variables, c_i captures unobserved household-specific effects, and υ_{it} captures idiosyncratic shocks. We estimate separate models for each of the income and poverty indicators discussed above. In all models, the main parameter of interest is β, which represents the average treatment effect of supermarket contracts on income and/or poverty.

Based on previous studies that evaluated the effects of supermarkets on smallholder income (Minten et al., 2009; Rao and Qaim, 2011; Andersson et al., 2015), we expect β to be positive and statistically significant in the models with household income or per capita income as outcome variables. Accordingly, β should be negative and statistically significant in the models with income poverty and the income poverty gap as outcome variables (meaning that supermarket contracts help to reduce income poverty). If the income gains are really used to satisfy basic needs, β should also be negative in the models with the MPI variables as outcomes. This has not been analyzed empirically before.

We estimate the models in equation (2) using random effects (RE) and fixed effects (FE) estimators, but mainly rely on the FE estimates, as they control for endogeneity due to time-invariant unobserved heterogeneity. However, while the FE estimator is suitable for linear models, it may result in inconsistent estimates for non-linear models (Cameron and Trivedi, 2005). This is of concern here, because several outcome indicators are dummies or censored or fractional variables. Hence, we use the FE estimator only for the household income and per capita income models, where the dependent variables are continuous. For all other models, we use the correlated random effects (CRE) estimator proposed by Mundlak (1978). As the FE estimator, the CRE estimator accounts for unobserved heterogeneity by allowing unobserved household-specific effects c_i to be determined by time-averages of the observed explanatory variables as follows:

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

where $\overline{\boldsymbol{X}}_i$ is a vector of the time-averaged explanatory variables $\boldsymbol{X}_{it}$, and ω_{it} is a random error term. Hence, the estimated CRE model can be expressed as follows:

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

which leads to consistent estimates also in non-linear models (Wooldridge, 2010). For the models with dummies as dependent variables (income poverty and MPI dummies), we use probit specifications in connection with the CRE estimator. For the models with censored or fractional variables as outcomes (income poverty gap and MPI intensity), we use Tobit specifications in connection with the CRE estimator.

3.2 Estimating heterogeneous treatment effects

The models in equations (2) and (4) are suitable for estimating average treatment effects of supermarket contracts, but they are not well suited to evaluate impact heterogeneity. Understanding impact heterogeneity is important because supermarket contracts may have different income effects on poor and non-poor households. To some extent, this is captured by using various poverty indicators as outcomes, but especially for policy purposes it could also be of interest to further analyze heterogeneous treatment effects, which we do with quantile regressions. Quantile regressions allow us to study the effects of supermarket contracts over the distribution of the dependent variables, rather than just examining average effects (Koenker and Hallock, 2001). We employ quantile regressions for panel data (QRPD), which also control for time-invariant unobserved heterogeneity (Powell, 2016).

We estimate the QRPD model for the three continuous outcome variables: household income, per capita income, and total household deprivation score.[2] The model is specified as follows:

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

where $Qy_{it}(\tau|\boldsymbol{Z}_{it})$ is the quantile of the outcome variable y_{it} at quantile τ (0< $\tau < 1$) conditional on the vector of explanatory variables $\boldsymbol{Z}_{it}$, which includes the supermarket contract dummy and other covariates. $\beta(\tau)$ is the vector of coefficients to be estimated. The

[2] The other outcomes are limited dependent variables with many zero observations, so that quantile regressions cannot be estimated for the entire distribution.

coefficients are estimated using the generalized method of moments (GMM) with $\hat{\beta}(\tau)$ expressed as:

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

where $\boldsymbol{b}$ is equivalent to the vector of parameters of the explanatory variables $\boldsymbol{Z}_{it}$, 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 household income, per capita income, and the total household deprivation score.

4. Results and discussion

4.1 Descriptive statistics

Table 2 shows summary statistics of selected socioeconomic variables, that we also use as control variables in the regression models. The vegetable-producing farms in Kiambu, Central Kenya, are typical smallholders with average farm sizes of about 2 acres. In addition to vegetables, most sample farms produce food crops such as maize, banana, and beans. Some also produce cash crops such as coffee and tea. Table 2 also shows differences in socioeconomic characteristics between farm households supplying vegetables to supermarkets under a marketing contract (SM) and those selling vegetables in traditional channels without a contract (TC). SM suppliers are generally better-off than TC farmers in terms of education, farm size, access to transportation, and other variables. These differences underline that controlling for observed and unobserved heterogeneity between SM and TC farmers is important when evaluating the treatment effects of supermarket contracts.

