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Commercialization of the small farm sector and multidimensional poverty

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Abstract

Global poverty rates have declined considerably, but the number of people living in extreme poverty remains high. Many of the poor are smallholder farmers. Agricultural commercialization – meaning a shift from subsistence to more market-oriented farming – can play a central role in improving smallholder welfare. Previous studies evaluated the impact of agricultural commercialization on income poverty, but whether income gains from commercialization are really used for satisfying basic needs was hardly analyzed up till now. Here, we evaluate the effect of commercialization on income poverty, as well as on the multidimensional poverty index that looks at deprivations in terms of education, nutrition, health, and other dimensions of living standard. Using data from 805 farm households in Kenya, we estimate average treatment effects. We also analyze impact heterogeneity with quantile regressions. Results show that commercialization significantly reduces both income poverty and multidimensional poverty. The magnitude of the income gains is positively correlated with income level, meaning that special market-linkage support for marginalized farms may be required to avoid rising income inequality. However, the effect in terms of reducing basic needs deprivations is strongest among the poorest households, suggesting that agricultural commercialization contributes effectively to achieving the sustainable development goals.

Key words: Agricultural commercialization; Welfare, Multidimensional poverty, Kenya

JEL codes: C21, I32, Q12, Q13

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Commercialization of the small farm sector and multidimensional poverty

1. Introduction

Global poverty rates have declined considerably over the last few decades, but the number of people still living in extreme poverty – below 1.90 US dollars a day – remains high (World Bank, 2016). Hence, eradication of poverty continues to be a top priority on the international development agenda (United Nations, 2016). Many of the world's poor are smallholder farmers who depend on agriculture as the main source of food, income, and employment. Against this background, agricultural development has been acknowledged as one of the main pathways for poverty alleviation (World Bank, 2015; Hazell et al., 2010; de Janvry & Sadoulet, 2009).

Commercialization of smallholder agriculture – meaning a shift from subsistence to more market-oriented farming – can lead to productivity growth, income growth, employment growth, and poverty reduction (Bellemare & Novak, 2017; Carletto, Corral, & Guefi, 2017; von Braun & Kennedy, 1994; Barrett, 2008). Agricultural commercialization also improves food supply in urban areas, with broader growth and welfare effects. Previous studies confirmed that commercialized farms have higher household incomes than subsistence-oriented farms, also after controlling for other relevant factors (von Braun, 1995; Tipraqsa & Schreinemachers, 2009). A few studies also showed that commercialization contributes to poverty reduction among African smallholders (Muricho et al., 2017; Muriithi & Matz, 2015; Olwande et al., 2015).

However, existing studies on poverty effects of commercialization only looked at income poverty. While income (or expenditure) data are widely used to analyze poverty, they cannot fully capture the multidimensional nature of poverty, including deprivations in education, health, nutrition, and other dimensions of living standard. The simple assumption that additional income earned from agricultural commercialization will automatically be spent on satisfying basic needs may not always be true. Different types of income may be controlled by different persons within the farm household and used for different purposes (Meemken, Spielman, & Qaim, 2017; von Braun & Kennedy, 1994).[1] We contribute to the literature by analyzing the impact of agricultural commercialization on multidimensional poverty, using the multidimensional poverty index described by Alkire & Santos (2014).[2] For comparison, we also analyze the impact of commercialization on income poverty.

The empirical research is based on data from a survey of smallholder farmers in Kenya. As is typical for sub-Saharan Africa, smallholder farmers in Kenya account for the lion's share of total agricultural output and for a large fraction of the population living below the poverty line (World Bank, 2017; Wiesmann et al., 2016; Olwande et al., 2015; Mathenge et al., 2014). For the impact analysis, we compare farmers with different levels of commercialization, using a control function approach with instruments to address issues of endogeneity. We estimate average treatment effects of commercialization, as well as heterogeneous treatment effects with quantile regressions. Heterogeneous effects can occur when certain types of households benefit more from commercialization than others. This is important to understand with a view to avoiding rising inequality.

The remainder of this article is organized as follows. Section 2 describes the household survey and the key indicators used to measure agricultural commercialization, income poverty, and multidimensional poverty. Section 3 describes the statistical approaches and the identification strategy. Estimation results are presented and discussed in section 4, while section 5 concludes.

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[1] A few studies have analyzed the effects of commercialization on nutrition (Carletto et al., 2017; Ogutu, Gödecke, & Qaim, 2017), but not on other dimensions of basic needs and living standard.
[2] In a recent study, Ayuya et al. (2015) used the multidimensional poverty index to analyze the impact of organic farming on smallholder poverty. This is different from the agricultural commercialization question pursued here.

2. Data collection and measurement of key variables

2.1 Farm household survey

We use data from a farm household survey that we conducted between October and December 2015 in Kisii and Nyamira counties in the western parts of Kenya. These two counties were purposively selected due to the small farm sizes, relatively high poverty rates, diverse agricultural production, and poor road and market infrastructure (Wiesmann et al., 2016; Kisii County Government 2013; Nyamira County Government 2013). Farmers in the study area grow a large number of different crops, such as maize, beans, cassava, sweetpotato, banana, and vegetables, mostly for home consumption, and to a lesser extent for local market sales. Cash crops such as coffee, tea, and sugar cane are also grown to a limited extent. Many farmers in Kisii and Nyamira are also involved in small-scale livestock keeping, including poultry, small ruminants, and cattle.

As recent census data were not available, we exploited the fact that many of the local farmers are organized in farmer groups or self-help groups for randomly selecting households for the survey. Farmer and self-help groups are registered with the Ministry of Gender, Children, and Social Development. Building on Ministry registries and with support from Africa Harvest, a non-governmental organization working in the region, a list of all active groups in Kisii and Nyamira was constructed. From this list, we excluded a few groups that had received specific development support during the last two years in order to avoid any sampling bias. From the remaining groups, we randomly selected 48 groups for our survey (32 groups in Kisii and 16 groups in Nyamira county). In each of these groups, complete member lists were compiled, from which 15-20 households were randomly selected, depending on group size. This resulted in a sample of 824 farm households, spread over 8 different sub-counties and 26 wards.

Data from each household were collected through face-to-face interviews with the household head or sometimes also with the spouse. Interviews were carried out in local languages by a team of interviewers, who were trained and supervised by the researchers. The structured questionnaire was carefully tested prior to the survey and included sections on household demographics, agricultural production and marketing, other economic activities of the household, and a large range of institutional and contextual characteristics. Due to missing data, some of the household observations had to be excluded. The sample for this analysis includes 805 households for which complete data are available.

2.2 Measuring agricultural commercialization

We measure commercialization based on farmers' agricultural production and marketing activities over the 12-month period prior to the survey. We consider all crop and livestock enterprises of the farm household. While semi-subsistence farming is commonplace in the study region, there are hardly any households in the sample who did not sell at least small quantities of their harvest. Hence, measuring commercialization with a simple dummy variable would not be very useful. Instead, we compute the level of commercialization as the share of total farm output sold, a continuous indicator ranging between zero and one. The same approach was also used in previous studies on the effects of commercialization (Carletto et al., 2017; Ogutu et al., 2017; von Braun & Kennedy, 1994).

Farmers in Kisii and Nyamira sell their harvest in different types of markets. Small quantities are typically sold to traders at the farm gate or in local village markets. Larger quantities are often sold in the more distant main agricultural markets. Tea and coffee are often delivered to special collection centers at fixed prices. Fixed price arrangements do not exist for food crops in the study region. To calculate the level of commercialization, we use sample average prices for each commodity to value sold and unsold farm output.

2.3 Measuring income poverty

To analyze the effect of agricultural commercialization on household income and income poverty, we use 12-month data on income from all farm and off-farm economic activities.

Farm income is calculated as the value of all agricultural output (sold or unsold) minus production costs. Off-farm income includes the income from all employed and self-employed activities of household members and any transfers and land and capital rents. We report annual household income on a per capita basis expressed in Kenyan shillings (Ksh).

To evaluate effects of commercialization on income poverty, we build on the Foster, Greer, & Thorbecke (1984) class of poverty indicators. We convert per capita income in Ksh to international dollars, using the purchasing power parity (PPP) exchange rate.[3] We define "income poverty" as a dummy variable that takes a value of one if a household's per capita income falls below the international poverty line of 1.90 US dollars a day, and zero otherwise. We also calculate an income poverty gap as follows:

$$y_i = \frac{z - v_i}{z} \tag{1}$$

where z is the poverty line, and v_i is per capita income of household *i*. Households with incomes above the poverty line are automatically assigned a zero value. The income poverty gap is a continuous variable ranging between zero and one.

2.4 Measuring multidimensional poverty

Unlike income poverty, which is an indirect approach to assess a household's ability to satisfy basic needs, the multidimensional poverty index (MPI) tries to assess directly whether or not different types of basic needs are actually satisfied. The MPI was proposed by Alkire & Santos (2014). We closely follow their approach and adjust it to the data available in our sample of farm households in Kenya. Adjustments to fit the local context are recommended in the literature (OPHI, 2017; Ayuya et al., 2015; Alkire & Santos, 2014)

[3] In 2015, the PPP exchange rate was 1 US dollar = Ksh 43.89, while the official market exchange rate was 1 US dollar = Ksh 96.30.

