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Empirical evidence from Kenya

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Abstract

Many developing countries are currently experiencing a rapid expansion of supermarkets. New supermarket procurement systems could have important implications for farming and wider rural development. While previous studies have analyzed farm profit and income effects, possible employment effects have received much less attention. Building on data from a recent survey of vegetable farmers in Kenya, in this article a double-hurdle model of hired labor use is developed and estimated. Farmer participation in supermarket channels increases the likelihood of hiring labor by 13% and overall demand for hired labor by 38%. A gender disaggregation shows that positive employment effects are especially pronounced for female hired labor. Given that agricultural wage labor is primarily an activity of low-income households in rural areas, the poor benefit over-proportionally.

JEL classification: C34, Q12, Q13, J43

Keywords: Supermarkets; Off-farm income; Hired labor; Double-hurdle model; Kenya

1. Introduction

Developing countries are experiencing increasing demand for high-value food products and agricultural supply chain modernization, spurred by rapid urbanization, rising incomes, and market liberalization (Reardon et al., 2009; Mergenthaler et al., 2009). As a result, a supermarket revolution is ongoing, with new opportunities for farmers to integrate into high-value markets (Reardon et al., 2003; Hernandez et al., 2007). These developments may have important implications for agricultural and wider rural growth. There may be direct gains in

income that accrue to farm households participating in high-value markets. Additionally, there may be indirect effects to households not directly participating. Negative indirect effects may occur if smallholder farmers are excluded and further marginalized through high-value market trends (Neven et al., 2009). Yet there may also be positive indirect effects through innovation spillovers to traditional markets and employment-generating impacts (Neven et al., 2009, Schipmann and Qaim, 2010). Due to their labor-intensive nature, employment-generating effects can be expected especially in high-value fruits and vegetables (Barrientos et al., 2005; Maertens and Swinnen, 2009).

The importance of rural employment and off-farm income has been reviewed in a stream of literature covering various developing countries (e.g., Davis et al., 2009; Oseni and Winters, 2009; Maertens, 2009). Overall, with increasing land and capital constraints, the role of off-farm income is increasing. While agricultural wage income constitutes a fairly small proportion of off-farm income in general, its relative role often increases with decreasing overall household incomes (Reardon, 1997; Kijima et al., 2006). Agricultural employment opportunities arising from the expansion of supermarkets could therefore benefit the poor over-proportionally.

Previous studies on employment effects of high-value agriculture have largely focused on non-traditional exports (Dolan, 2004; Maertens and Swinnen, 2009). Yet, as Neven et al. (2009) and Simmons et al. (2005) suggest, increasing domestic demand for high-value products may entail new employment opportunities as well. Surprisingly, few studies have attempted to estimate and quantify employment effects of the supermarket revolution. Existing research compares labor demand between farmers in supermarket and traditional channels without controlling for other factors (Neven et al., 2009). Here, we contribute to the literature by estimating labor use models, in order to derive net employment effects of farmers' participation in supermarket channels. To properly account for the decision-making

process involved in hiring in labor, we use a double-hurdle model. Results are also disaggregated by gender.

The analysis is based on data from a survey of vegetable farmers in central Kenya – one of the countries experiencing rapid supermarket expansion. Supermarkets already accounted for 20% of food retailing in urban Kenya by 2002 (Neven and Reardon, 2004; Nyoro et al., 2007). The share of fresh fruits and vegetables in supermarket retailing is still relatively low but has been rising rapidly (Neven and Reardon, 2004). These dynamics could produce substantial employment effects, especially when supermarkets gradually spread from the larger cities to smaller cities and towns, as is already observed in parts of Asia and Latin America.

The article proceeds as follows. The next section presents the analytical framework and estimation procedure. In section three, we describe the data and show sample descriptive statistics. In section four, we present and discuss the estimation results, before concluding in section five.

2. Analytical framework and estimation procedure

Agricultural labor use models have been frequently estimated in the literature, either referring to individual cropping activities or to the farm as a whole (cf. Espey and Thilmany, 2000; Simmons et al., 2005). However, available studies mostly restrict the decision to hire in labor and the decision on use intensity to a single process. Yet there is no *a priori* reason why this should be true, especially in a developing country smallholder context, where market failures are widespread and farm-household decisions are interconnected. Rather, observed demand for hired labor can be expressed as a two-stage decision, involving first the decision whether or not to hire labor at all, followed by the decision on the exact quantity of labor to hire. The decision to hire labor can be represented as

$$d_i^* = \alpha x_i + u_i; \quad u_i \sim N(0, 1) \quad (1)$$

with

$$d_i = \begin{cases} 1 & \text{if } d_i^* > 0 \\ 0 & \text{otherwise,} \end{cases} \quad (2)$$

while the decision on how much labor to hire can be described as

$$y_i^* = \beta z_i + v_i; \quad v_i \sim N(0, \sigma^2) \quad (3)$$

with

$$y_i = \begin{cases} y_i^* & \text{if } y_i^* > 0 \text{ and } d_i = 1 \\ 0 & \text{otherwise.} \end{cases} \quad (4)$$

d_i is a discrete variable measuring whether or not outside labor is hired, and d_i^* is a latent (unobserved) variable for d_i . y_i refers to the observed amount of labor hired, and y_i^* represents the latent variable for y_i . The decision to hire labor and the quantity of hired labor used are influenced by variables x_i and z_i respectively, which are allowed to overlap. Demand for agricultural inputs, including labor, is influenced by factors that can be broadly categorized into farm and household characteristics, market characteristics, and agro-ecological conditions (Xu et al., 2009). We are particularly interested in the effect of supermarket participation on hired labor demand. Therefore, we include a dummy variable capturing supermarket participation in x and z .

Equation (4) shows that positive quantities of hired labor are observed only if $d_i = 1$ and $y_i^* > 0$. Due to this left-censoring of the dependent variable, the ordinary least squares estimator is inconsistent. Instead, such models are commonly estimated with the tobit estimator. However, the tobit model assumes that zero observations represent a corner solution in the sense that – if relative prices (wages and/or output prices) changed, positive values of hired labor would be realized (Blaylock and Blisard, 1992). In reality, there may be cases of zero

observations where even relatively large changes in relative prices would not induce positive outcomes. Zero observations may arise either because desired demand is non-positive (deliberate zeros) or because of inhibiting factors when desired demand is actually positive (censored). An example of a deliberate zero is when careful handling of some types of vegetables grown by farmers requires use of more diligent family labor. Under such circumstances, farmers may not hire in labor even though their economic characteristics would allow them to do so. Another limitation of the tobit model is that it restricts coefficients in the two decision stages to the same sign and magnitude (Wooldridge, 2002).