(Insert Table 2 here)

Table 3 presents descriptive statistics for the income and poverty indicators used as outcome variables in this study. Panel A of Table 3 shows that SM suppliers have significantly higher household and per capita incomes than TC farmers. SM suppliers are also significantly less likely to suffer from income poverty, and they have a much smaller income poverty gap than TC farmers. Panel B of Table 3 shows comparisons for the MPI indicators. The mean household deprivation score of 0.276 for the sample as a whole implies that households are deprived in 27.6% of the total possible deprivations on average. About 39% of the households are classified as multidimensionally poor (MPI dummy equal to one).[3] The MPI intensity is 0.168 on average. SM suppliers are significantly better-off than TC farmers in terms of all three MPI indicators.

(Insert Table 3 here)

Table 4 shows the proportion of households deprived in terms of each of the ten MPI indicators. Overall, sample households are least deprived in terms of child schooling and most deprived in terms of sanitation. Almost 90% of the households have no improved toilet facility and more than half have no access to safe drinking water. For almost all indicators, SM farmers are less deprived than TC farmers. The last column in Table 4 shows correlation coefficients between deprivation in terms of each indicator and household income. For most indicators, the correlations are negative, as one would expect. Interestingly, however, for the two nutrition indicators and for child schooling the correlations are not statistically significant, underlining that income is not a perfect proxy for all dimensions of household welfare and poverty.

(Insert Table 4 here)

[3] As explained above, a household is classified as MPI poor when the total household deprivation score is 0.33 or higher. Interestingly, the MPI poverty rate of 39% in the sample is somewhat higher than the income poverty rate of 33%.

4.2 Effects of supermarket contracts on income and income poverty

In this subsection, we present and discuss the average treatment effects of supermarket contracts on income and income poverty, estimated with panel data regression models. Table 5 shows the RE and FE estimates for household and per capita income. As discussed, we prefer the FE estimates as they account for unobserved time-invariant heterogeneity. Results in column (2) of Table 5 suggest that supermarket contracts increase annual household income by 147 thousand Ksh, which is equivalent to an income gain of 63% when compared to the mean income of TC farmers. Previous studies in Kenya also showed that supplying supermarkets results in sizeable income gains for smallholder farmers (Rao and Qaim, 2011; Andersson et al., 2015). The magnitude of the effect of supermarket contracts on per capita is 40 thousand Ksh (column 4 of Table 5), which is also equivalent to a gain of almost 60%.

(Insert Table 5 here)

These sizeable positive income effects of supermarket contracts also contribute significantly to poverty reduction as is shown in Table 6. Column (2) of Table 6 suggests that having a supermarket contract reduces the probability of income poverty by 11.8 percentage points. Comparing this with the observed 37% prevalence of income poverty among TC farmers means that supermarket contracts reduce poverty by about one-third. In addition, column (4) of Table 6 suggests that supermarket contracts reduce the income poverty gap by 10 percentage points, equivalent to a 42% reduction in the average poverty gap among TC farmers.

(Insert Table 6 here)

4.3 Effects of supermarket contracts on multidimensional poverty

Table 7 shows effects of supermarket contracts on MPI poverty. Supermarket contracts reduce the likelihood of MPI poverty by 18 percentage points (column 2 of Table 7). This estimate is equivalent to a 42% reduction in the prevalence of multidimensional poverty among TC farmers. Furthermore, column (4) suggests that supermarket contracts reduce the MPI intensity by 7.2 percentage points (39% reduction).

(Insert Table 7 here)

While previous research had shown that supermarkets can not only contribute to income gains but also to improved nutrition among smallholder farmers (Chege et al., 2015), effects on other dimensions of welfare – such as health, housing conditions, and child education – have not been analyzed before. Our results clearly suggest that supplying supermarkets improves smallholder living standards in terms of multiple dimensions. Comparing results between Tables 6 and Table 7 even reveals that supermarket contracts have larger effects on MPI poverty (reduction of 18 percentage points) than on income poverty (reduction of 11.8 percentage points). These are very welcome findings from a social development perspective.