The MPI measures acute poverty by capturing information on the proportion of households within a given population that experience multiple deprivations (multidimensional headcount ratio), and the intensity of their deprivation relative to minimum international standards of well-being. Alkire & Santos (2014) propose three dimensions of poverty – education, health, and living standard – and 10 indicators for which deprivations are assessed. We use the same dimensions and indicators as proposed by Alkire & Santos (2014), except for three modifications. The first modification is that we do not use the education indicator "no household member has completed 5 years of education", as 99% of our sample have at least one member with 5 or more years of education. We replace this indicator with "the household head has less than 5 years of education". The second and third modifications are that we do not use the health indicators "any child has died in the family" and "any child or adult is malnourished", as we do not have suitable individual-level health and nutrition data. Instead, we use household-level calorie consumption and dietary diversity scores. Descriptions of all 10 indicators used in this study with the corresponding cutoffs are shown in Table 1.

(Table 1 about here)

Using the zero and one values for each of the 10 indicators, we calculate different MPI measures for each sample household. First, we calculate the "total household deprivation score" by summing up the weighted values for each of the 10 indicators, using weights as shown in Table 1. The total household deprivation score ranges between zero and one, with larger values indicating higher levels of deprivation. Second, we create a "multidimensional poverty dummy", which takes a value of one if a household's total deprivation score is equal to or larger than a certain threshold, and zero otherwise. We use the common threshold of 0.33 (Alkire & Santos, 2014). The logic behind this MPI dummy is that a household is considered multidimensionally poor only if it suffers from deprivations in terms of several indicators. Third, we create the "multidimensional poverty intensity", which is equal to the deprivation score if the household is multidimensionally poor (MPI dummy = 1), and zero otherwise.[4] The interpretation of the MPI intensity is similar to the poverty gap, as it measures the magnitude of household deprivations relative to a poverty threshold.

We will use all three MPI measures to evaluate the effects of agricultural commercialization on MPI poverty. A relevant question in this context is to what extent we can actually expect possible income gains from commercialization to affect the different MPI dimensions and indicators. For the indicator related to the household head's level of education an effect can hardly be expected, because adult individuals are unlikely to return to school when their income increases. However, for most of the other indicators related to child education, nutrition, housing conditions, and asset ownership (Table 1) changes through income gains and other possible effects of commercialization are plausible.

3. Estimation strategy

To determine the effects of commercialization on income poverty and MPI poverty, we estimate the following set of regressions:

$$y_i = \alpha_0 + \alpha_1 C_i + \alpha_2 \boldsymbol{X}_i + \varepsilon_i \tag{2}$$

where y_i is the poverty indicator for household i, C_i is the level of commercialization, $\boldsymbol{X}_i$ is a vector of control variables, and ε_i is a random error term. We estimate separate models for each of the different poverty indicators (see previous subsection), always controlling for relevant household, farm, and contextual variables that may influence poverty through pathways other than commercialization. For the models with continuous dependent variables (income, poverty gap, deprivation scores, MPI intensity), we use ordinary least squares (OLS) estimators. Some of these variables are censored at zero and one, so that we also use

[4] Thus, the MPI intensity can either be 0 or take values in the range between 0.33 and 1. For an individual household it cannot take value between 0 and 0.33, even though the sample mean value can be in this range when taking the average across all households, including MPI poor and non-poor.

fractional logit estimators as robustness checks (Papke & Wooldridge, 1996). For the models with binary dependent variables (income poverty dummy, MPI dummy), we use logit estimators.

The main coefficient of interest in equation (2) is α_1, which measures the effect of commercialization on household income or poverty. We expect a positive coefficient α_1 when using absolute household income as the dependent variable, and a negative coefficient α_1 when using the poverty indicators. In other words, we expect commercialization to have income-increasing and poverty-reducing effects. However, the level of commercialization is potentially endogenous, which would lead to correlation between C_i and ε_i and biased estimates of α_1. Endogeneity of C_i may arise from unobserved heterogeneity, reverse causality, or measurement error. We test and control for endogeneity bias with a control function approach and instrumental variables, as explained below.

3.1 Control function approach

We use a control function (CF) approach (Wooldridge, 2015; Rivers & Vuong, 1988; Smith & Blundell, 1986) to account for potential endogeneity of the commercialization variable C_i. The CF approach uses instrumental variables (IV) for proper identification of causal effects and is more flexible with respect to functional form than standard IV estimators, such as two-stage least squares. Our choice of the CF approach is motivated by the censored nature of the commercialization variable, which can lead to non-linear corner solutions. In such cases, the CF approach is more efficient than two-stage least squares (Verkaart et al., 2017; Wooldridge, 2015).

The CF approach involves predicting residuals from a first-stage regression model of the determinants of commercialization, which must include one or more valid instruments. We use a fractional logit estimator for this first-stage regression. The predicted residuals are then included as an additional covariate in the second-stage regression – the income or poverty model in equation (2). A significant coefficient of the residual term in equation (2) would mean that C_i is endogenous. In that case, including the residual term would correct for endogeneity bias of the coefficient α_1. However, an insignificant residual term would mean that the null hypothesis of exogeneity of C_i cannot be rejected. In that case, excluding the residual term would produce unbiased and more efficient estimates.

3.2 Instrumental variables

As indicated, the CF approach requires one or more valid instruments in the first-stage regression. For an instrument to be valid it has to be correlated with the level of commercialization (C_i) but must not affect income or poverty outcomes (y_i) through other mechanisms. We use two instruments, namely the average number of motorcycles owned by households living in the same ward as the farmer himself/herself, and the average number of main market sellers in the ward. In Kenya, a ward is an administrative unit that is larger than a village, but smaller than a sub-county. As explained above, the farm survey covered farm households in 26 different wards. On average, 31 households were interviewed in each ward. The two instruments are explained and tested for validity in the following.

The first instrument – the average number of motorcycles in the ward – is constructed by counting the number of motorcycles owned by sample households in each ward (excluding the farmer himself/herself), and then dividing by the number of sample households in the ward. Less than 10% of the households own any motorized means of transportation (average number of motorcycles in the sample is 0.08). Yet, the markets are often distant, so that it is difficult for farmers to make larger sales of agricultural output without using a motor vehicle. Since most of the feeder roads in the study area are not paved and public transport services barely exist, motorcycles owners tend to provide transport services to households located in the same area. Farmers often use these transport services, as do local traders who buy farm produce at the farm gate and sell in more distant markets. Thus, more motorcycles in the ward imply better market access. The average number of motorcycles in the ward is significantly correlated with the level of commercialization (p-value=0.007). Hence, the first condition for instrument validity is satisfied.

To test for the second condition of instrument validity we need to show that the number of motorcycles does not affect income and poverty through mechanisms other than commercialization. Since we use the average number of motorcycles owned by households in the ward, as opposed to individual household ownership, the instrument is not significantly associated with any of the household-level poverty indicators, neither with nor without controlling for other possible poverty determinants (Table A1 in the Appendix). We also tested for possible correlations between the instrument and other farm and household-level characteristics, as it is possible that transport services also change households' access to information, inputs, and technologies. None of the correlation coefficients was found to be statistically significant (Table A2 in the Appendix). Nor did we find any significant correlation between the number of motorcycles in the ward and other ward-level wealth indicators (Table A3). These test results suggest that the second condition of instrument validity is also satisfied.

The second instrument – the average number of main market sellers in the ward – is constructed by counting the number of farmers in each ward who sold at least some of their produce in main agricultural markets (excluding the farmer himself/herself) and then dividing by the number of sample households in the ward. As mentioned above, the main agricultural markets are the locations where larger quantities of agricultural output are typically sold (smaller quantities are also sold at the farm gate or in local village markets). Hence, farmers who sell some or all of their produce in the more distant main markets are likely to have a higher level of commercialization. One-third of the farm households in our sample sell at least some of their harvest in agricultural main markets. As expected, these farmers have significantly larger farm output and sales revenues than their colleagues not selling in the agricultural main markets (Table A4).

However, why should the presence of main market sellers in the ward affect the level of commercialization of other farmers? The choice of this instrument is inspired by the recent strand of literature on peer learning, showing that farmers tend to learn about the benefits of innovations from their peers (Magnan et al., 2015; Krishnan & Patnam, 2013). We posit that farmers in the same ward will likely belong to the same social networks. Hence, farmers who benefit from selling in main agricultural markets may potentially influence their peers to also supply such markets, entailing higher levels of commercialization. Farmers living in the same neighborhood may also benefit from collective action, which can help reduce transaction costs and enhance market participation (Fischer & Qaim, 2012). Andersson et al. (2015) used data from Kenya to show that farmers whose neighbors supplied supermarkets were more likely to also supply supermarkets, because of joint organization and shared transport costs. In our data, we find that the average number of main market sellers in the ward is significantly correlated with the degree of commercialization of individual farmers (p-value=0.000). Hence, the first condition of instrument validity is satisfied.