To account for these shortcomings, we use the double-hurdle (DH) model that acknowledges the two-stage decision while also allowing for the option of deliberate zero observations.¹ The DH model was originally developed by Cragg (1971), and its variants have recently been applied in studies of input demand and technology adoption (Langyintuo and Mungoma, 2008; Shiferaw et al., 2008; Xu et al., 2009). Following the specification in equations (1) through (4) and assuming independent error terms, the likelihood function for the DH model can be expressed as follows (Jones, 1989):

$$L(y_i|x_i, \theta) = \prod_{y_i=0} [1 - \Phi(x_i\alpha/\sigma_u)] \Phi(z_i\beta/\sigma_v) \\ \times \prod_{y_i>0} \Phi(x_i\alpha/\sigma_u) \Phi(z_i\beta/\sigma_v) \frac{\phi[(y_i - z_i\beta)/\sigma_v]}{\sigma_v \Phi(z_i\beta/\sigma_v)} \quad (5)$$

where ϕ and Φ are probability density and cumulative distribution functions of the normal distribution, σ_u is the standard deviation of u_i which is assumed to be one as shown in equation (1). σ_v is the standard deviation of v_i . Dividing by $1/\Phi(z_i\beta/\sigma_v)$ (included in the last term) ensures that the density integrates to unity over $y > 0$. Equation (5) can then be

¹The two-step decision can also be handled by *heckit* models. However, *heckit* models assume that, once respondents have positive desired demand for hired labor, they cannot report zero values (Blaylock and Blisard, 1992).

solved for α , β , and σ_v^2 through maximum likelihood estimation. For brevity, in the following we write σ instead of σ_v .

Since the tobit model is nested in the DH model, we can choose which of the two is more appropriate in a particular situation based on a likelihood ratio (LR) test. If we assume independent error terms, the log-likelihood of the DH model is equivalent to the sum of the log-likelihoods of the probit and the truncated regressions. An LR test of the tobit restriction can therefore be carried out as follows (Greene, 2008):

$$\text{LR statistic} = -2[\ln L_T - (\ln L_P + \ln L_{TR})] \quad (6)$$

where L_T is the likelihood of the tobit model, L_P is the likelihood of the probit model, and L_{TR} is the likelihood of the truncated regression model. The LR statistic has a χ^2 distribution.

Upon estimation of the DH model one can also estimate the expected effect of individual explanatory variables on the probability of hiring in labor and on the quantity of hired labor used. First, we estimate the probability of hiring in labor as

$$P(d_i^* > 0 | x_i) = \Phi(x_i\alpha). \quad (7)$$

The conditional expected quantity of hired labor can then be estimated as

$$E(y_i | y_i > 0, z_i) = z_i\beta + \sigma \times \lambda(z_i\beta/\sigma). \quad (8)$$

Similarly, the unconditional expected quantity of hired labor can be estimated as

$$E(y_i | x_i, z_i) = \Phi(x_i\alpha)[z_i\beta + \sigma \times \lambda(z_i\beta/\sigma)]. \quad (9)$$

The term $\lambda(z_i\beta/\sigma)$ in equations (8) and (9) is the inverse Mills ratio expressed as

$$\lambda(z_i\beta/\sigma) = \phi(z_i\beta/\sigma)/\Phi(z_i\beta/\sigma) \quad (10)$$

The marginal effect of each independent variable can then be estimated following procedures outlined in Burke (2009). For a given observation, the marginal effect of an independent variable, x_j , around the probability that $y > 0$ is

$$\frac{\partial P(y>0|x)}{\partial x_j} = \alpha_j \phi(x\alpha) \quad (11)$$

The marginal effect of the same independent variable, x_j , on the expected value of y , given that $y > 0$ (conditional average partial effect – CAPE) is

$$\frac{\partial E(y_i|y_i>0,z_i)}{\partial x_j} = \beta_j [1 - \lambda(z_i\beta/\sigma)\{z_i\beta/\sigma + \lambda(z_i\beta/\sigma)\}] \quad (12)$$

The marginal effect of the independent variables on the unconditional expected value of y (unconditional average partial effect – UAPE) is

$$\frac{\partial E(y_i|x_i,z_i)}{\partial x_j} = \alpha_j \phi(x\alpha) \times \{z_i\beta/\sigma + \lambda(z_i\beta/\sigma)\} + \Phi(x_i\alpha) \times \beta_j [1 - \lambda(z_i\beta/\sigma)\{z_i\beta/\sigma + \lambda(z_i\beta/\sigma)\}] \text{ if } x_j \in x, z. \quad (13)$$

If x_j is only determining the probability equation, then $\beta_j = 0$, and the second term in equation (13) drops out. Alternatively if x_j is only in the second stage model, then $\alpha_j = 0$ and the first term drops out. Either way, the marginal effect will still be a function of parameters and explanatory variables in both stages of the regression (Burke, 2009).

3. Data and descriptive statistics

3.1. Farm survey

The data used in this study were collected in 2008 through a survey of vegetable farmers in Kiambu District, Central Province of Kenya. This district is relatively close to Nairobi, where most of the country's supermarkets can be found. But even before supermarkets started their operation, Kiambu was one of the main vegetable-supplying areas for the capital city. Based

on information from the district agricultural office, four of the main vegetable-producing divisions were chosen. In these four divisions, 31 administrative locations were purposively selected, again using statistical information on vegetable production. Within the locations, vegetable farmers were sampled randomly. Since farmers who participate in supermarket channels are still the minority, we purposely oversampled them using complete lists obtained from supermarkets and supermarket traders. In total, our sample comprises 402 farmers: 133 supermarket suppliers and 269 traditional channels suppliers.