4.4 Heterogeneous effects of supermarket contracts

The results discussed so far provide interesting insights into the average treatment effects of supermarket contracts on income and multidimensional poverty. The fact that supermarket contracts help reduce poverty is a clear indication that not only the better-off but also poor and deprived farm households benefit. We now analyze heterogeneous effects to better understand whether the effect sizes differ by household living standard. In other words, we address the question of whether poorer households benefit to the same extent as the somewhat richer ones. As explained, we use quantile regressions for panel data to analyze possible impact heterogeneity.

Figure 1 shows the quantile regression results with household income, per capita income, and total household deprivation score as dependent variables. All quantiles, from the poorest to richest 10%, benefit significantly from supermarket contracts, which as such is an important result. However, as can also be seen from Figure 1, the absolute income gains (panel A) and also the per capita income gains (panel B) are much larger for richer than for poorer households, suggesting that – in spite of their poverty-reducing effects – supermarket contracts contribute to rising income inequality. This is plausible, because richer households tend to have larger farms so they benefit more from positive economies-of-scale in production and marketing. Larger producers are also sometimes able to negotiate better prices with supermarkets because of lower transaction costs per unit of produce.

(Insert Figure 1 here)

That the absolute income gains from supermarket contracts are larger for the richest households with the largest farms is hardly surprising, but panel (C) of Figure 1 shows another interesting facet, namely that the poorest households benefit most from contract-induced reductions in total deprivation scores. On the one hand, this is expected as the poorest households suffer most from basic needs deprivations. On the other hand, this result further underlines that supermarket contracts really lead to measurable improvements in terms of multiple welfare and poverty dimensions, especially for the poorest households.

5. Conclusion

Many countries in Africa are seeing a rapid growth of supermarkets with significant implications for agricultural procurement and domestic food supply chains. Especially in the fresh fruit and vegetable segment, supermarkets are often contracting farmers directly to ensure consistent and high-quality supply. Previous research had analyzed the effects of supermarket contracting on smallholder productivity and income, mostly with cross-section or short panel data. We have added to this literature by using panel data collected over a period of seven years and using econometric models with household fixed effects for more robust causal inference. Furthermore, beyond income we have evaluated the effects of supermarket contracts on multidimensional poverty and also used quantile regressions to better understand impact heterogeneity.

The data from vegetable producers in Kenya suggest that supermarkets and their marketing contracts contribute to sizeable income gains and poverty reduction in the small farm sector. Having a supermarket contract increases household income and per capita income by around 60% on average, also after controlling for possible confounding factors. These income gains are primarily due to the fact that supermarkets pay higher prices than buyers of vegetables in traditional markets. Earlier research also showed that supermarket contracts can lead to higher productivity and efficiency through the price incentives and through facilitating farmers' access to technology and information (Hernandez et al., 2007; Minten et al., 2009; Rao et al., 2012). Our analysis further revealed that the income gains lead to significant poverty reduction. After controlling for other factors, having a supermarket contract reduces the likelihood of being income-poor by 12 percentage points. Sizeable gains in smallholder income and economic welfare through supermarket contracts are consistent with previous research in Kenya and other developing countries (Minten et al., 2009; Rao and Qaim, 2011; Michelson, 2013; Andersson et al., 2015).

Beyond income and income poverty, our results also showed that supermarkets contribute to a reduction in multidimensional poverty in the small farm sector. Having a supermarket contract reduces the likelihood of being multidimensionally poor by 18 percentage points. The multidimensional poverty concept evaluates the satisfaction of basic needs, such as nutrition, health, education, and housing conditions. The main mechanism through which supermarket contracts may reduce basic needs deprivations is a rise in household income. But, depending on how income is spent, a rise in income alone is not a sufficient condition for multidimensional poverty reduction. Our results suggest that the additional income from selling vegetables to supermarkets is indeed spent on satisfying basic needs. This is especially remarkable given that the commercialization of smallholder agriculture is often associated with stronger male control of farm income, and males sometimes spend less on nutrition and health than females (Chege et al., 2015). Strikingly, in the study region in Kenya the reducing effect of supermarket contracts on multidimensional poverty is even larger than the effect on income poverty.