But is the number of main market sellers in the ward also affecting income or poverty outcomes directly? This could happen when more commercialized and better-off households cluster in the same wards. However, such clustering does not seem to occur in the study region. The instrument is not correlated with any of the ward-level wealth indicators, as shown in Table A3 in the Appendix. Nor do we find significant correlation between the instrument and individual farm household characteristics (Table A2). When correlating the number of main market sellers in the ward with household-level poverty indicators, some of the correlation coefficients are statistically significant. However, once we control for commercialization in regression models the instrument coefficients turn insignificant (Table

A1 in the Appendix). Hence, there do not seem to be effects of the instrument on income or poverty through mechanisms other than commercialization, so the second condition for instrument validity is also satisfied.

We also tested for overidentifying restrictions with both instruments, as shown in Table A5 in the Appendix. Based on the test results we cannot reject the null hypothesis of joint instrument exogeneity. We conclude that the two instruments are valid.

3.3 Quantile regressions

The effects of commercialization on household income and poverty may be heterogeneous, meaning that some households may benefit more than others. From a social development perspective, we are particularly interested to understand whether the poorest households benefit to the same extent as the relatively richer ones. The model in equation (2) estimates average treatment effects, it cannot estimate impact heterogeneity. We use quantile regressions to examine potential impact heterogeneity of agricultural commercialization. Quantile regressions allow one to examine whether the effect of a particular regressor changes over the conditional distribution of the dependent variable, instead of only analyzing the regressor’s average effect (Koenker & Hallock, 2001; Buchinsky, 1998).

The conditional quantile functions of the income and poverty indicators (y_i) given regressor x_i (in our case the level of commercialization, C_i) can be expressed as follows:

$$y_i = x_i' b_t + u_{t_i}, \qquad Q_t(y_i \mid x_i) = x_i' b_t, \tag{3}$$

where $Q_t(y_i \mid x_i)$ is the conditional quantile of y_i at quantile t , with $0 < t < 1$. b_t is the vector of parameters to be estimated. The parameters are obtained by minimizing the following equation, which is solved by linear programming:

$$\min_{\beta_\tau} \frac{1}{n} \left\{ \sum_{i: y_i \geq x_i'\beta_\tau} \tau \, | y_i - x_i'\beta_\tau | + \sum_{i: y_i < x_i'\beta_\tau} (1-\tau) \, | y_i - x_i'\beta_\tau | \right\} \quad (4)$$

Equation (4) implies that the parameters can be estimated at different points or quantiles (τ) of the dependent variable by minimizing the sum of asymmetrically weighted absolute residuals (Koenker & Hallock, 2001).

We estimate quantile regressions for key continuous outcome variables – namely per capita income, multidimensional poverty intensity, and total household deprivation scores – in order to evaluate potential effects of commercialization on inequality. Effects of commercialization are estimated at five different quantiles ($\tau = 0.10$, 0.25, 0.50, 0.75, and 0.90). We use the same variables as in equation (2) as regressors. For interpretation of the effects of C_i it is important to consider the distribution of the dependent variable. When using absolute income as dependent variable, $\tau = 0.10$ represents the poorest group of households. When using the MPI intensity and total deprivation scores as dependent variables, $\tau = 0.10$ represents the least-poor households.

4. Results and discussion

4.1 Descriptive statistics

Table 2 shows summary statistics for the full sample of farm households and also disaggregated by level of commercialization. For these descriptive comparisons we subdivide the sample into quartiles according to the household level of commercialization and compare the most commercialized (highest quartile – MC25%) with the least commercialized (lowest quartile – LC25%) households.

(Table 2 about here)

On average, sample households sell 44% of their farm output, while the most and least commercialized quartiles sell 70% and 16% of their farm output, respectively (Table 2). As one would expect, more commercialized households tend to have larger farm sizes, higher levels of education, more assets, and better access to credit and extension. Commercialization is also positively associated with several other socioeconomic variables, as well as with farm input use and productivity.

Table 3 presents the share of households deprived in each of the 10 MPI indicators. A large variation across the different indicators is observed. While a relatively small share of the sample households is deprived in terms of the education indicators, most of the households are deprived in terms of access to electricity (89%) and modern cooking fuel (97%). Figure 1 confirms that deprivations are much more prevalent for the living standard indicators than for the education and health indicators. Figure 1 also shows that the least-commercialized households suffer significantly more from deprivations than the most-commercialized households in terms of all three MPI dimensions.

(Table 3 about here)

(Figure 1 about here)

Table 4 presents summary statistics for the different poverty indicators. Sixty-two percent of the households are poor in terms of income poverty, meaning that they have less than 1.90 US dollars per capita and day in PPP terms. The income poverty headcount is much larger among the least-commercialized than among the most-commercialized households. The income poverty gap is also much larger among the least-commercialized households.

(Table 4 about here)

In terms of multidimensional poverty, the mean total deprivation score of 0.34 implies that the average household suffers from 34% of the possible deprivations. As explained in section 2, a household is classified as MPI poor when the total household deprivation score is larger than 0.33; this applies to 51% of the households. The MPI intensity is 0.24 across all households.[5] Table 4 shows that the least-commercialized farm households are significantly more affected by the prevalence and depth of MPI poverty than the most commercialized households.

While the comparisons between more and less commercialized households are in line with our hypothesis that commercialization contributes to poverty reduction, the differences in Table 4 cannot be interpreted as causal effects, because they do not control for possible confounding factors. We control for confounding factors in the following subsections through the regression models explained in section 3.

4.2 Average treatment effects

The first-stage results of the CF approach are shown in Table A6 in the Appendix. The residuals from this first-stage regression are included in the CF models in Tables 5-7. The residual term is insignificant in all of the models, so we cannot reject the null hypothesis of commercialization being exogenous. Hence we prefer the models without the residual terms for interpretation, because these produce more efficient estimates. However, we show both versions of the models. The signs and magnitudes of the estimated commercialization coefficients are similar with and without the residual terms included, which underlines the robustness of the general findings.

Table 5 presents the effects of commercialization on per capita income. Commercialization has a positive and significant effect. The level of commercialization is a continuous variable ranging from zero to one, which has to be taken into account when interpreting the coefficient magnitudes. The estimate in column (1) of Table 5 suggests that a 0.1 increase (10 percentage points) in the level of commercialization increases annual per capita income by 5,000 Ksh,

[5] The MPI intensity calculated here is very similar to the MPI intensity of 0.25 reported in a recent study for rural Kenya in general (OPHI, 2017).

which is equivalent to a 14% gain relative to the total sample mean income. Relative to the lower mean income of the least commercialized households, 5,000 Ksh of additional income would represent a gain of 29%. A hypothetical shift from a zero level of commercialization to 44% – the sample mean level of commercialization – would more than double per capita income. These are net income gains of commercialization after controlling for other important factors that can also influence income such as education, farm size, ownership of other productive assets, agroecology, as well as infrastructure and institutional conditions.

(Table 5 about here)

Given the large standard deviation of per capita income, we also estimated the same model with a log-transformation of the dependent variable. Results are shown in columns (3) and (4) of Table 5. This alternative specification confirms the large positive income effects of agricultural commercialization. The estimates suggest that a 10 percentage point increase in the level of commercialization would increase per capita income by 17% after controlling for other factors.

Table 6 shows the effects of commercialization on income poverty. The average partial effect estimate of -0.506 in column (1) implies that full commercialization would halve the probability of falling below the poverty line of 1.90 US dollars a day. A 10 percentage point increase in the level of commercialization would reduce the prevalence of income poverty by 5.1 percentage points. Columns (3) and (4) of Table 6 show that commercialization also reduces the income poverty gap significantly. Holding other factors constant, a 10 percentage point increase in the level of commercialization reduces the poverty gap by an average of 5.3 percentage points. This is equivalent to a 16% reduction in the mean poverty gap of the total sample. Fractional logit specifications of the poverty gap model are shown in Table A7 in the Appendix with very similar results.

(Table 6 about here)

Table 7 shows the effects of commercialization on multidimensional poverty. The average partial effect estimate of 0.226 in column (1) implies that full commercialization would reduce the probability of being MPI poor by 22.6 percentage points. A 10 percentage point increase in the level of commercialization reduces the prevalence of MPI poverty by 2.3 percentage points. Columns (3) and (4) of Table 7 show that commercialization also reduces the multidimensional poverty intensity. A 10 percentage point increase in the level of commercialization reduces the MPI intensity by approximately 1.5 percentage points. Fractional logit specifications of the MPI intensity model are shown in Table A7 in the Appendix with very similar results.

(Table 7 about here)

4.3 Mechanisms of poverty reduction

The results in Tables 6 and 7 suggest that the effects of commercialization on multidimensional poverty are smaller than the effects on income poverty. This is not surprising. Income poverty falls automatically when poor households experience income gains that are sufficiently large to lift them above the income poverty line. However, whether the additional income is really used to satisfy basic needs is a question that cannot be answered with income-related poverty indicators alone.