A structured questionnaire was used to collect information from farmers regarding vegetable production and marketing. Furthermore, information on other farm and non-farm economic activities as well as on household and contextual characteristics was collected. Farmers produce vegetables in addition to maize, bananas, and other cash crops. The main vegetables produced are leafy types, including exotic ones such as spinach and kale, and indigenous ones such as *amaranthus* and black nightshade, among others. Even though some supermarket suppliers in our sample also sell parts of their produce in traditional channels, all of them reported supermarkets to be their main marketing channel for vegetables. In contrast, none of the traditional channel farmers in our sample sells vegetables to supermarkets.²

Traditional channels consist of direct spot market trading and sales to middlemen/intermediaries at the farm gate. This mostly involves one-off transactions with neither promise for repeated transactions nor prior agreements on product delivery or price. In contrast, supermarkets do have agreements with vegetable farmers regarding product price, physical quality and hygiene, and consistency and regularity of supply. We hypothesize that these requirements may lead to higher demand for labor. All agreements are verbal with no written contracts. Some farmers also supply supermarkets through specialized traders, who

² While in some other parts of Kenya, high-value vegetable exports are important (Asfaw et al., 2010), this is not the case in Kiambu District. In fact, none of our sample farmers reported producing vegetables for export.

then use similar verbal contracts in order to be able to supply supermarkets on stipulated terms.³

3.2. Descriptive analysis

Farmers in the two market channels differ with respect to some of the socioeconomic variables, as shown in Table 1. In terms of farm and household characteristics, we observe significant differences in total land ownership, area cultivated with vegetables, education, occupational characteristics, and use of irrigation technology. On average, supermarket farmers have larger land holdings and more years of schooling. Moreover, even though the majority of farmers in both channels has own farming as their main occupation, 8% of the supermarket farmers reported non-agricultural wage employment as their main occupation, compared to only 4% of the traditional channel farmers.

Insert Table 1 here

Data about inputs used and outputs obtained in vegetable cultivation were elicited at the plot level. Since most farmers maintain several vegetable plots, we asked them to provide details for their main plot. Table 1 shows that an average vegetable plot has a size of only 0.08 acres. Depending on the types of vegetables grown and the farmers' individual cultivation patterns, cropping cycles for vegetables vary in length between two and twelve months. Labor use was reported by farmers for the last cropping cycle on their main plot. In order to have a common reference, in the lower part of Table 1 we divided the reported labor days by plot size and cycle length, so that labor use is expressed per acre-months. On average, farmers in supermarket channels use more hired labor, whereas traditional channel farmers use more family labor. Substitution of hired for family labor among supermarket farmers may possibly

³ Initially, supermarkets in Kenya purchased fresh vegetables in traditional wholesale markets, which can still be observed today. However, supermarkets have diversified their procurement to include contracted farmers and specialized traders, in order to ensure price stability and consistency in quality and supply.

be explained by higher degrees of commercialization and higher opportunity costs of family labor time. Interestingly, the difference in hired labor use is particularly pronounced for women workers. Dolan (2004) also showed for Kenya that substantially more female labor is employed in non-traditional export crops.

Hired labor use statistics in Table 1 are also disaggregated by farm operation. The bulk of hired labor is used in land preparation, weeding, and harvesting, which holds true for farmers in both market channels. Yet, the two channels show significant differences in labor use for weeding, application of pesticides, fertilizer, and manure, as well as for packing of vegetables. These differences are partly due to supermarket quality and consistency requirements. For instance, pesticide applications help reduce pest damage and improve the product's outward appearance. Fertilizer and manure contribute to faster plant regeneration after harvesting, and supermarkets also require some on-farm cleaning and bundling, in order to minimize labor costs in supermarket stores.

But beyond concrete requirements, changes in farmers' economic incentives probably also play a role in explaining differences in hired labor use. Higher and more stable output prices in supermarket channels tend to encourage higher input intensities. Moreover, higher returns may contribute to easing liquidity constraints often faced by smallholder producers. This increase in the use of hired labor could be beneficial especially for poor households in rural areas, for whom agricultural wage employment is an important source of off-farm income. Indeed, Figure 1 shows that agricultural wage income is more important for poorer than for relatively richer households in our sample. In this connection, it should be noted that our sample is not representative of all rural households in Kiambu District or other regions of Kenya, because we only sampled vegetable farmers. Many of the poorest households do not

grow vegetables commercially, and for them agricultural wage incomes are even more important on average.

Insert Fig. 1 here

4. Econometric results and discussion

In this section, we discuss results of the DH model for labor use, as outlined in section 2. The dependent variable is the quantity of labor hired on the main vegetable plot for one cropping cycle. In order to control for differences in acreage and cycle length, “adjusted plot size” is introduced as an explanatory variable, which is plot size multiplied by cycle length. We estimate a model for total hired labor on the plot. In addition, since the descriptive analysis suggested that there may be gender differences, we estimate separate models for female and male hired labor.

4.1. Specification tests

Before discussing the estimation results, we conduct some tests in order to justify the specification of the DH models. As summarized above, the DH model is an alternative to the tobit specification; in fact, the tobit model is nested in the DH model. We therefore test for the appropriateness of the DH specification over the tobit alternative, following the steps outlined in equation (6). The test results are shown in the upper part of Table 2. In all the three cases (total hired labor, female hired labor, and male hired labor), the tobit restriction is rejected, so that the DH model is preferred.

Insert Table 2 here

The main focus of our analysis is the potential impact of farmer participation in supermarket channels on demand for hired labor. Supermarket channel participation is expressed as a dummy variable. However, this variable may potentially be endogenous, because some

unobserved factors could simultaneously influence the use of hired labor and participation in supermarket channels. We test for endogeneity following a two-step approach suggested by Rivers and Vuong (1988).

In the first step, we estimate a probit model of participation in supermarket channels. In this probit model, we include a variable capturing participation in a market linkage initiative by a locally active NGO as an instrument. Correlation analysis confirms that this NGO linkage variable is significantly correlated with supermarket participation but not with demand for hired labor. The NGO links farmers in the study area to supermarket channels through various institutional support mechanisms.⁴ In the second step, predicted residuals from this probit are included as an additional explanatory variable in (i) the probit explaining the decision to hire labor (first stage) and in (ii) the truncated regression explaining the quantity of labor hired (second stage). The *t*-statistic for the coefficient of this residual term provides a valid test for the null hypothesis that the supermarket participation variable is exogenous (Wooldridge, 2002). As the test results in the lower part of Table 2 show, this null hypothesis cannot be rejected in any of the models, so that we proceed with the DH model without instrumentation.