The quantile regressions showed that the income gains of supermarket contracts are significant for all types of households, but that the absolute gains are larger for the higher-income segments. This is hardly surprising, since richer households also tend to have larger farms and therefore sell larger quantities of vegetables to supermarkets. Hence, supermarkets may contribute to rising income inequality in the small farm sector. However, in terms of reducing basic needs deprivations, the effects of supermarkets are larger for the poorest households.

Based on these findings, we conclude that the growing role of supermarkets in developing countries and the contracting of smallholders can contribute to poverty reduction and improved human wellbeing. Previous research showed that not all smallholders may have access to supermarket contracts due to various reasons, including high transaction costs as well as financial and human capital constraints (Neven et al., 2009; Andersson et al., 2015; Ochieng et al., 2017). Policy support to facilitate smallholder participation in high-value supply chains may be required to avoid undesirable social outcomes. On the other hand, high-value supply chains may also create new types of jobs in farming, post-harvest handling, and food processing (Rao and Qaim, 2013). Such new types of jobs could be particularly relevant for marginalized smallholders who do not manage to supply supermarkets themselves. Policymakers should observe related developments and possibly incentivize the generation of some of these new jobs in rural areas.

The results from Kenya should not be generalized, as the conditions in other geographical settings may differ. It should also be stressed that our study region in Kiambu County is located near Nairobi, where the role of supermarkets is already larger than in remoter rural areas. However, it has been observed in many countries that supermarkets start their businesses in and around large cities before spreading out also to smaller towns and rural areas (Reardon et al., 2003; Reardon et al., 2012; Rischke et al., 2015). Hence, the results from Kiambu may provide some indication of possible future developments also in other parts of Kenya. We are not aware of other regions in Kenya or elsewhere in developing countries where the effects of supermarkets on smallholder farmers have been tracked for a number of years with panel data.

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

Dimension/ indicator	Deprivation cut-off	Weight
Education		
Years of schooling	Household 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 vitamin A per AE and day	1/6
Nutrition 2	Household consumes less than 2400 kcal per AE and day	1/6
Living standard		
Electricity	Household has no access to electricity	1/18
Sanitation	Household 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

Notes: The indicators are the same as those in Alkire and Santos (2014), except for small modifications in three of them (years of schooling, nutrition 1, nutrition 2) as explained in the text. AE, adult equivalent.

Table 2. Summary statistics of socioeconomic variables for farmers with and without supermarket contract

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	

Notes: Observations from all three survey rounds were pooled. Mean values are shown with standard deviations in parentheses. SM, supermarket supplier; TC, traditional channel supplier. * significant at the10% level; *** significant at the1% level.

Table 3. Income and poverty indicators for farm households with and without supermarket contract

Variables	Full sample	SM	TC	Mean difference
Panel A: Income and income poverty				
Household income (1000 Ksh)	309.177	536.379	235.476	300.903***
	(441.010)	(679.957)	(292.953)	
Per capita income (1000 Ksh)	90.817	156.169	69.618	86.551***
	(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				
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	

Notes: For the income and income poverty indicators (panel A), observations from all three survey rounds (2008, 2012, 2015) were pooled. Monetary values were deflated. For the multidimensional poverty indicators (panel B), data from two survey rounds (2012, 2015) were pooled. Mean values are shown with standard deviations in parentheses. SM, supermarket supplier; TC, traditional channel supplier; Ksh, Kenyan shilling. *** significant at the 1% level.

Table 4. Proportion of households deprived in terms of MPI indicators (indicators ranked by proportion of deprived households)

Indicator	Deprivation cut-off	Full sample	SM	TC	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 vitamin A per AE and day (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 the 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 per AE and day (dummy)	0.192	0.172	0.197	-0.025	-0.017
		(0.394)	(0.379)	(0.398)		
Years of schooling	Household 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 toilet facility is not improved (dummy)	0.895	0.777	0.925	-0.148***	-0.230***
		(0.307)	(0.418)	(0.264)		
	Observations	782	157	625		

Notes: Data from two survey rounds (2012, 2015) were pooled. Mean values are shown with standard deviations in parentheses. MPI, multidimensional poverty index; SM, supermarket supplier; TC, traditional channel farmer; AE, adult male equivalent. ** significant at the 5% level; *** significant at the 1% level.