The results with the multidimensional poverty indicators in Table 7 suggest that the additional income from commercialization is indeed used to satisfy basis needs to a significant extent. In other words, agricultural commercialization contributes to poverty reduction regardless of whether poverty is assessed and measured through indirect or direct approaches. As one would expect, the multidimensional poverty effects differ by MPI dimension, as is shown in Table A8 in the Appendix. And this also explains why the MPI effects are smaller than the income poverty effects. Commercialization has a small decreasing effect on education deprivations, but this effect is not statistically significant. As discussed above, education deprivations among sample households are relatively small anyway, and the education level of the household head will hardly change through additional commercialization income.

The commercialization effect on living standard deprivations is somewhat larger and statistically significant (Table A8). While some of the living standard indicators – such as housing conditions, cooking fuel and asset ownership – can easily be improved when the income increases, other indicators – such as access to electricity and safe drinking water – may require broader infrastructure investments that are beyond the scope of individual households. The largest effects of commercialization on MPI poverty are observed in terms of reducing health deprivations. As explained, the indicators used for the health dimension are calorie consumption and dietary quality, which households can improve through rising incomes. Given widespread food insecurity among smallholder farm households, the finding that commercialization improves nutrition is certainly welcome.

So far, we have assumed that the effects of commercialization on multidimensional poverty are primarily channeled through the income pathway. This is confirmed in Table A9 in the Appendix, where we regress the MPI intensity on income and other explanatory variables. Income gains contribute significantly to reducing MPI intensity. Interestingly, the effect is stronger for farm income than for total household income. Tables A10 and A11 in the Appendix show some of the main pathways how commercialization contributes to rising farm and total household incomes, namely through production increases resulting from higher input intensity and productivity. Table A11 also shows that agricultural productivity and the value of production significantly contribute to income poverty and multidimensional poverty reduction.

4.4 Heterogeneous treatment effects

We now examine whether the effects of commercialization on income and multidimensional poverty are heterogeneous. As mentioned, it is possible that different types of households benefit more or less than others. We estimate heterogeneous treatment effects with quantile regressions. The estimation results are shown in Tables A12-A14 in the Appendix. The commercialization effects are shown graphically in Figure 2.

(Figure 2 about here)

Panel (A) of Figure 2 shows the quantile effects of commercialization on per capita income. With per capita income as dependent variable, the 0.10 quantile includes the poorest, whereas the 0.90 quantile includes the riches sample households. As can be seen, commercialization has significantly positive effects on per capita income across all quantiles. However, the absolute income gains for the poorest households are smaller than those for the richest households. This difference between the lowest and highest quantile is statistically significant (Table 8). Hence, commercialization increases income inequality.

(Table 8 about here)

Panel (B) of Figure 2 depicts the quantile effects for multidimensional poverty intensity. Here it is important to stress that larger values of the dependent variable indicate higher levels of poverty, so the quantile interpretation is reversed: the lowest quantile represents the better-off households, meaning those least affected by multidimensional poverty. As can be seen, commercialization significantly reduces MPI intensity for the poorer households in the higher quantiles. Although some variation occurs, the differences between the effects for these upper quantiles are not statistically significant (Table 8). For the lower quantiles, effects could not be estimated, because the better-off households have an MPI intensity of zero.

However, many of the households not classified as MPI poor still suffer from deprivations in terms of individual indicators. Therefore, we also estimated a quantile regression using the total household deprivation score as dependent variable. Results are shown in panel (C) of Figure 2. Again, the lowest quantile represents the better-off households, meaning those least affected by the different deprivations. As can be seen, commercialization significantly reduces total household deprivations across all quantiles, except for the richest households (0.10 quantile). The effects are stronger for the poorest households, and the difference between the highest and lowest quantile is statistically significant (Table 8). These results suggest that – in spite of rising income inequality – agricultural commercialization effectively contributes to satisfying basic needs, especially among the most deprived farm households.

5. Conclusion

Using data from smallholder farm households in Kenya and various regression techniques, we have analyzed the effects of agricultural commercialization on household income, income poverty, and multidimensional poverty. The contribution to the literature lies particularly in the analysis of impacts on multidimensional poverty. Looking at various dimensions of poverty, as we have done using the multidimensional poverty index (MPI) proposed by Alkire & Santos (2014), is important, because it cannot simply be assumed that income gains from commercialization will always be spent on satisfying basic needs. The MPI captures three dimensions of poverty, namely education, health/nutrition, and living standard, each with various indicators. Another novelty of our study is that we have estimated heterogeneous treatment effects of commercialization using quantile regressions, which has not been done previously.

Results showed that commercialization increases per capita income in smallholder farm households and reduces income poverty and multidimensional poverty. Even though the effects are significant for all of the outcome variables, the impact on income poverty is stronger than the impact on multidimensional poverty. This is plausible because some of the basic needs deprivations can be remedied more easily than others. For instance, households can improve their nutrition and housing conditions when their income increases, but may depend on public infrastructure investments before they can notably improve their access to electricity and safe drinking water. Hence, impact evaluations based on income poverty measures alone may overestimate reductions in terms of various household deprivations.

The quantile regression results showed that absolute gains in per capita income through commercialization are larger for the richer than for the poorer households, suggesting that commercialization contributes to rising income inequality. However, we did not find heterogeneous effects of commercialization on the multidimensional poverty intensity. For reductions in total household deprivations we even found stronger effects for the most deprived households. We conclude that agricultural commercialization is an important and effective mechanism towards achieving the sustainable development goals.

An important policy implication is that commercialization can be fostered through enhancing smallholder market access in terms of investments in road and market infrastructure and strengthening relevant market institutions. Market-linkage support specifically tailored to the needs of the poor may potentially also help to avoid rising income inequality. However, commercialization alone will not suffice to eradicate multidimensional poverty in the small farm sector. Complementary interventions to improve access to sanitation, healthcare, drinking water, education, and sustainable energy will be required such that rising household demand for these basic goods and services resulting from income gains is effectively met by high-quality supply.

While our results proved to be robust across different model specifications, two limitations should briefly be discussed. First, we relied on cross-section observational data which means that dealing with possible endogeneity is challenging. Follow-up research with panel data could further improve the identification strategy and could also provide interesting insights into possible longer-term effects of commercialization. Second, the concrete results from smallholder farmers in Kenya should not be generalized. The situation of farmers in the study area is typical for the African small farm sector, so that some broader general lessons can be learned. But in terms of the specific effects of commercialization on different MPI indicators, results may differ by geographical context.

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Table 1. Dimensions and indicators of the multidimensional poverty index

Dimension and indicator	Description and deprivation cutoff	Relative weight
Education		
Years of schooling	The household head has less than 5 years of education	1/6
Child school attendance	The household has a school-aged child not attending school up to class 8	1/6
Health		
Nutrition 1	The household consumes less than 2400 kcal per day and adult male equivalent (AE)	1/6
Nutrition 2	The household has a dietary diversity score of 5 or less out of 10 possible food groups [a]	1/6
Living standard		
Electricity	The household has no electricity	1/18
Sanitation	The household's toilet facility is not improved, or it is improved but shared with other households	1/18
Drinking water	The household does not have access to safe drinking water	1/18
Floor	The household has dirt, sand, or dung floor	1/18
Cooking fuel	The household cooks with dung, wood or charcoal	1/18
Asset ownership	The 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 very similar to those in Alkire & Santos (2014), except for small modifications in three indicators (years of schooling, nutrition 1, nutrition 2) as explained in the text. [a] The 10 food groups used are those recommended for the minimum dietary diversity score for women (FAO and FHI 360, 2016).

Table 2. Summary statistics by level of commercialization

Variables	Full sample Mean	MC25% Mean	LC25% Mean	Mean difference
Socioeconomic characteristics				
Commercialization (share of farm output sold, 0-1)	0.44	0.70	0.16	0.55***
	(0.21)	(0.09)	(0.09)	
Age of household head (years)	49.27	48.35	48.34	0.01
	(12.57)	(11.22)	(13.63)	
Male household head (dummy)	0.77	0.82	0.67	0.15***
	(0.42)	(0.39)	(0.47)	
Education of household head (years)	8.94	9.69	7.80	1.89***
	(3.77)	(3.19)	(4.09)	
Household size (adult equivalents)	3.99	3.92	3.89	0.03
	(1.58)	(1.62)	(1.63)	
Farm size (acres)	1.61	2.04	1.14	0.90***
	(1.27)	(1.55)	(0.95)	
Farm productive assets (1,000 Ksh)	19.93	23.78	15.54	8.24***
	(23.69)	(25.43)	(20.84)	
Household income (1,000 Ksh/year)	180.53	281.36	90.69	190.67***
	(218.46)	(285.81)	(103.12)	
Off-farm income (dummy)	0.81	0.78	0.81	-0.04
	(0.39)	(0.42)	(0.39)	
Access to credit (dummy)	0.78	0.80	0.69	0.11**
	(0.41)	(0.40)	(0.46)	
Distance to closest market (km)	4.91	4.60	4.97	-0.37
	(7.01)	(5.25)	(7.53)	
Distance to closest extension agent (km)	4.34	3.89	5.52	-1.63***
	(4.93)	(4.67)	(5.40)	
Household head/spouse is a group official (dummy)	0.35	0.41	0.28	0.13***
	(0.48)	(0.49)	(0.45)	
Poor agroecology [a] (dummy)	0.13	0.07	0.16	0.09***
	(0.34)	(0.26)	(0.37)	
Farm production diversity (no. of food crop/livestock species)	11.11	11.21	10.33	0.88**
	(4.39)	(4.72)	(4.06)	
Livestock ownership (tropical livestock units - TLU)	1.73	1.60	1.41	0.19
	(1.62)	(1.65)	(1.42)	
Motorcycles in ward (number [b])	0.08	0.10	0.08	0.02***
	(0.05)	(0.06)	(0.05)	
Main market sellers in ward (number [b])	0.32	0.36	0.29	0.07***
	(0.11)	(0.12)	(0.11)	
Farm productivity and input use				
Value of crop output (1,000 Ksh/acre)	75.81	105.13	70.32	34.80***
	(81.94)	(110.42)	(97.12)	
Seed expenditure (Ksh/acre)	3184.90	3212.07	3018.04	194.03
	(3892.72)	(3792.63)	(2411.09)	
Fertilizer expenditure (Ksh/acre)	6269.29	6569.09	5383.40	1185.69**
	(5479.26)	(6338.84)	(4515.33)	
Manure expenditure (Ksh/acre)	708.89	666.33	608.87	57.46
	(2958.03)	(2794.36)	(2171.11)	
Pesticide expenditure (Ksh/acre)	659.72	911.25	330.46	580.79***
	(1626.87)	(2038.22)	(1080.75)	
Observations	805	201	202	