4.2. Double-hurdle model results for total hired labor

Results of the DH model are presented in Table 3. We first refer to the model for total hired labor. The estimates show that supermarket farmers are more likely to hire labor than their counterparts in traditional channels. Farmers with more land and those who use irrigation are also more likely to hire labor. Conditional on the first-stage decision being positive, supermarket participation, land size, and being a male farmer positively and significantly influence the quantity of labor demand. These findings confirm that participation in

⁴ Since the NGO linkage variable may itself be endogenous, we tested for this option through the use of additional instruments, including variables for household assets, infrastructure, and group membership. The hypothesis of exogeneity could not be rejected.

supermarket channels influences both the likelihood of hiring in labor and the intensity of hired labor use.

Self-employment outside the farm, use of irrigation, access to credit, and adjusted plot size also positively influence the intensity of hired labor use, conditional on farmers hiring labor. These results are as expected. Strikingly, the agricultural wage rate has no statistically significant impact on labor demand, and the price of purchased manure has a negative effect. The latter may be due to the fact that manure application is fairly labor-intensive. Thus, higher manure prices discourage manure application, leading to lower hired labor demand.

Insert Table 3 here

Based on the DH model, conditional and unconditional marginal effects were calculated as explained in section 2; they are shown in Table 4. The first column suggests that supermarket participation increases the likelihood of hiring labor by about 9 percentage points. Relative to a 70% mean likelihood of farmers in traditional channels to hire labor, this represents a 13% increase. The conditional average partial effect (CAPE) of supermarket participation can be interpreted as follows: when the first-stage decision is positive, then supermarket participation increases hired labor demand on the vegetable plot by 3.3 labor days. More interesting is the unconditional average partial effect (UAPE), as this can be interpreted as the combined effect of both decision stages and is therefore of higher practical relevance. The UAPE reveals that participation in supermarket channels increases hired labor use by 4.1 labor days. Compared to the mean hired labor use by farmers in traditional channels, which is 10.7 labor days per plot and cropping cycle, this implies a 38% increase. Land size, which is an indicator of farmers' wealth, also has a positive and significant net effect on the quantity of labor hired. Similarly, male farmers use significantly more hired labor than female farmers in vegetable production. This may potentially be due to cultural factors and gender

differences in the opportunity cost of time.

Insert Table 4 here

The results also provide some evidence of substitution between family and hired labor. Farmers whose main occupation is self-employment outside the farm use 11 hired labor days more on their vegetable plot than farmers whose main occupation is non-agricultural employment; they also use more hired labor than their colleagues whose primary occupation is farming. This is not surprising, because self-employed activities often belong to the most lucrative off-farm income sources. It is also possible that income from self-employment lowers liquidity constraints faced by farmers, thus improving their ability to hire labor. Similar effects were found by Maertens (2009) in Senegal's export vegetable sector. That farmers often lack sufficient funds to employ hired labor is also supported by the positive and significant influence of credit access. Finally, as expected, larger adjusted plot sizes imply the use of more hired labor.

4.3. Double-hurdle model results for female and male hired labor

We now analyze demand for hired labor differentiating by gender of laborers. The descriptive analysis in Table 1 revealed that supermarket farmers hire more female labor than their counterparts in traditional channels. We therefore estimate gender-specific DH models, using the same specification as above; the only difference is that – instead of total hired labor – we use female and male hired labor as dependent variables. The results of these additional models are shown on the right-hand side of Table 3. Supermarket farmers are more likely to hire female labor than farmers in traditional channels. Furthermore, conditional on farmers hiring female labor, supermarket farmers hire more female labor than their counterparts supplying traditional channels. This makes sense, because women are mostly hired for weeding and vegetable packing operations, for which significant differences between

supermarket and traditional channels can be observed. In contrast, in the male hired labor model we do not find a significant effect of supermarket participation, neither in the first nor in the second decision stage.

Many of the other variables that were shown to play a role for total hired labor are not statistically significant in the gender-specific models. This suggests that for many of the other operations the gender of laborers is considered less important. Interestingly, however, the gender of the farm operator matters. Male farmers are more likely to hire male labor. Yet, if male farmers do hire female labor, then they hire more female labor than female farmers. Again, this is potentially due to cultural factors.

As above, we also use the coefficient estimates to calculate marginal effects for the gender-specific models. They are shown in Table 5. Given that the supermarket effects are not statistically significant for male hired labor, we only show the results for female hired labor. The effect of supermarket participation on the likelihood of hiring labor is somewhat stronger for female labor than for total labor (see above). Supermarket participation increases the likelihood of hiring female labor by 11.7 percentage points. Given a 44% mean likelihood of hiring female labor among traditional channel farmers, this represents an increase of almost 27%.

Insert Table 5 here

The UAPE shown in the last column of Table 5 reveals that supermarket participation increases demand for female hired labor by 3.8 labor days per plot. If we compare this to the 4.1 additional days for total hired labor, it becomes obvious that the positive farm employment effects of supermarkets are largely attributable to more female labor being hired. The 3.8 days imply an increase of almost 80% over the average amount of female labor hired by traditional channel farmers. Other factors significantly influencing demand for female

hired labor include gender of the farmer, access to credit, and adjusted vegetable plot size. Moreover, farmers who work as wage laborers on other farms hire much less female labor than the reference group consisting of farmers who have non-agricultural employment. This makes sense, because non-agricultural employment is often more remunerative than agricultural employment on own or other farms.

5. Conclusion

The expansion of supermarkets in developing countries presents potentials for employment generation. The production of high-value crops – such as vegetables – is often quite labor-intensive, thus entailing employment opportunities for agricultural wage laborers. Agricultural wages make up a relatively small share of rural off-farm income in general, but they are often an important income source for the poorest population segments. While a few previous studies have analyzed rural labor market implications of emerging high-value food supply chains, most of them refer to the agricultural export sector. There is hardly any research on the employment effects of domestic high-value market developments, epitomized by the supermarket revolution. In this article, we have addressed this research gap by using Kenya as an empirical example. Building on data from a recent survey of vegetable farmers, we have developed and used a double-hurdle model to estimate the determinants of hired labor use in vegetable production.