Table 5. Effects of supermarket contracts 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 contract (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		3.140***		5.490***
Hausman test χ^2		14.190		50.210***
Observations	1184	1184	1184	1184

Notes: Coefficient estimates from panel regression models 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 10% level; ** significant at the 5% level; *** significant at the1% level.

Table 6. Effects of supermarket contracts on income poverty and the income poverty gap

	Income poverty (dummy)		Income poverty gap (0-1)	
Variables	(1) RE Probit	(2) CRE Probit	(3) RE Tobit	(4) CRE Tobit
SM contract (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	121.920***	126.970***	111.890***	127.580***
Log likelihood	-662.882	-653.019	-864.982	-853.879
Observations	1184	1184	1184	1184

Notes: Average partial effects estimated with panel regression models are shown with standard errors in parentheses. SM, supermarket; RE, random effects; CRE, correlated random effects. CRE models additionally include averages of time-varying variables, which are not shown for brevity. Full estimation results are shown in Table A1 in the Appendix. [a] Year 2008 is the base category. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 7. Effect of supermarket contracts on multidimensional poverty

	MPI dummy		MPI intensity	
Variables	(1) RE Probit	(2) CRE Probit	(3) RE Tobit	(4)CRE Tobit
SM contract (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)	-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) [a]	-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	61.460***	73.000***	90.990***	114.180***
Log likelihood	-455.287	-433.166	-430.851	-418.420
Observations	782	782	782	782

Notes: Average partial effects estimated with panel regression models are shown with standard errors in parentheses. MPI, multidimensional poverty index; SM, supermarket; RE, random effects; CRE, correlated random effects. CRE models additionally include averages of time-varying variables, which are not shown for brevity. Full estimation results are shown in Table A2 in the Appendix. [a] Year 2012 is the base category. * significant at 10% level; ** significant at the 5% level; *** significant at the 1% level.