Notes: Standard deviations are shown in parentheses. MC25%, 25% most commercialized households; LC25%, 25% least commercialized households; Ksh, Kenyan shillings. [a] Variable takes a value of one if a farmer reported serious crop loss due to pests and diseases. [b] Ward-level variables were divided by the number of households interviewed in each ward to allow meaningful comparison. *, **, and *** significant at 10%, 5%, and 1% level, respectively.

Table 3. Share of households deprived in terms of MPI indicators (indicators ranked by share of deprived households)

Indicator	Deprivations cutoffs	Full sample	MC25%	LC25%	Mean difference
Years of schooling	Household head has less than 5 years of education (dummy)	0.130	0.070	0.203	-0.133***
		(0.337)	(0.255)	(0.403)	
Nutrition 2 (dietary quality)	Household consumed 5 or less out of 10 possible food groups (dummy)	0.142	0.090	0.248	-0.158***
		(0.349)	(0.286)	(0.433)	
Child school attendance	Household has a school-aged child not attending up to class 8 (dummy)	0.154	0.144	0.178	-0.033
		(0.361	(0.352)	(0.384)	
Nutrition 1 (calorie consumption)	Household consumes less than 2400 kcal/day/AE (dummy)	0.266	0.179	0.337	-0.157***
		(0.442)	(0.384)	(0.473)	
Asset ownership	Household does not own more than one of specified assets [a] (dummy)	0.338	0.279	0.436	-0.157***
		(0.473)	(0.449	(0.497)	
Sanitation	Household's toilet facility is not improved (dummy)	0.553	0.488	0.649	-0.161***
		(0.498)	(0.487)	(0.479)	
Drinking water	Household does not have access to safe drinking water (dummy)	0.557	0.532	0.633	-0.101**
		(0.497)	(0.500)	(0.483)	
Floor	Household has dirt, sand, or dung floor (dummy)	0.737	0.711	0.787	-0.076*
		(0.441	(0.454)	(0.410)	
Electricity	Household has no electricity (dummy)	0.889	0.861	0.911	-0.050
		(0.314)	(0.347)	(0.286)	
Cooking fuel	Household cooks with dung, wood, or charcoal (dummy)	0.968	0.955	0.985	-0.030*
		(0.177)	(0.207)	(0.121)	
	Observations	805	201	202	

Note: Standard deviations are shown in parentheses. For further details of indicator descriptions, see Table 1. MC25%, 25% most commercialized households, LC25%, 25% least commercialized households, AE, male adult equivalent. *, **, and *** significant at 10%, 5%, and 1% level, respectively.

Table 4. Poverty indicators by level of commercialization

Variable	Full sample Mean	MC25% Mean	LC25% Mean	Mean Difference
Household income (1,000 Ksh)	180.53	281.36	90.69	190.67***
	(218.46)	(285.81)	(103.12)	
Per capita income (1,000 Ksh)	35.09	54.38	17.29	37.09***
	(44.90)	(59.92)	(19.26)	
Income poverty (dummy)	0.62	0.40	0.83	-0.43***
	(0.49)	(0.49)	(0.38)	
Income poverty gap (0-1)	0.34	0.16	0.56	-0.40***
	(0.34)	(0.25)	(0.34)	
Total household deprivation score (0-1)	0.34	0.29	0.40	-0.11***
	(0.17)	(0.14)	(0.18)	
Multidimensional poverty (dummy)	0.51	0.39	0.65	-0.26***
	(0.50)	(0.49)	(0.48)	
Multidimensional poverty intensity (0-1)	0.24	0.17	0.33	-0.16***
	(0.25)	(0.22)	(0.27)	
Observations	805	201	202	

Notes: Standard deviations are shown in parentheses. MC25%, 25% most commercialized households; LC25%, 25% least commercialized households; Ksh, Kenyan shillings; *, **, and *** significant at 10%, 5%, and 1% level, respectively.

Table 5. Effect of commercialization on per capita income

	Per capita income (1,000 Ksh)		Log of per capita income	
	(1)	(2)	(3)	(4)
Variables	OLS	CF	OLS	CF
Commercialization (0-1)	50.124***	52.855***	1.688***	1.712***
	(8.448)	(9.508)	(0.143)	(0.196)
Age of household head (years)	-0.087	-0.097	-0.002	-0.002
	(0.143)	(0.134)	(0.002)	(0.002)
Age squared (years)	0.008	0.010	-0.000	-0.000
	(0.010)	(0.008)	(0.000)	(0.000)
Male household head (dummy)	8.454***	8.259***	0.324***	0.323***
	(2.932)	(2.764)	(0.079)	(0.067)
Education of household head (years)	1.530***	1.468***	0.042***	0.042***
	(0.366)	(0.370)	(0.009)	(0.009)
Household size (number)	-5.570***	-5.482***	-0.132***	-0.131***
	(1.050)	(1.080)	(0.014)	(0.017)
Farm size (acres)	3.328	2.550	0.124***	0.117**
	(1.824)	(3.444)	(0.037)	(0.054)
Farm size squared (acres)	0.154	0.351	0.000	0.002
	(0.781)	(1.562)	(0.018)	(0.022)
Farm size cubed (acres)	0.105	0.089	0.000	-0.000
	(0.127)	(0.296)	(0.002)	(0.003)
Farm productive assets (1,000 Ksh)	0.486***	0.479***	0.009***	0.009***
	(0.094)	(0.084)	(0.001)	(0.001)
Access to credit (dummy)	2.786	2.329	0.150***	0.146**
	(3.276)	(3.141)	(0.049)	(0.068)
Distance to closest market (km)	0.013	0.026	0.001	0.001
	(0.271)	(0.252)	(0.005)	(0.004)
Group official (dummy)	-1.278	-1.538	-0.011	-0.013
	(2.945)	(2.957)	(0.054)	(0.053)
Off-farm income (dummy)	18.511***	18.492***	0.797***	0.797***
	(3.316)	(3.110)	(0.072)	(0.066)
Poor agroecology (dummy)	2.724	3.517	0.111	0.118
	(3.349)	(4.419)	(0.070)	(0.085)
Livestock ownership (TLU)	1.111	1.224	0.073***	0.074***
	(1.014)	(0.959)	(0.018)	(0.017)
Residual from first stage		-3.174		-0.029
		(8.985)		(0.167)
Sub-county dummies	Yes	Yes	Yes	Yes
Constant	-9.212	-6.521	1.225***	1.250***
	(9.483)	(10.465)	(0.199)	(0.266)
Observations	805	805	805	805
R-squared	0.366	0.366	0.567	0.567

Notes: Coefficient estimates are shown with robust standard errors in parentheses. In columns (1) and (2), standard errors are clustered at farmer group level. In columns (2) and (4), standard errors are bootstrapped with 1000 replications. OLS, ordinary least squares; CF, control function estimator; TLU, tropical livestock units. *, **, and *** significant at 10%, 5%, and 1% level, respectively.

