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The case of vegetable production in Kenya

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Abstract

Supermarkets and high-value exports are currently gaining ground in the agri-food systems of many developing countries. While recent research has analyzed income effects in the small farm sector, impacts on farming efficiency have hardly been studied. Using a survey of Kenyan vegetable growers and a stochastic frontier approach, we show that participation in supermarket channels increases mean technical efficiency by 19%. This gain is bigger at lower levels of efficiency, suggesting the potential for positive income distribution effects. However, disadvantaged farms often have problems in meeting strict supermarket requirements. Innovative market linkage initiatives can increase the probability of participation significantly.

Keywords: supermarkets, small farms, technical efficiency, stochastic frontier, sample selection, Kenya

JEL classification: Q12, O12, O13, D24

1. Introduction

Domestic agri-food systems in many developing countries are still dominated by traditional and informal supply chains, characterized by smallholder farmers, middlemen, and spot-market trading. However, rapid urbanization and rising living standards are creating increasing demand for high-value food products and a tendency towards supply chain modernization (Swinnen, 2007). In addition to dietary diversification, the growing number of middle-class consumers has preferences for higher levels of food quality, food safety, and convenience (Pingali, 2007; Mergenthaler *et al.*, 2009). These requirements are difficult to meet through traditional marketing channels, especially for highly perishable fresh horticultural and animal products. Therefore, modern food supply chains often involve tighter vertical coordination, with super- and hypermarkets rapidly gaining importance (Reardon *et al*., 2003; Neven and Reardon, 2004).

Modernizing supply chains present challenges and opportunities for developing country farmers. Food quality and food safety are associated with informational uncertainties and higher transaction costs (Okello and Swinton, 2006; Pingali *et al.*, 2007). To minimize such costs, modern retailers often impose strict standards, which might potentially exclude resource-poor agricultural producers facing technical, financial, or human capital constraints. On the other hand, supermarket procurement channels might increase the efficiency of production and trade, which could also be associated with more transparency and better prices for suppliers (Gulati *et al.*, 2007; Ngugi *et al.*, 2007). If these channels were accessible for small farms, this could lead to positive household income effects among the poor. Supplying supermarkets can also contribute to market assurance and thus income stability, as the transactions often involve contractual agreements. Such issues have inspired significant interest among researchers seeking to understand the effects of modernizing supply chains for poverty and rural development.

Recent research has analyzed the determinants of farmer participation in modern supply chains, including supermarket and export channels, and impacts on farm and household incomes (Neven *et al.*, 2005; Hernandez *et al.*, 2007; Wollni and Zeller, 2007). There are also studies that have looked into effects for more traditional markets, and spill-overs on land use and rural employment (Minten *et al*., 2007; Maertens and Swinnen, 2009; Schipmann and Qaim, 2009).

However, restructuring supply chains might also have impacts on technical efficiency in farm production, an aspect that has not been analyzed so far. Moreover, there is limited knowledge on how the access of smallholder farmers to high-value supply chains can be facilitated through institutional support. This article contributes to the literature by addressing these two issues.

Compared to traditional farming and spot-market sales, producing high-value foods for modern supply chains often entails more sophisticated planning and use of better production techniques. Sometimes, special extension and other agricultural support services are provided to farmers (Masakure and Henson, 2005). Fulfilling delivery requirements imposed by supermarkets may also necessitate use of irrigation technology. In addition, food quality and food safety requirements can affect the choice of inputs and the timing of input application. And finally, better output prices and improved farm incomes can influence input demand and output supply. We hypothesize that these mechanisms contribute to a net increase in technical efficiency. If this is the case, modern supply chains could contribute to agricultural productivity growth, which is urgently needed for poverty reduction and rural development (World Bank, 2007). Here, we evaluate the impacts of participation in supermarket channels on technical efficiency through stochastic frontier analysis, taking special account of sample selection issues. Moreover, we analyze the determinants of farmer participation with a particular emphasis on the role of institutional support mechanisms.

The empirical analysis builds on a comprehensive cross-section survey of vegetable farmers in Central Kenya. Overall, the expansion of supermarkets in Sub-Saharan Africa is not yet as strong as in Asia and Latin America (Reardon *et al.*, 2003; Gulati *et al.*, 2007), but in Kenya supermarkets already account for 20% of food retailing in urban areas (Neven and Reardon, 2004; Nyoro *et al.*, 2007). While the focus of supermarkets is largely on processed foods, they are also gaining shares in fresh product markets. In Kenya, supermarkets accounted for about 4% of urban retailing in fresh fruits and vegetables in 2002, with a rapidly rising trend (Neven and Reardon, 2004). Supermarket procurement strategies have already influenced the horticultural sector around the city of Nairobi, and this phenomenon is likely to spread geographically as market shares are growing. Hence, understanding the implications is of crucial relevance for rural development research and policy.