Our estimates show that farmer participation in supermarket channels increases the likelihood of hiring labor in vegetable production by 13% and overall demand for hired labor by 38%. These are strong effects. They are partly due to specific supermarket quality and consistency requirements, which necessitate more labor for some on-farm operations, including new tasks such as washing and bundling the fresh produces. Furthermore, higher and more stable output prices in supermarket channels encourage higher input and labor intensities in general.

The recent expansion of supermarkets in Kenya and the increasing share of fresh produce in supermarket retailing therefore clearly have employment-generating impacts in rural areas. Profit and income effects for farmers supplying vegetables to supermarkets were demonstrated elsewhere (e.g., Hernandez et al., 2007; Neven et al., 2009). But these studies also revealed that disadvantaged farm households often find it difficult to supply supermarkets directly, due to technical, human capital, or institutional constraints. While support mechanisms are needed to better link smallholder farmers to high-value supply chains, the labor market results presented here suggest that rural households may benefit even when they are not (yet) supplying supermarkets directly.

The employment effects can also have wider implications for poverty reduction and rural development. First, agricultural wage labor is primarily an activity of low-income households, so that the poor benefit over-proportionally. Second, our gender disaggregation shows that positive employment effects are especially pronounced for female hired laborers, who often belong to the poorest and most vulnerable population groups. Better employment opportunities for rural women also imply higher female incomes. As is known from the literature, female incomes have more positive marginal effects than male incomes for household welfare and nutrition (Quisumbing et al., 1995). Third, higher earnings from agricultural employment may also lead to productivity gains in traditional agriculture. Especially when agricultural growth is hampered by credit constraints, the additional resources can be used by farmers for the adoption of innovations and the purchase of inputs. Such positive feedbacks from off-farm income to agriculture and food security were recently shown by Oseni and Winters (2009) and Babatunde and Qaim (2010).

The supermarket revolution in Kenya is still in its early stages. Experience from other regions in the world shows that supermarket expansion and a maturing modern retail sector are often associated with stricter product and process standards, which could further increase the

demand for hired labor in rural areas. Kenya is among the leading African countries in terms of the supermarket expansion, but the trend is also picking up in other countries. Thus, the supermarket revolution has the potential to cause broader positive growth and employment effects in Africa. Sound policies need to ensure that these potentials are realized and that possible negative distributional effects are avoided.

References

- Asfaw S., Mithöfer, D., and Waibel, H., 2010. Agrifood supply chain, private-sector standards, and farmers' health: evidence from Kenya. *Agricultural Economics* 41(3-4), 251-263.
- Babatunde, R.O. and Qaim, M., 2010. Impact of off-farm Income on food security and nutrition in Nigeria. *Food Policy* 35(4), 303-311.
- Barrientos, S., Kritzinger, A., Oundo, M., and Smith, S., 2005. Gender, work and vulnerability in African horticulture. *IDS Bulletin* 36(2), 74-79.
- Blaylock, J.R., and Blisard, W.N., 1992. US cigarette consumption: the case of low-income women. *American Journal of Agricultural Economics* 74(3), 698-705.
- Burke, W. J., 2009. Fitting and interpreting Cragg's tobit alternative using Stata. *Stata Journal* 8(4), 584-592.
- Cragg, J. G., 1971. Some statistical models for limited dependent variables with application to the demand for durable goods. *Econometrica* 39(5), 829-844.
- Davis, B., Winters, P., Reardon, T., and Stamoulis, K., 2009. Rural nonfarm employment and farming: household-level linkages. *Agricultural Economics* 40(2), 119-123.

Dolan, C.S., 2004. On farm and pack-house: employment at the bottom of a global value chain. *Rural Sociology* 69(1), 99-126.

Espey, M., and Thilmany, D.D., 2000. Farm labor demand: a meta-analysis of wage elasticities. *Journal of Agricultural and Resource Economics* 25(1), 252-266.

Greene, W.H., 2008. *Econometric Analysis*. Upper Saddle River, NJ: Prentice Hall.

Hernandez, R., Reardon, T., and Berdegué, J., 2007. Supermarkets, wholesalers, and tomato growers in Guatemala. *Agricultural Economics* 36(3), 281-290.

Jones, A. M., 1989. A double-hurdle model of cigarette consumption. *Journal of Applied Econometrics* 4(1), 23-39.

Kijima, Y., Matsumoto, T., and Yamano, T., 2006. Nonfarm employment, agricultural shocks, and poverty dynamics: evidence from rural Uganda. *Agricultural Economics* 35(3), 459-467.

Langyintuo, A. S., and Mungoma, C., 2008. The effect of household wealth on the adoption of improved maize varieties in Zambia. *Food Policy* 33(6), 550-559.

Maertens, M., 2009. Horticulture exports, agro-industrialization, and farm-nonfarm linkages with the smallholder farm sector: evidence from Senegal. *Agricultural Economics* 40(2), 219-229.

Maertens, M., and Swinnen, J.F.M., 2009. Trade, standards, and poverty: evidence from Senegal. *World Development* 37(1), 161-178.

Mergenthaler, M., Weinberger, K., and Qaim, M., 2009. The food system transformation in developing countries: a disaggregate demand analysis for fruits and vegetables in Vietnam. *Food Policy* 34(5), 426-436.

Neven, D., Odera, M. M., Reardon, T., and Wang, H., 2009. Kenyan supermarkets, emerging middle-class horticultural farmers, and employment impacts on the rural poor. *World Development* 37(11), 1802-1811.

Neven, D., and Reardon, T., 2004. The rise of Kenyan supermarkets and the evolution of their horticultural product procurement systems. *Development Policy Review* Vol. 22(6), 669-699.

Nyoro, J. K., Ariga, J., and Ngugi, I.K., 2007. "Countries with emerging modern supply chains: Kenya, in B. Vorley, et al., eds., *Regoverning Markets: A Place for Small-Scale Producers in Modern Agrifood Chains?* Hampshire, UK: Gower Publishing Limited, 163 - 171.