Table 6. Effect of commercialization on income poverty

	Income poverty (dummy)		Income poverty gap (0-1)	
	(1)	(2)	(3)	(4)
Variables	Logit	CF	OLS	CF
Commercialization (0-1)	-0.506***	-0.573***	-0.531***	-0.562***
	(0.072)	(0.110)	(0.049)	(0.075)
Age of household head (years)	0.001	0.002	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Age squared (years)	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Male household head (dummy)	-0.179***	-0.175***	-0.127***	-0.125***
	(0.052)	(0.041)	(0.031)	(0.025)
Education of household head (years)	-0.014***	-0.013**	-0.013***	-0.012***
	(0.004)	(0.005)	(0.003)	(0.003)
Household size (number)	0.071***	0.069***	0.041***	0.040***
	(0.007)	(0.008)	(0.005)	(0.005)
Farm size (acres)	-0.045***	-0.025	-0.036**	-0.027
	(0.019)	(0.030)	(0.014)	(0.020)
Farm size squared (acres)	0.000	-0.005	0.001	-0.001
	(0.012)	(0.016)	(0.007)	(0.008)
Farm size cubed (acres)	-0.001	-0.001	0.000	0.000
	(0.002)	(0.003)	(0.001)	(0.001)
Farm productive assets (1,000 Ksh)	-0.004***	-0.004***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.000)	(0.000)
Access to credit (dummy)	-0.063**	-0.051	-0.067***	-0.062**
	(0.030)	(0.040)	(0.019)	(0.025)
Distance to closest market (km)	0.001	0.001	0.000	-0.000
	(0.002)	(0.002)	(0.001)	(0.001)
Group official (dummy)	-0.007	-0.001	0.000	0.003
	(0.032)	(0.031)	(0.020)	(0.020)
Off-farm income (dummy)	-0.292***	-0.291***	-0.227***	-0.227***
	(0.036)	(0.044)	(0.020)	(0.023)
Poor agroecology (dummy)	-0.003	-0.022	-0.029	-0.038
	(0.050)	(0.054)	(0.026)	(0.031)
Livestock ownership (TLU)	-0.018*	-0.020*	-0.023***	-0.025***
	(0.010)	(0.010)	(0.005)	(0.006)
Residual from first stage		0.079		0.036
		(0.096)		(0.064)
Sub-county dummies	Yes	Yes	Yes	Yes
Constant			0.905***	0.874***
			(0.067)	(0.093)
Observations	805	805	805	805
(Pseudo) R-squared	0.342	0.343	0.472	0.472

Notes: In columns (1) and (2), average partial effects are shown with robust standard errors in parentheses. In columns (3) and (4), coefficient estimates are shown with robust standard errors in parentheses. In columns (1) and (3), standard errors are clustered at farmer group level. In columns (2) and (4), standard errors are bootstrapped with 1000 replications. OLS, ordinary least squares; CF, control function estimator; TLU, tropical livestock units. *, **, and *** significant at 10%, 5%, and 1% level, respectively.

Table 7. Effect of commercialization on multidimensional poverty

	Multidimensional poverty (dummy)		Multidimensional poverty intensity (0-1)	
	(1)	(2)	(3)	(4)
Variables	Logit	CF	OLS	CF
Commercialization (0-1)	-0.226***	-0.189	-0.153***	-0.144***
	(0.083)	(0.124)	(0.042)	(0.057)
Age of household head (years)	-0.001	-0.001	-0.000	-0.000
	(0.001)	(0.002)	(0.001)	(0.001)
Age squared (years)	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Male household head (dummy)	-0.028	-0.031	-0.022	-0.023
	(0.038)	(0.043)	(0.022)	(0.022)
Education of household head (years)	-0.040***	-0.041***	-0.024***	-0.024***
	(0.004)	(0.005)	(0.002)	(0.003)
Household size (number)	0.019**	0.021**	0.014***	0.014***
	(0.009)	(0.009)	(0.005)	(0.005)
Farm size (acres)	-0.027	-0.038	-0.015	-0.018
	(0.019)	(0.035)	(0.009)	(0.016)
Farm size squared (acres)	-0.006	-0.004	-0.001	-0.000
	(0.010)	(0.017)	(0.005)	(0.007)
Farm size cubed (acres)	0.002	0.002	0.001	0.001
	(0.001)	(0.003)	(0.001)	(0.001)
Farm productive assets (1,000 Ksh)	-0.004***	-0.004***	-0.002***	-0.002***
	(0.001)	(0.001)	(0.000)	(0.000)
Access to credit (dummy)	-0.102***	-0.108***	-0.049***	-0.050**
	(0.029)	(0.041)	(0.016)	(0.020)
Distance to closest market (km)	-0.001	-0.001	-0.001*	-0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Group official (dummy)	-0.014	-0.017	-0.024	-0.024
	(0.031)	(0.037)	(0.016)	(0.017)
Off-farm income (dummy)	-0.049	-0.050	-0.031	-0.031
	(0.053)	(0.044)	(0.025)	(0.020)
Poor agroecology (dummy)	0.013	0.023	0.013	0.015
	(0.051)	(0.057)	(0.026)	(0.027)
Livestock ownership (TLU)	-0.018	-0.017	-0.013***	-0.012**
	(0.011)	(0.013)	(0.005)	(0.006)
Residual from first stage		-0.044		-0.010
		(0.108)		(0.051)
Sub-county dummies	Yes	Yes	Yes	Yes
Constant			0.670***	0.678***
			(0.053)	(0.073)
Observations	805	805	805	805
(Pseudo) R-squared	0.199	0.199	0.300	0.301

Notes: In columns (1) and (2), average partial effects are shown with robust standard errors in parentheses. In columns (3) and (4), coefficient estimates are shown with robust standard errors in parentheses. In columns (1) and (3), standard errors are clustered at farmer group level. In columns (2) and (4), standard errors are bootstrapped with 1000 replications. OLS, ordinary least squares; CF, control function estimator; TLU, tropical livestock units. *, **, and *** significant at 10%, 5%, and 1% level, respectively.

Table 8.Wald test for equality of quantile coefficients (conditional slope parameters)

Poverty indicator	Wald test F-statistic of t = 0.90 versus…	
	t = 0.10	t = 0.50
Per capita income (Ksh 1,000)	5.60**	1.68
Multidimensional poverty intensity (0-1)	-	0.44
Total household deprivation score (0-1)	2.78*	0.55

Notes: * and ** significant at 10% and 5% level, respectively.

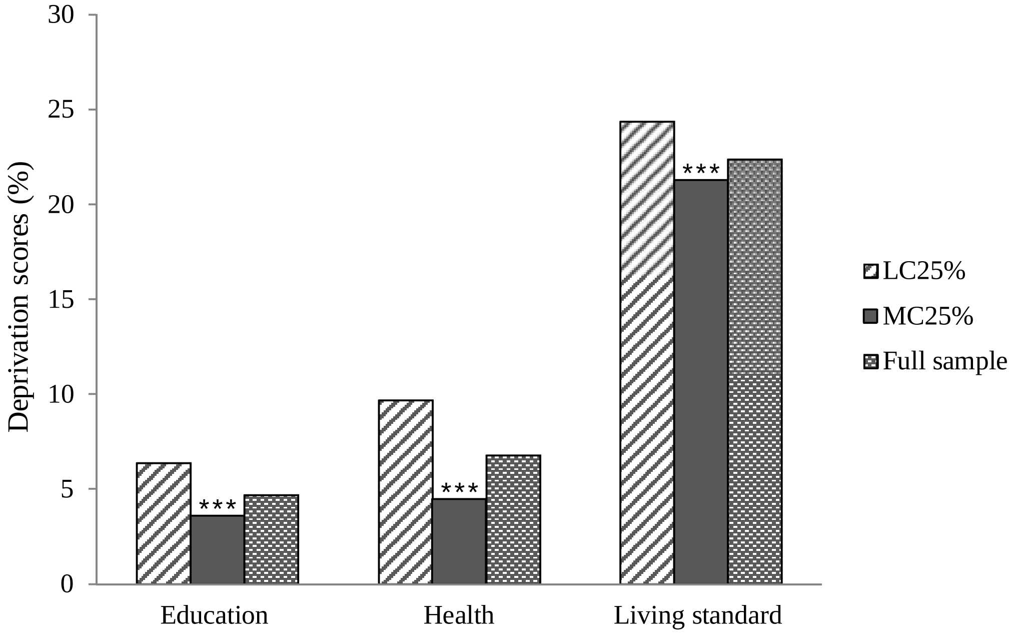

Figure 1. Mean household deprivation scores by multidimensional poverty dimension.

Notes: Deprivation scores in each of the three dimensions can range between 0 and 33%. MC25%, 25% most commercialized households; LC25%, 25% least commercialized households *** Difference between most and least commercialized households is significant at 1% level.