The rest of this article is organized as follows. The next section presents an analytical framework and details of the econometric estimation procedures. This is followed by section 3, elaborating on the survey data and sample descriptive statistics. Section 4 presents and discusses the estimation results, while section 5 concludes.

2. Analytical framework and estimation procedures

2.1. Modelling the decision to participate in supermarket channels

In order to meet consumer demand for food quality, food safety, and consistency in supply, supermarkets increasingly source fresh produce via highly integrated arrangements with farmers. In return for fulfilling the requirements imposed, farmers gain market assurance and are offered stable and sometimes better prices. However, farmers who are unable to meet the requirements run the risk of being excluded from supermarket channels. The opportunities for income generation and the risk of exclusion for disadvantaged farmers can inspire institutional support from organizations keen on improving social outcomes. To model these dynamics, we first assume that farmers choose between supplying supermarkets and spot markets based on their capabilities and expected utility of returns (π). The supermarket option is chosen if expected utility of returns from supermarket channels $[U_S^*(\pi)]$ is greater than expected utility of returns from spot market channels $[U_T^*(\pi)]$. Participation in supermarket channels can therefore be related to a set of explanatory variables as follows:

$$U_S^*(\pi) = \alpha' Z_i + \theta I_i + \varepsilon_i \tag{1}$$

where α and θ are vectors of parameters to be estimated, and ε is a random error term. Variables in Z include household and farm characteristics, and I is a variable capturing participation of farmers in institutional support programs. However, utility is not observable; only participation in one of the two marketing channels is observed. Participation can be represented by a dummy variable $D(\pi)$ that takes the value 1 if a farmer participates in supermarket channels $\{U_S^*(\pi) > U_T^*(\pi)\}$, and 0 otherwise $\{U_S^*(\pi) \leq U_T^*(\pi)\}$. The probability of participation in supermarket channels can then be expressed as:

$$\Pr(D = 1) = \Pr\big(U_S^*(\pi) > U_T^*(\pi)\big) \tag{2a}$$

$$= \Pr(\varepsilon_i > -\alpha' Z_i - \theta I_i) = 1 - F(-\alpha' Z_i - \theta I_i) \tag{2b}$$

where F is the cumulative distribution function for ε. We estimate this model with a probit function, in order to identify the determinants of farmer participation in supermarket channels.

2.2. Modelling technical efficiency

Besides influencing participation, standards imposed by supermarkets can also affect the production technology used by participants. For instance, use of irrigation might be necessary to ensure regular and consistent supply. Farmers might also be required to schedule their production and adopt certain techniques that influence product quality. Beyond such requirements, innovations and markets for modern inputs might become more accessible through training and positive household income effects. These factors are likely to influence technical efficiency – an effect that we want to estimate econometrically.

In order to estimate technical efficiency, we first assume that farmers maximize expected net returns, which can be represented as:

$$\max_{\omega} E(PQ(X,Z) - R'X) \tag{3}$$

where *E* is the expectation operator conditional on information available to farmers; *P* is output price, and *Q* is the expected output level; *X* is a vector of inputs, and *Z* a vector of household characteristics. *R* is a vector of input prices. Net returns can thus be expressed as a function of variable input prices, output prices, household characteristics, and technology choice *d* as follows:

$$\pi = \pi(R, d, P, Z) \tag{4}$$

We assume that participation in supermarket channels (*D*) influences the technology employed and also the output price. Hence, normalizing a well specified profit function and applying Hotelling's lemma to the maximization problem in equation (3) yields an output supply function as follows:

$$Q = Q(R, d(D), P(D), Z) \tag{5}$$

Since our goal is to link output to technology in a manner that allows for measurement of technical efficiency effects, the usual mean response production function, which implicitly assumes that all farmers are efficient, is inappropriate. Instead we apply stochastic frontier analysis that enables us to model technical inefficiency of farmers (Coelli, 1995; Coelli *et al.*, 2005). The model estimates a frontier production function, representing a best-practice technology against which the efficiency of individual farms in the sample can be measured. The frontier model can be expressed as follows:

$$ln\, q_i = F(x_i; \beta) + v_i - u_i \tag{6}$$

where q_i is the vegetable output of farm i, x_i is a vector of input quantities used by farm i, and β is a vector of parameters to be estimated. $F(.)$ denotes the frontier function, v_i is the stochastic error term with an independent and identical distribution $N(0,\sigma_v^2)$, and u_i is a one-sided error term representing technical inefficiency in production. v_i and u_i are distributed independently and are also independent of x_i. Since the frontier represents the best-practice technology, technical efficiency can be defined as the ratio of the observed output (q_i) to maximum possible output ($F(x_i; \beta)$) as follows:

$$TE = \frac{q_i}{F(x_i;\beta)} \tag{7}$$

Therefore, $TE \leq 1$ and, since by definition $u_i \geq 0$, $TE = \exp(-u_i)$. Assuming a half-normal distribution $[N^+(0, \sigma_u^2)]$ for u_i,[2] maximum likelihood techniques can be used to jointly estimate parameters of the frontier, technical efficiency, as well as the variance parameters $\sigma = (\sigma_v^2 + \sigma_u^2)^{1/2}$; and $\lambda = \sigma_u/\sigma_v$. The parameter λ can be used to test for the presence of inefficiency (Kumbhakar and Lovell, 2003). As $\lambda \rightarrow 0$, the symmetric error dominates the one-sided error, and we fall back to the mean response model. By contrast, as $\lambda \rightarrow +\infty$ the one-sided error dominates the symmetric error, leading to the frontier model.

[2] While the half-normal distribution is a frequent assumption for u_i in stochastic frontier analysis, other distributions such as the exponential or truncated normal can also be used. While different distributional assumptions can give rise to different predictions of technical efficiency, rankings of results are often quite robust to distributional choice (Coelli *et al.*, 2005).

To estimate the influence of supermarket channel participation on technical inefficiency we use a heteroscedastic stochastic frontier model. This model exploits heteroscedasticity in the non-negative error term (u_i) to identify causes of technical inefficiency (Kumbhakar and Lovell, 2003). The variance in u_i is modelled as a function of farm-specific variables as follows:

$$\sigma_{ui}^2 = z_i\delta + \gamma D \tag{8}$$

where z_i is a vector of household characteristics associated with technical inefficiency of farms, D is a dummy variable for participation in supermarket channels, and δ and γ are vectors of unknown coefficients. The joint maximum likelihood estimation of the heteroscedastic frontier and the inefficiency model yields estimates for β, δ, γ, and also for the level of technical inefficiency. Our hypothesis of a positive impact of supermarket channel participation on technical efficiency implies a negative (inefficiency reducing) and significant coefficient γ.

2.3 Potential selection bias

The remaining challenge in our estimation is that we are using non-experimental data; evaluating treatment effects in such cases can be challenging due to a possible selection bias. To measure unbiased effects we need differences in efficiency outcomes with and without treatment $u_1 - u_0$. However, we do not know the efficiency of farmers that participate in supermarket channels without treatment. In other words, the counterfactual is not observed. Furthermore, treatment is not randomly assigned to farm households, but they choose market outlets themselves based on some inherent characteristics. Supermarkets may also systematically choose suppliers based on certain criteria. Thus, participants and non-participants in supermarket channels may be systematically different. Under such circumstances, observed differences in efficiency may mistakenly be attributed to participation in a particular marketing channel.

Several approaches have been applied to address selectivity in frontier analysis. A conventional approach is to use the two-step estimation procedure developed by Heckman (1976), for which recent examples include Sipiläinen and Lansink (2005) and Solis *et al.* (2007). However, this approach was developed for linear regression models, and is less suitable for non-linear ones such as the stochastic frontier. Different panel data estimation techniques have been developed to deal with unobserved heterogeneity in stochastic frontier models (Abdulai and Tietje, 2007), but unfortunately we do not have panel data available for vegetable farmers in Kenya. Recently, Greene (2008) proposed a simulation based estimation method for the stochastic frontier model with sample selection, which can be used with cross-section data. However, while this method yields consistent estimates, it assumes that unobservables in the selection equation are uncorrelated with the inefficiency (Greene, 2008: 11). Besides, the model assumes the basic form of frontier model (Greene, 2007) and hence does not allow for modelling the causes of (in)efficiency. Since this is actually the key focus of our study, we decided to deal with selectivity by regressing on propensities scores, as described by Imbens (2004). We are not aware of any previous study that has used regression on propensity scores in the context of stochastic frontier analysis. Our approach is elaborated in the following.