Oseni, G., Winters, P., 2009. Rural nonfarm activities and agricultural crop production in Nigeria. *Agricultural Economics* 40(2), 189-201.

Quisumbing, A.R., Brown, L.R., Feldstein, H.S., Haddad, L., Pena, C., 1995. Women: The Key to Food Security. *Food Policy Report*, Washington, DC: International Food Policy Research Institute.

Reardon, T., 1997. Using evidence of household income diversification to inform study of the rural nonfarm labor market in Africa. *World Development* 25(5), 735-747.

Reardon, T., Barrett, C.B., Berdegué, J.A., and Swinnen, J.F.M., 2009. Agri-food industry transformation and small farmers in developing countries. *World Development* 37(11), 1717-1727.

Reardon, T., Timmer, C. P., Barrett, C. B., and Berdegué, J.A., 2003. The rise of supermarkets in Africa, Asia, and Latin America. *American Journal of Agricultural Economics* 1140-1146.

Rivers, D., and Vuong, Q.H., 1988. Limited information estimators and exogeneity tests for simultaneous probit models. *Journal of Econometrics* 39(3), 347-366.

Schipmann C., and Qaim, M., 2010. Spillovers from modern supply chains to traditional markets: Product innovation and adoption by smallholders. *Agricultural Economics* 41 (3-4), 361-371.

Shiferaw, A.B., Tewodros, A. K., and Liang, Y., 2008. Technology adoption under seed access constraints and the economic impacts of improved pigeonpea varieties in Tanzania. *Agricultural Economics* 39(3), 309-323.

Simmons, P., Winters, P., and Patrick, I., 2005. An analysis of contract farming in East Java, Bali, and Lombok, Indonesia. *Agricultural Economics* 33(3), 513-525.

Wooldridge, J. M., 2002. *Econometric Analysis of Cross Section and Panel Data*. Boston: MIT Press.

Xu, Z., Burke, W.J., Jayne, T.S., and Govereh, J., 2009. Do input subsidy programs "crowd in" or "crowd out" commercial market development? Modeling fertilizer demand in a two-channel marketing system. *Agricultural Economics* 40(1), 79-94.

Table 1
Socioeconomic characteristics for the whole sample and by market channel

	Whole sample (<i>n</i> = 402)	Supermarket (<i>n</i> = 133)	Traditional (<i>n</i> = 269)
Farm and household characteristics			
Total area owned (<i>acres</i>)	2.1 (3.8)	2.7** (5.6)	1.9 (2.5)
Area cultivated with vegetables (<i>acres</i>)	0.8 (1.2)	1.2*** (1.5)	0.7 (0.9)
Household size (<i>adult equivalents</i>)	4.0 (0.2)	4.0 (0.2)	4.0 (0.2)
Gender of operator (<i>male dummy</i>)	0.90 (0.30)	0.93* (0.25)	0.88 (0.32)
Age of operator (<i>years</i>)	49 (14)	47* (13)	49 (15)
Education of operator (<i>years</i>)	9.2 (3.8)	10.3*** (3.1)	8.7 (4.1)
Main occupation			
Working on own farm (<i>dummy</i>)	0.84 (0.37)	0.79** (0.41)	0.86 (0.35)
Non-agricultural employment (<i>dummy</i>)	0.05 (0.22)	0.08** (0.26)	0.04 (0.19)
Agricultural wage employment (<i>dummy</i>)	0.01 (0.09)	0.01 (0.09)	0.01 (0.09)
Self-employed outside farm (<i>dummy</i>)	0.10 (0.31)	0.13 (0.34)	0.09 (0.29)
Use of irrigation (<i>dummy</i>)	0.77 (0.42)	0.88*** (0.33)	0.71 (0.45)
Access to credit (<i>dummy</i>)	0.10 (0.30)	0.11 (0.31)	0.10 (0.30)
Size of main vegetable plot (<i>acres</i>)	0.08 (0.09)	0.09* (0.09)	0.08 (0.09)
Labor use in vegetables (<i>labor days per acre-months</i>)			
Total labor	95.1 (105.6)	91.4 (121.2)	96.9 (97.1)
Family labor	59.1 (87.2)	48.4** (109.7)	64.4 (73.2)
Hired labor	36.0 (57.3)	43.0** (62.0)	32.5 (54.6)
Hired labor by gender of laborers			
Hired female labor	19.1 (42.1)	23.9* (51.9)	16.7 (36.2)
Hired male labor	16.9 (37.1)	19.1 (30.2)	15.8 (40.1)
Hired labor by operation			
Land preparation	6.3 (20.6)	6.0 (11.4)	6.4 (23.9)
Planting	3.6 (10.6)	3.6 (5.7)	3.7 (12.3)
Gap filling	0.1 (0.7)	0.1 (0.6)	0.1 (0.7)
Weeding	14.7 (29.1)	18.8** (37.8)	12.6 (23.4)
Irrigation	2.3 (13.9)	2.7 (18.6)	2.0 (10.8)
Pesticide application	0.7 (4.6)	1.2* (6.9)	0.5 (2.7)
Application of fertilizer & manure	0.6 (3.4)	1.1** (4.4)	0.3 (2.7)
Harvesting	7.2 (18.7)	8.4 (19.4)	6.6 (18.3)
Packing	0.5 (3.7)	1.0** (5.5)	0.2 (2.3)

Note: Mean values are shown with standard deviations in parentheses.

*, **, *** Significantly different at the 10%, 5%, and 1% level, respectively.