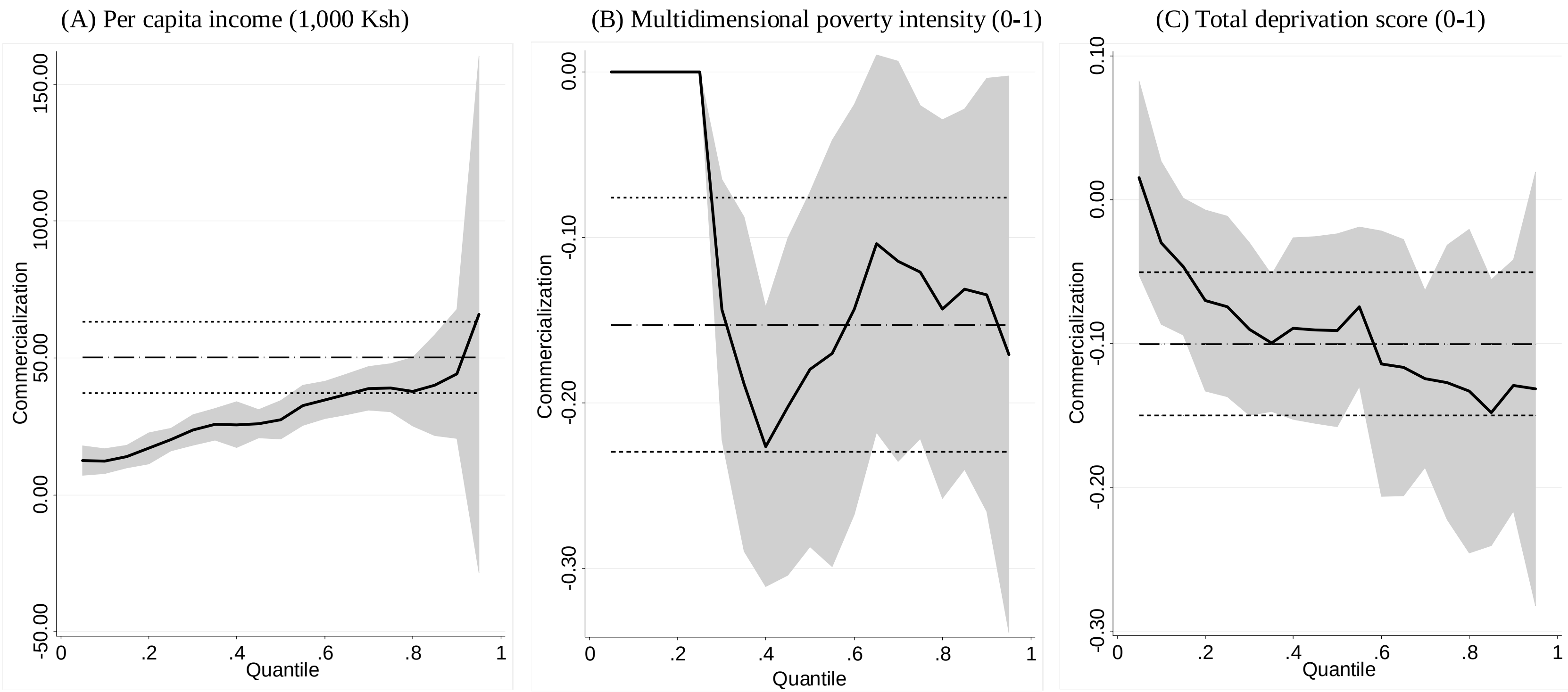

Figure 2. Quantile regression estimates for per capita income, multidimensional poverty intensity, and total household deprivation score.

Notes: Conditional quantile estimates are shown with thick solid lines. Shaded areas indicate 95% confidence intervals. Dashed-dotted horizontal lines show point estimates from ordinary least square models. Dotted horizontal lines show 95% confidence intervals from ordinary least square models. Details of the estimation results are shown in Tables A12-A14 in the Appendix.

APPENDIX

Table A1. Association between instruments and poverty indicators

Poverty indicators	Motorcycles in ward		Main market sellers in ward	
	Correlation coefficient	Regression coefficient	Correlation coefficient	Regression coefficient
Household income (1,000 Ksh)	0.040 (0.257)	48.045 (0.585)	0.073 (0.039)	21.024 (0.609)
Per capita income (1,000 Ksh)	-0.011 (0.749)	-40.478 (0.215)	0.033 (0.349)	-6.540 (0.662)
Income poverty (dummy)	-0.037 (0.289)	-1.106 (0.600)	-0.092 (0.010)	-0.865 (0.300)
Household poverty gap (0-1)	-0.043 (0.224)	-0.290 (0.775)	-0.112 (0.001)	-0.274 (0.573)
Multidimensional poverty (dummy)	-0.006 (0.866)	1.163 (0.544)	-0.035 (0.316)	0.533 (0.581)
Multidimensional poverty intensity (0-1)	-0.029 (0.405)	0.023 (0.886)	-0.058 (0.098)	0.017 (0.847)

Notes: The average number of motorcycles and of main market sellers in the ward are used as instruments for commercialization. *p*-values are shown in parentheses. The regression coefficients were estimated with models that include the instruments plus all other explanatory variables as those used in Tables 5-7 of the main paper.

Table A2. Correlation between instruments and farm household characteristics

Variables	Motorcycles in ward		Main market sellers in ward	
	Correlation coefficients	*p*-value	Correlation coefficients	*p*-value
Household nutrition knowledge score [a]	0.032	0.355	-0.022	0.536
Household seed expenditure per acre	-0.015	0.668	-0.047	0.184
Household fertilizer expenditure per acre	-0.025	0.477	-0.019	0.589
Household pesticide expenditure per acre	-0.057	0.106	-0.054	0.129
Household manure expenditure per acre	0.018	0.605	0.001	0.973

Notes: The average number of motorcycles and of main market sellers in the ward are used as instruments for commercialization. [a] Household nutrition knowledge was computed based on four questions related to knowledge of micronutrients and micronutrient deficiencies.

Table A3. Correlation between instruments and mean wealth characteristics at ward level

Variables	Motorcycles in ward		Main market sellers in ward	
	Correlation coefficients	*p*-value	Correlation coefficients	*p*-value
Mean education of household head (years)	0.054	0.794	0.137	0.505
Mean household income (1,000 Ksh)	0.038	0.852	0.164	0.424
Mean farm productive assets (1,000 Ksh)	-0.039	0.851	0.083	0.687
Mean farm size (acres)	0.036	0.860	0.221	0.278

Notes: The average number of motorcycles and of main market sellers in the ward are used as instruments for commercialization. Socioeconomic characteristics were computed by averaging across all sample households in the ward.

Table A4. Mean differences in output and sales between main market sellers and non-sellers

Variables	Full sample	Main market sellers	Main market non-sellers	Mean difference
Value of output (1,000 Ksh)	139.382	178.152	120.990	57.162***
	(176.251)	(240.692)	(131.716)	
Value of sales (1,000 Ksh)	71.976	102.937	57.289	45.648***
	(108.139)	(146.002)	(80.552)	
Value of inputs (1,000 Ksh)	13.798	16.842	12.354	4.488***
	(14.120)	(17.214)	(12.138)	

Notes: Standard deviations are shown in parentheses. Ksh, Kenyan shillings; 1 US dollar = 96.3 Ksh. *, **, and *** significant at 10%, 5%, and 1% level, respectively.

Table A5. Overidentification tests for joint instrument exogeneity with different poverty indicators

Variables	*p*-value
Per capita income (1,000 Ksh)	0.120
Log of per capita income	0.526
Income poverty (dummy)	0.103
Household poverty gap (1-0)	0.777
Multidimensional poverty (dummy)	0.288
Multidimensional poverty intensity (1-0)	0.777

Note: Based on the insignificant *p*-values we fail to reject the null hypothesis of joint exogeneity of the two instruments.

Table A6. First-stage regression model for determinants of commercialization

Variables	GLM (fractional logit) Commercialization
Main market traders in ward (number)	2.314***
	(0.448)
Motorcycles in ward (number) [a]	-2.448***
	(0.901)
Age of household head (years)	0.003
	(0.003)
Age squared (years)	-0.000**
	(0.000)
Male household head (dummy)	0.019
	(0.059)
Education of household head (years)	0.020**
	(0.009)
Household size (number)	-0.030*
	(0.016)
Farm size (acres)	0.239***
	(0.037)
Farm size squared (acres)	-0.064***
	(0.019)
Farm size cubed (acres)	0.005**
	(0.002)
Farm productive assets (1,000 Ksh)	0.002*
	(0.001)
Access to credit (dummy)	0.166**
	(0.082)
Distance to closest market (km)	-0.003
	(0.004)
Group official (dummy)	0.087*
	(0.053)
Off-farm income (dummy)	0.019
	(0.069)
Poor agroecology (dummy)	-0.219***
	(0.075)
Livestock ownership (TLU)	-0.034*
	(0.019)
Constant	-1.325***
	(0.247)
Sub-county dummies	Yes
Log pseudo-likelihood	-379.534
p-values showing instrument relevance	
p-value of motorcycles in ward=0.007	
p-value of main market sellers in ward=0.000	
p-value of excluded instruments (joint significance)=0.000	
Observations	805

Notes: Coefficient estimates are shown with robust standard errors clustered at farmer group level in parentheses. GLM, generalized linear model; TLU, tropical livestock units. [a] The negative coefficient for motorcycles in the ward is due to the correlation of this variable with main market sellers in the ward. When separate regressions are run with each of the instruments, the coefficients are both positive, as one would expect. *, **, and *** significant at 10%, 5%, and 1% level, respectively.