Assuming there is no selection bias, the coefficient γ in equation (8) should represent a measure of the average treatment effect (ATE) of supermarket participation, which can be expressed as follows:

$$ATE = E(u_1 - u_0) \tag{9}$$

However, for each person we can only estimate either u_1 or u_0 and not both. The estimated outcome can therefore be expressed as:

$$u = (1 - D)u_0 + \ Du_1 = u_0 + D(u_1 - u_0) \tag{10}$$

If treatment were randomized across agents, *D* would be statistically independent of $(u_1 - u_0)$, and the coefficient on *D* would be a consistent estimate of ATE. However, participation in supermarket channels is not randomized. To estimate ATE, we need an identifying assumption, which ensures statistical independence between *D* and $(u_1 - u_0)$. This is achieved using the conditional mean independence assumption (Rosenbaum and Rubin, 1983), which states that, conditional on a vector of observed covariates (***z***) that determine treatment, *D* and (u_1, u_0) are independent. Hence $E(u_0|\boldsymbol{z}, D) = E(u_0|\boldsymbol{z})$ and $E(u_1|\boldsymbol{z}, D) = E(u_1|\boldsymbol{z})$. In other words, if we can observe enough information that determines treatment (contained in **z**), then $(u_1 - u_0)$ might be mean independent of *D*, conditional on **z** (Wooldridge, 2002). If we can express efficiency outcomes in terms of their mean and stochastic components as $u_1 = \mu_1 + v_1$ and $u_0 = \mu_0 + v_0$, where $\mu_{1g} = E(u_g)$, $g = 0{,}1$, then

$$u_1 - u_0 = (\mu_1 - \mu_0) + (v_1 - v_0) = ATE + (v_1 - v_0) \tag{11}$$

where $(v_1 - v_0)$ represent person-specific gains from participation. Equation (10) could then be expressed as:

$$u = \mu_0 + D(\mu_1 - \mu_0) + v_0 + D(v_1 - v_0). \tag{12}$$

If we assume further that v_1 and v_0 have zero mean conditional on **z**, we obtain a standard regression model:

$$E(u|D, \boldsymbol{z}) = \mu_0 + \gamma D + g_0(\boldsymbol{z}) \tag{13}$$

where $\gamma \equiv ATE$ and $g_0(\boldsymbol{z}) = E(v_0|\boldsymbol{z})$. We can further estimate $g_0(\boldsymbol{z})$ as $E(v_0|\boldsymbol{z}) = \eta_0 + h_0(\boldsymbol{z})\omega_0$ to obtain

$$E(u|D, \boldsymbol{z}) = \alpha_0 + \gamma D + h_0(\boldsymbol{z})\omega_0 \tag{14}$$

where $\alpha_0 = \mu_0 + \eta_0$. Consequently when $E(v_1 - v_0|\boldsymbol{z}) = 0$, $E(u|D, \boldsymbol{z})$ is additive in *D* and a function of **z**, and standard regression can be used to estimate γ as ATE (Wooldridge, 2002). In other words, by having enough controls in **z**, the equation is arranged such that $(u_1 - u_0)$ and unobservables are 'appropriately unrelated' (Wooldridge, 2002: 611-612). Elements of ***z*** therefore act as proxies for unobservables, and the function $h_0(\boldsymbol{z})\omega_0$ is an example of a control function, which, when added to the regression of *u* on intercept and *D*, controls for possible selection bias. But this only holds under the restrictive assumption that $(v_1 - v_0)$ has zero mean conditional on **z**, which implies that the treatment effect is the same for everyone in the population. This is unlikely to be the case, however. We can relax this assumption by estimating ATE as:

$$E(u|D, \boldsymbol{z}) = \alpha_0 + \gamma D + g_0(\boldsymbol{z}) + D[g_1(\boldsymbol{z}) - g_0(\boldsymbol{z})] \tag{15}$$

where $\gamma = ATE$, $g_0(\boldsymbol{z}) = E(v_0|\boldsymbol{z})$, and $g_1(\boldsymbol{z}) = E(v_1|\boldsymbol{z})$. Consequently, based only on the conditional mean independence assumption, $E(u|D, \boldsymbol{z})$ is additive in *D*, and a function of **z**, and an interaction term between *D* and another function of **z**. Furthermore, the coefficient on *D* is the average treatment effect. Following Wooldridge (2002), the above equation can be implemented as:

$$E(u|D, \boldsymbol{z}) = \alpha_0 + \gamma D + \boldsymbol{z}\omega_0 + D(\boldsymbol{z} - \overline{\boldsymbol{z}})\varphi \tag{16}$$

where ω_0 and φ are vectors of unknown parameters and $\overline{\boldsymbol{z}} \equiv E(\boldsymbol{z})$. Subtracting the mean from $\boldsymbol{z}$ ensures that $\gamma = ATE$. One can also use functions of $\boldsymbol{z}$ instead of the whole vector of $\boldsymbol{z}$, for instance, employing propensity scores – defined as the conditional probability of treatment given covariates ($\boldsymbol{z}$). Hence, we use regression on propensity scores in the inefficiency model, in order to consistently estimate impacts of participation in supermarket channels on technical efficiency. In particular, we estimate:

$$ln\ q_i = F(x_i; \beta) + v_i - u_i$$

$$\text{where} \quad \exp(-u_i) = z_i\delta_2 + \gamma D_i + PS_i\omega + D_i(PS_i - \overline{PS})\varphi \tag{17}$$

Propensity score (PS) in our case is defined as the conditional probability that a farmer participates in supermarket channels given covariates [$PS = \hat{p}(D = 1|\boldsymbol{z})$]; it is estimated using a probit function. PS is therefore an example of a function that controls for possible selection bias.

3. Data and descriptive statistics

3.1. Farm survey

Data for this study was collected in 2008 from Kiambu District of Central Province in Kenya. Kiambu is located in relative proximity to Nairobi; even before the spread of supermarkets it has been 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 that participate in supermarket channels are still the minority, we oversampled them using complete lists obtained from supermarkets and supermarket traders. In total, our sample comprises 402 farmers – 133 supermarket suppliers and 269 supplying vegetables to traditional markets. Using a structured questionnaire, these farmers were interviewed on vegetable production and marketing details, other farm and non-farm economic activities, as well as household and contextual characteristics.

Both types of farmers produce vegetables in addition to maize, bananas, and a number of other crops. The main vegetables produced are leafy vegetables, including exotic ones such as spinach and kale, and indigenous ones such as *amaranthus* and black nightshade, among others.[3] Figure 1 shows the different marketing channels for vegetables used by sample farmers. Some supermarket suppliers also sell vegetables in traditional spot markets when they have excess supply. However, for analytical purposes, farmers that supply at least part of their vegetables to supermarkets are classified as supermarket suppliers.

Insert Figure 1 here

Spot markets sales are one-off transactions between farmers and retailers or consumers with neither promise for repeated transactions nor prior agreements on product delivery or price. Depending on the demand and supply situation, prices are subject to wide fluctuation. Farmers who are unable to supply directly to wholesale or retail markets sell their produce to spot market traders who act as intermediaries. Such traders collect vegetables at the farm gate without any prior agreement. In contrast, supermarkets do have agreements with vegetable farmers regarding product price, physical quality and hygiene, and consistency and regularity in supply (Ngugi *et al.*, 2007). Price agreements are made before delivery, and prices are relatively stable. Payments

[3] Recently, African indigenous vegetables have received renewed attention from upper and middle income consumers (Moore and Raymond, 2006; Ngugi *et al.*, 2007).

are usually only once a week or every two weeks. All agreements are verbal with no written contract. Some farmers also supply supermarkets through special traders. Based on similar verbal agreements, these traders again maintain regular contacts with farmers, in order to be able to supply supermarkets in a timely and consistent way. Strict supply requirements by supermarkets have led to specialization among traders. Consequently supermarket traders tend to exclusively supply modern retail outlets.[4]

Given the risk of exclusion from emerging modern supply chains for disadvantaged farmers, there are various organizations in Kenya linking smallholders to supermarket and export channels. One such organization active in Kiambu is the NGO Farm Concern International (FCI). FCI trains farmer groups on production of indigenous vegetables before linking them to various supermarkets in Nairobi (Moore and Raymond, 2006; Ngugi *et al.*, 2007). Market mediation by FCI lowers transaction costs of searching trading partners, screening them, and negotiating agreements for both farmers and supermarkets. Such transaction costs could otherwise constitute an entry barrier for small-scale producers. Furthermore, FCI promotes collective action and – through training efforts – helps farmers to meet the strict delivery standards imposed by supermarkets. Another service provided by the NGO is invoice discounting, that is, FCI pays farmers directly upon delivery of produce, recovering its funds when supermarkets process payment after one or two weeks. These initiatives therefore constitute an institutional innovation that facilitates market access by farmers who might otherwise have been excluded from high-value markets. FCI currently has 80 vegetable farmers

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

involved in this project in Kiambu District. Out of these, more than half were already supplying supermarkets at the time of our survey.