Table 2
Specification tests for double-hurdle models

<i>Test against tobit specification (H_0: tobit specification is appropriate)</i>			
	LR statistic (χ^2)	Critical χ^2_{19} value	Conclusion
Total hired labor	223.06	30.14	H_0 rejected
Female hired labor	81.60	30.14	H_0 rejected
Male hired labor	226.56	30.14	H_0 rejected
<i>Test for endogeneity of supermarket participation variable (H_0: variable is exogenous)</i>			
		p-value	Conclusion
Total hired labor	First stage	0.972	H_0 not rejected
	Second stage	0.543	H_0 not rejected
Female hired labor	First stage	0.929	H_0 not rejected
	Second stage	0.657	H_0 not rejected
Male hired labor	First stage	0.360	H_0 not rejected
	Second stage	0.387	H_0 not rejected

Table 3
Maximum likelihood estimates of double-hurdle models

Variables	Total hired labor		Female hired labor		Male hired labor	
	Decision to hire	Labor quantity	Decision to hire	Labor quantity	Decision to hire	Labor quantity
Participation in supermarket channel (<i>dummy</i>)	0.303*	24.322*	0.295*	28.499**	0.138	22.382
(0.182)	(12.576)	(0.155)	(12.982)	(0.165)	(37.621)	
Total area owned (<i>acres</i>)	0.073*	4.848**	0.079**	1.593	0.102**	11.402
(0.042)	(2.366)	(0.037)	(2.056)	(0.041)	(11.601)	
Household size (<i>adult equivalents</i>)	-0.100	31.041	0.414	-19.806	-0.067	150.784
(0.395)	(28.219)	(0.355)	(28.789)	(0.369)	(154.319)	
Gender of operator (<i>male dummy</i>)	0.227	78.079**	0.003	72.247*	0.484**	114.837
(0.242)	(36.426)	(0.228)	(38.232)	(0.231)	(139.518)	
Age of operator (<i>years</i>)	-0.003	0.091	0.003	-0.477	-0.001	-1.597
	(0.007)	(0.489)	(0.006)	(0.516)	(0.006)	(2.001)
Education of operator (<i>years</i>)	-0.036	-2.799	-0.012	-1.094	-0.015	-12.599
(0.023)	(1.714)	(0.020)	(1.572)	(0.021)	(11.564)	
Working on own farm ^a (<i>dummy</i>)	0.261	42.377	0.114	8.050	0.039	240.071
(0.329)	(30.182)	(0.298)	(25.710)	(0.323)	(236.052)	
Agricultural wage employment ^a (<i>dummy</i>)	0.233	-419.650	1.002	-652.099	-0.381	-621.204
(0.832)	(435.276)	(0.837)	(587.134)	(0.837)	(1,352.771)	
Self-employed outside farm ^a (<i>dummy</i>)	0.280	90.179**	0.379	43.238	-0.207	325.084
(0.392)	(36.506)	(0.354)	(30.336)	(0.376)	(293.940)	
Use of irrigation (<i>dummy</i>)	0.319*	31.249*	0.174	13.103	0.272	57.692
(0.177)	(18.438)	(0.170)	(16.844)	(0.171)	(80.406)	
Access to credit (<i>dummy</i>)	0.383	34.187**	0.343	33.229**	0.208	8.839
	(0.259)	(16.993)	(0.220)	(16.286)	(0.228)	(60.041)
Daily wage rate (<i>Ksh/day</i>)	0.000	-0.024	-0.000	-0.182	0.005*	-0.652
(0.003)	(0.168)	(0.002)	(0.202)	(0.002)	(0.827)	
Price of fertilizer (<i>Ksh/kg</i>)	0.001	-0.310	0.000	0.029	0.000	-1.077
(0.003)	(0.227)	(0.003)	(0.233)	(0.003)	(1.107)	
Price of pesticide (<i>Ksh/ml</i>)	0.015	-0.918	0.022	0.190	0.005	-23.531
(0.021)	(1.690)	(0.018)	(1.325)	(0.019)	(23.302)	
Price of purchased manure (<i>Ksh/kg</i>)	0.075	-14.593**	-0.056	2.494	0.022	-44.088
(0.088)	(6.806)	(0.077)	(6.013)	(0.080)	(40.242)	
Limuru region ^b	-0.097	45.600*	-0.394	7.759	0.172	609.257
	(0.329)	(26.022)	(0.317)	(20.445)	(0.311)	(589.286)
Githunguri/Lower Lari region ^b	-0.034	-57.031*	-0.642*	-53.205*	0.338	367.666
(0.383)	(33.112)	(0.368)	(31.781)	(0.369)	(435.831)	
Kikuyu/Westland region ^b	0.383	-13.332	-0.466	-29.175	0.689**	473.081
(0.335)	(26.040)	(0.318)	(23.010)	(0.314)	(495.478)	
Exotic vegetables (<i>dummy</i>)		-26.516*		-21.570		-104.595
	(15.604)			(15.449)		(99.862)
Adjusted plot size (<i>acres-months</i>)		82.643***		57.188***		161.880
	(17.104)			(15.108)		(127.447)
Share of land under vegetables	0.186		0.327		0.307	
(0.223)		(0.203)			(0.210)	
Constant	0.033	-287.771**	-1.951	-60.037	-1.537	-1,297.135
	(1.682)	(146.658)	(1.517)	(134.076)	(1.575)	(1,251.864)
Sigma		35.025***		28.824***		49.276**
		(5.270)		(5.369)		(22.164)
Number of observations	400	400	400	400	400	400
Log-likelihood		-1271.328		-922.108		-957.757

Note: Standard errors are shown in parentheses.

*, **, *** Significantly different at the 10%, 5%, and 1% level, respectively.

^a The reference occupation is non-agricultural employment.

^b The reference region is Lari.

Table 4
Marginal effects of double-hurdle model (total hired labor)