Table A7. Effect of commercialization on income poverty gap and multidimensional poverty intensity, estimated with fractional logit models

	Income poverty gap (0-1)		Multidimensional poverty intensity (0-1)	
	(1)	(2)	(3)	(4)
Variables	Fractional logit	CF	Fractional logit	CF
Commercialization (0-1)	-0.481***	-0.507***	-0.129***	-0.127**
	(0.047)	(0.071)	(0.039)	(0.057)
Age of household head (years)	0.001	0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Age squared (years)	0.000	0.000	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Male household head (dummy)	-0.108***	-0.106***	-0.007	-0.007
	(0.027)	(0.023)	(0.019)	(0.020)
Education of household head (years)	-0.013***	-0.012***	-0.023***	-0.023***
	(0.003)	(0.003)	(0.002)	(0.002)
Household size (number)	0.043***	0.042***	0.014***	0.014***
	(0.005)	(0.005)	(0.004)	(0.004)
Farm size (acres)	-0.033***	-0.025	-0.014	-0.015
	(0.013)	(0.020)	(0.004)	(0.016)
Farm size squared (acres)	0.001	0.000	-0.003	-0.003
	(0.007)	(0.009)	(0.005)	(0.007)
Farm size cubed (acres)	-0.001	-0.001	0.001	0.001
	(0.001)	(0.002)	(0.001)	(0.001)
Farm productive assets (1,000 Ksh)	-0.003***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.000)
Access to credit (dummy)	-0.061***	-0.056***	-0.045***	-0.029**
	(0.017)	(0.024)	(0.014)	(0.014)
Distance to closest market (km)	0.000	0.000	-0.002*	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
Group official (dummy)	0.004	0.006	-0.021	-0.036***
	(0.020)	(0.020)	(0.016)	(0.011)
Off-farm income (dummy)	-0.213***	-0.213***	-0.031	-0.024*
	(0.017)	(0.021)	(0.023)	(0.013)
Poor agroecology (dummy)	-0.027	-0.035	0.012	0.006
	(0.026)	(0.030)	(0.024)	(0.019)
Livestock ownership (TLU)	-0.025***	-0.026***	-0.013**	-0.011***
	(0.007)	(0.007)	(0.006)	(0.004)
Residual from first stage		0.030		-0.002
		(0.063)		(0.050)
Sub-county dummies	Yes	Yes	Yes	Yes
Observations	805	805	805	805
Log pseudo-likelihood	-320.825	-320.826	-305.255	-305.254

Notes: Average partial effects are shown with robust standard errors in parentheses. In columns (1) and (3), standard errors are clustered at farmer group level. In columns (2) and (4), standard errors are bootstrapped with 1000 replications. CF, control function estimator; TLU, tropical livestock units. *, **, and *** significant at 10%, 5%, and 1% level, respectively.

Table A8. Effect of commercialization on different multidimensional poverty dimensions

Variables	Education deprivations	Health deprivations	Living standard deprivations
Commercialization (0-1)	-0.007	-0.058***	-0.025**
	(0.011)	(0.018)	(0.013)
Control variables	Yes	Yes	Yes
Observations	805	805	805
Log pseudo-likelihood	-107.411	-149.372	-292.941

Notes: Average partial effects are shown with robust standard errors in parentheses. The dependent variables are deprivation scores in each of the three dimensions, all three ranging between 0 and 0.33. The same explanatory variables as used in Tables 5-7 of the main paper were used for estimation but are not shown here for brevity. ** and *** significant at 5% and 1% level, respectively.

Table A9. Effects of income on multidimensional poverty intensity

	(1)	(2)	(3)
Variables	MPI intensity (0-1)	MPI intensity (0-1)	MPI intensity (0-1)
Per capita income (1,000 Ksh)	-0.008***		
	(0.000)		
Household income (1,000 Ksh)		-0.001***	
		(0.000)	
Farm income (1,000 Ksh)			-0.003***
			(0.001)
Control variables	Yes	Yes	Yes
Constant	1.271***	1.102***	1.174***
	(0.276)	(0.273)	(0.271)
Observations	805	805	805
Log pseudo-likelihood	-304.689	-305.098	-304.546

Notes: Coefficient estimates are shown with robust standard errors clustered at farmer group level in parentheses. All models were estimated with a fractional logit estimator. The same explanatory variables as used in Tables 5-7 of the main paper were used for estimation but are not shown here for brevity. *, **, and *** significant at 10%, 5%, and 1% level, respectively.

Table A10. Effects of commercialization on farm input use and land productivity

Variable	Seed cost per acre	Fertilizer cost per acre	Manure cost per acre	Pesticide cost per acre	Value of output per acre
Commercialization	1874.632***	4400.213***	1917.692***	1199.029***	68.752***
	(624.347)	(1035.559)	(454.973)	(422.123)	(22.885)
Constant	2093.498*	4096.084***	1218.896**	414.260	55.766***
	(1133.162)	(1400.210)	(585.913)	(333.402)	(19.763)
Control variables	Yes	Yes	Yes	Yes	Yes
Observations	805	805	805	805	805
R-squared	0.104	0.144	0.098	0.064	0.101

Notes: Coefficient estimates are shown with robust standard errors clustered at farmer group level in parentheses. All models estimated with OLS except for the manure model, which was estimated with a control function estimator (bootstrapped standard errors with 1000 replications), due to commercialization being endogenous in the manure model. The same explanatory variables as used in Tables 5-7 of the main paper were used for estimation but are not shown here for brevity. *, **, and *** significant at 10%, 5%, and 1% level, respectively.

Table A11. Associations between farm inputs, output, income, and poverty

Variables	(1) Per capita income	(2) Log per capita income	(3) Income poverty gap (0-1)	(4) MPI intensity (0-1)
Total value of inputs (1,000 Ksh)	0.608***	0.015***	-0.006***	-0.002***
	(0.136)	(0.002)	(0.001)	(0.000)
Total value of output (1,000 Ksh)	-0.103***	-0.002***	-0.002***	-0.002**
	(0.018)	(0.003)	(0.000)	(0.000)
Value of output per acre (1,000 Ksh)	0.095***	0.003***	-0.002***	-0.001*
	(0.022)	(0.001)	(0.000)	(0.000)

Notes: Coefficient estimates are shown with robust standard errors clustered at farmer group level in parentheses. Each coefficient was estimated with a separate model. Models in columns (1) and (2) estimated with ordinary least squares. Models in columns (3) and (4) estimated with fractional logit. In all models, the same explanatory variables as used in Tables 5-7 of the main paper were used for estimation but are not shown here for brevity. *, **, and *** significant at 10%, 5%, and 1% level, respectively.

Table A12. Quantile regression for per capita income (1,000 Ksh)

		Quantile				
Variables	OLS	0.10	0.25	0.50	0.75	0.90
Commercialization (0-1)	50.124***	12.353***†	20.175***†	27.339***†	39.071***	44.172***
	(8.448)	(2.716)	(2.702)	(4.567)	(5.488)	(13.026)
Constant	-9.212	-6.412*	-9.756***	-5.907***	-7.175	12.406
	(9.483)	(3.586)	(4.791)	(5.968)	(8.196)	(18.693)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
(Pseudo) R-squared	0.366	0.154	0.185	0.248	0.288	0.338

Notes: N = 805. OLS coefficient estimates are shown with robust standard errors clustered at farmer group level in parentheses. Quantile regression coefficients are shown with bootstrapped standard errors (1000 replications) in parentheses. The same explanatory variables as used in Tables 5-7 of the main paper were used for estimation but are not shown here for brevity *, **, and *** significant at 10%, 5%, and 1% level, respectively. † coefficient is significantly different from OLS estimate.

Table A13. Quantile regression for multidimensional poverty intensity (0-1)

		Quantile		
Variables	OLS	0.50	0.75	0.90
Commercialization (0-1)	-0.153***	-0.180***	-0.121**	-0.135**
	(0.042)	(0.056)	(0.051)	(0.055)
Constant	0.670***	0.727***	0.761***	0.864***
	(0.053)	(0.080)	(0.068)	(0.094)
Control variables	Yes	Yes	Yes	Yes
(Pseudo) R-squared	0.300	0.259	0.185	0.180

Notes: N = 805. OLS coefficient estimates are shown with robust standard errors clustered at farmer group level in parentheses. Quantile regression coefficients are shown with bootstrapped standard errors (1000 replications) in parentheses. Regression for the 0.10 and 0.25 quantiles could not be estimated due to a large proportion of zeros for the MPI intensity in these relatively better-off groups. The same explanatory variables as used in Tables 5-7 of the main paper were used for estimation but are not shown here for brevity *, **, and *** significant at 10%, 5%, and 1% level, respectively.

Table A14. Quantile regression for total household deprivation scores (0-1)

Variables	OLS	Quantile 0.10	0.25	0.50	0.75	0.90
Commercialization (0-1)	-0.100***	-0.030†	-0.074***	-0.091***	-0.127***	-0.129**
	(0.025)	(0.035)	(0.033)	(0.034)	(0.039)	(0.051)
Constant	0.628***	0.383***	0.502***	0.610***	0.702***	0.862***
	(0.034	(0.051)	(0.048)	(0.050)	(0.057)	(0.082)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
(Pseudo) R-squared	0.343	0.169	0.169	0.205	0.217	0.225

Notes: *N* = 805. OLS coefficient estimates are shown with robust standard errors clustered at farmer group level in parentheses. Quantile regression coefficients are shown with bootstrapped standard errors (1000 replications) in parentheses. The same explanatory variables as used in Tables 5-7 of the main paper were used for estimation but are not shown here for brevity *, **, and *** significant at 10%, 5%, and 1% level, respectively. † coefficient is significantly different from OLS estimate.