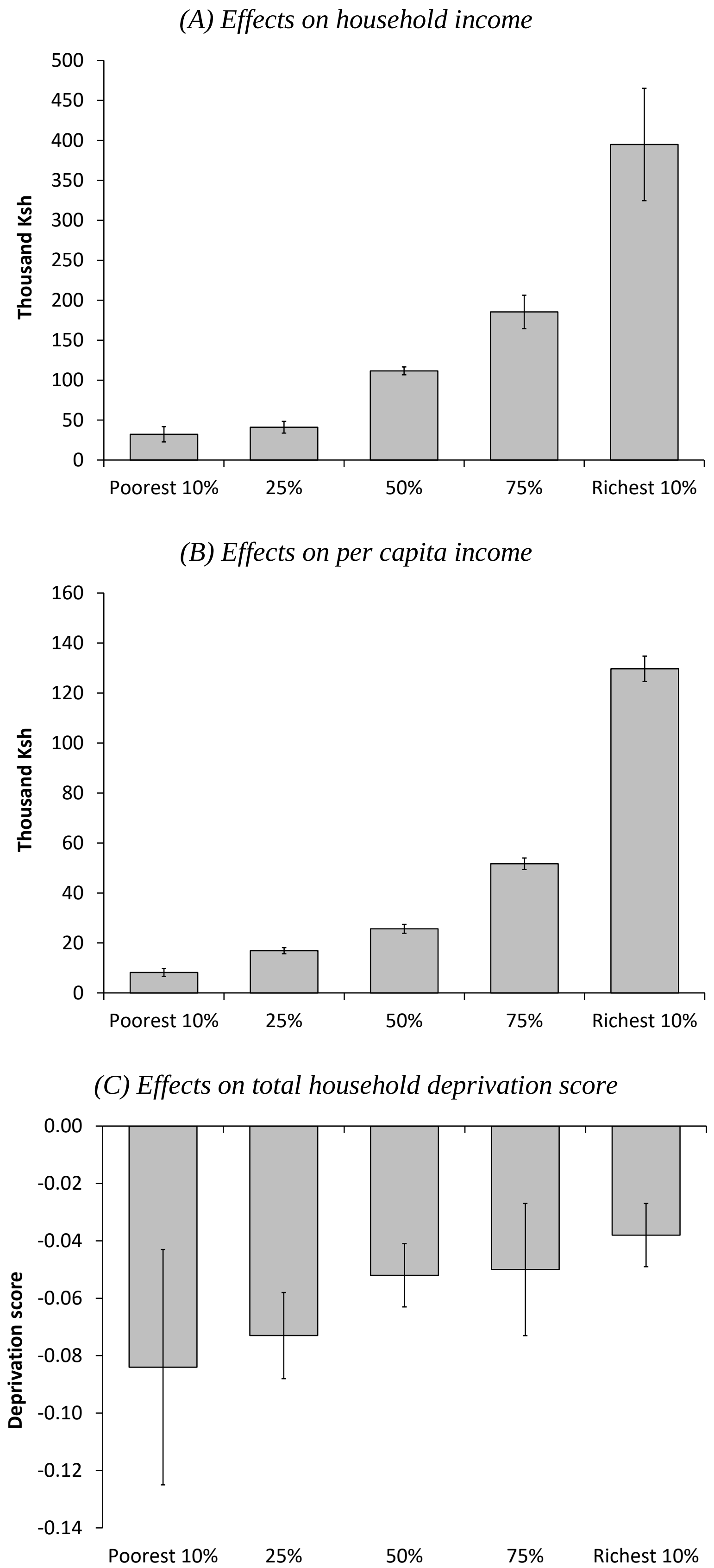

Figure 1. Heterogeneous effects of supermarket contracts on household income and deprivation.

Notes: Point estimates (average marginal effects) from panel data quantile regressions are shown with standard error bars. The same control variables as in Tables 5 and 7 were included in estimation.

Appendix

Table A1. Effects of supermarket contracts on income poverty and the income poverty gap (full results)

	Income poverty (dummy)		Income poverty gap (0-1)	
Variables	(1) RE Probit	(2) CRE Probit	(3) RE Tobit	(4) CRE Tobit
SM contract (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)
Mean values of observed variables				
Age of household head (years)		-0.002**		-0.001
		(0.004)		(0.002)
Male household head (dummy)		-0.196*		-0.165**
		(0.096)		(0.073)
Post-primary education of head (dummy)		-0.147*		-0.104
		(0.072)		(0.063)
Household size (number)		-0.010		-0.009
		(0.016)		(0.013)
Farm size (acres)		-0.030		-0.023
		(0.022)		(0.017)
Farm size squared (acres)		0.001		0.000
		(0.001)		(0.001)
Off-farm income (dummy)		-0.044		-0.057
		(0.061)		(0.047)
Group membership (dummy)		-0.099		-0.065
		(0.067)		(0.051)
Public transport available (dummy)		-0.115*		-0.050
		(0.063)		(0.048)
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

Notes: Average partial effects are shown with standard errors in parentheses. SM, supermarket; RE, random effects; CRE, correlated random effects. [a] Year 2008 is the base category. * significant at 10% level; ** significant at 5% level; *** significant at 1% level.

Table A2. Effects of supermarket contracts on multidimensional poverty (full results)

	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)	-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) [a]	-0.099***	-0.120***	-0.045***	-0.055***
	(0.286)	(0.043)	(0.014)	(0.017)
Mean values of observed variables				
Age of household head (years)		-0.003		-0.002
		(0.007)		(0.003)
Male household head (dummy)		-0.166		-0.065
		(0.163)		(0.062)
Post-primary education (dummy)		-0.502***		-0.199***
		(0.179)		(0.073)
Household size (number)		-0.014		-0.006
		(0.025)		(0.010)
Farm size (acres)		-0.013		-0.008
		(0.030)		(0.012)
Farm size squared (acres)		-0.000		-0.000
		(0.001)		(0.000)
Off-farm income (dummy)		-0.106		-0.041
		(0.090)		(0.036)
Group membership (dummy)		-0.057		-0.022
		(0.099)		(0.039)
Public transport available (dummy)		0.130		0.047
		(0.095)		(0.038)
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

Notes: Average partial effects are shown with standard errors in parentheses. MPI, multidimensional poverty index; SM, supermarket; RE, random effects; CRE, correlated random effects. [a] Year 2012 is the base category. * Significant at 10% level; ** significant at 5% level; *** significant at 1% level.