Variables	Decision to hire labor		Marginal effects for quantity of labor used			
	Marginal effects	SE	CAPE	SE ^c	UAPE	SE ^c
Participation in supermarket channels (<i>dummy</i>)	0.089*	0.051	3.261*	2.136	4.103**	1.931
Total area owned (<i>acres</i>)	0.022*	0.013	0.722*	0.415	0.872*	0.470
Household size (<i>adult equivalents</i>)	-0.031	0.121	4.622	5.291	3.170	4.453
Gender of operator (<i>male dummy</i>)	0.074	0.083	11.627*	6.416	10.004**	5.012
Age of operator (<i>years</i>)	-0.001	0.002	0.014	0.085	-0.001	0.070
Education of operator (<i>years</i>)	-0.011	0.007	-0.417	0.275	-0.478**	0.237
Working on own farm ^a (<i>dummy</i>)	0.085	0.112	6.310	5.935	6.014	4.993
Agr. wage employment ^a (<i>dummy</i>)	0.065	0.209	-62.490	41.345	-47.601	35.973
Self-employed outside farm ^a (<i>dummy</i>)	0.078	0.099	13.429**	6.600	11.629*	5.968
Use of irrigation (<i>dummy</i>)	0.103*	0.060	4.653*	2.616	4.972**	2.371
Access to credit (<i>dummy</i>)	0.103*	0.060	5.091*	2.975	5.584**	2.749
Daily wage rate (<i>Ksh/day</i>)	0.000	0.001	-0.004	0.025	-0.001	0.021
Price of fertilizer (<i>Ksh/kg</i>)	0.000	0.001	-0.046	0.035	-0.032	0.032
Price of pesticide (<i>Ksh/ml</i>)	0.005	0.006	-0.137	0.425	-0.043	0.350
Price of purchased manure (<i>Ksh/kg</i>)	0.023	0.027	-2.173**	1.031	-1.372	0.921
Limuru region ^b	-0.030	0.104	6.790	4.319	4.869	3.558
Githunguri/Lower Lari region ^b	-0.011	0.121	-8.493*	5.041	-6.749	4.138
Kikuyu/Westland region ^b	0.115	0.099	-1.985	4.186	0.081	4.004
Share of land under vegetables	0.130	0.081			0.791	1.031
Adjusted plot size (<i>acre-months</i>)			12.306***	2.503	9.569***	1.826
Exotic vegetables (<i>dummy</i>)			-3.948	2.705	-3.070	2.233
<i>Number of observations</i>	400		400		400	

*, **, *** Significantly different at the 10%, 5%, and 1% level, respectively.

^a The reference occupation is non-agricultural employment.

^b The reference region is Lari.

^c These are bootstrapped standard errors.

Table 5
Marginal effects of double-hurdle model (female hired labor)

Variables	Decision to hire labor		Marginal effects for quantity of labor used			
	Marginal effects	SE	CAPE	SE ^c	UAPE	SE ^c
Participation in supermarket channels (<i>dummy</i>)	0.117*	0.061	4.499**	2.285	3.811**	1.540
Total area owned (<i>acres</i>)	0.031**	0.015	0.252	0.600	0.517	0.383
Household size (<i>adult equivalents</i>)	0.165	0.141	-3.127	5.601	0.385	3.631
Gender of operator (<i>male dummy</i>)	0.001	0.091	11.405**	4.780	6.004**	2.865
Age of operator (<i>years</i>)	0.001	0.002	0.075	0.108	0.054	0.064
Education of operator (<i>years</i>)	-0.005	0.008	-0.173	0.272	-0.148	0.180
Working on own farm ^a (<i>dummy</i>)	0.045	0.118	1.271	6.612	1.228	4.042
Agr. wage employment ^a (<i>dummy</i>)	0.352	0.217	-102.943***	18.377	-49.167***	14.921
Self-employed outside farm ^a (<i>dummy</i>)	0.150	0.136	6.826	6.597	5.443	4.503
Use of irrigation (<i>dummy</i>)	0.069	0.067	2.069	2.489	1.941	1.703
Access to credit (<i>dummy</i>)	0.136	0.085	5.246**	2.545	4.437**	1.814
Daily wage rate (<i>Ksh/day</i>)	-0.000	0.001	0.029	0.033	-0.016	0.021
Price of fertilizer (<i>Ksh/kg</i>)	0.000	0.001	0.005	0.042	0.004	0.022
Price of pesticide (<i>Ksh/ml</i>)	0.009	0.007	0.030	0.445	0.124	0.232
Price of purchased manure (<i>Ksh/kg</i>)	-0.022	0.031	0.394	1.110	-0.066	0.645
Limuru region ^b	-0.154	0.121	1.225	3.760	-1.286	2.523
Githunguri/Lower Lari region ^b	-0.245*	0.130	-8.399*	4.819	-7.557**	3.267
Kikuyu/Westland region ^b	-0.184	0.123	-4.606	3.883	-4.703	2.753
Share of land under vegetables	0.130	0.081			1.605	0.986
Adjusted plot size (<i>acre-months</i>)			9.028***	2.405	4.742***	1.139
Exotic vegetables (<i>dummy</i>)			-3.405	3.213	-1.789	1.697
Number of observations	400		400		400	

*, **, *** Significantly different at the 10%, 5%, and 1% level, respectively.

^a The reference occupation is non-agricultural employment.

^b The reference region is Lari.

^c These are bootstrapped standard errors.

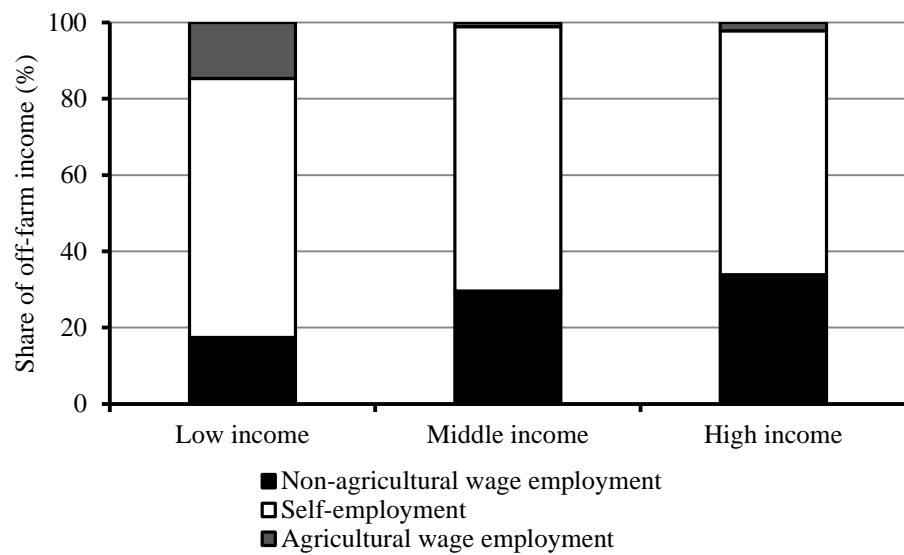


Fig. 1. Composition of off-farm income among sample farmers (by income tercile).