3.2. Descriptive statistics

Table 1 compares selected variables between supermarket and spot market suppliers in our sample. On average, farmers supplying supermarkets own more land.[5] They are also better educated and have significantly higher farm, non-farm, and total household incomes. While supermarket suppliers have an annual mean per capita income of 167 thousand Kenyan shillings (Ksh) (2230 US dollars), average per capita incomes among spot market suppliers are only around 77 thousand Ksh (1025 US dollars). Supermarket farmers have a larger share of their land under vegetables, which is an indication of their higher degree of specialization. In addition, significantly larger proportions of supermarket suppliers use advanced irrigation technology, such as water pumps and sprinklers,[6] and have their own means of transportation. This gives them an advantage in terms of meeting supermarket requirements for consistency and regularity in supply. Yet there are no significant differences between the two groups in terms of access to a reliable water source, the share of the vegetable area under irrigation, and experience in vegetable farming.

Insert Table 1 here

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[5] The mean farm size in Kenya is 6.7 acres (Jayne *et al.*, 2003), but this also includes large plantations. In terms of per capita incomes, households in Kiambu are slightly richer than those in most other rural districts of the country. The rural poverty rate in Kiambu was 22% in the early 2000s (Ndeng'e *et al.*, 2003).

[6] We use the term "advanced irrigation technology" to differentiate from those farmers that only use very simple tools like watering cans. More sophisticated techniques, such as drip irrigation, are rare in the Kenyan small farm sector.

In the lower panel of Table 1 we present plot level variables related to vegetable production. The two groups show significant differences in the value of output per acre: vegetable farmers in supermarket channels have significantly higher sales revenues per acre, which is due to both higher yields and higher prices. With respect to inputs, the groups differ in terms of fertilizer, farmyard manure, and labour use. Famers in supermarket channels use significantly more purchased farmyard manure and hired labour. However, they use significantly less fertilizer and family labour. These comparisons suggest that production practices and technologies differ considerably. Whether this also affects technical efficiency, as we have hypothesized, will be analyzed in the next section.

4. Results and discussion

In this section, we first analyze the determinants of participation in supermarket channels, before the results of the stochastic frontier estimation are presented.

4.1. Determinants of participation in supermarket channels

As described above, a probit model is estimated to identify the determinants of farmer participation in supermarket channels. Alongside typical farm and household characteristics, such as farm size, education, and asset ownership, we are interested in the role that institutional support through FCI plays. Therefore, we include participation in the FCI market linkage program as an additional explanatory variable – defined as a dummy. Yet, participation in that program might potentially be endogenous; it could be affected by unobservables that also influence participation in supermarket channels, which would lead to a bias in the coefficient estimate. We test for endogeneity of the FCI dummy using a two-step approach suggested by

Rivers and Vuong (1988). Using membership in a farmer group, which is correlated with FCI but not with supermarket channel participation, as an instrument, we run a probit regression of FCI. Predicted residuals from this regression are then included as additional explanatory variable in supermarket participation model and the null hypothesis to be tested is that residuals are not significant – implying exogeneity of FCI variable. The test fails to reject this null hypothesis (p = 0.294), so that we proceed using a standard probit model.

The estimation results are shown in Table 2, expressed as marginal effects at sample mean values. Strikingly, farm size has no significant influence on participation, that is, small farms in the study region are as likely to be supermarket suppliers as larger ones. Likewise, livestock income has no significant effect. We included this variable, as the descriptive statistics above showed that supermarket suppliers tend to use much larger amounts of manure, so that one could have expected a positive effect. This, however, might be counteracted by the higher degree of specialization in vegetables among supermarket suppliers.

Insert Table 2 here

Explanatory variables that do have significant effects include farmer age and education. Each additional year of age reduces the probability of participating in supermarket channels by 0.5 percentage points, everything else being constant. This is similar to findings by Hernandez *et al.* (2007), who showed in a study in Guatemala that younger vegetable farmers are more likely to participate in supermarket channels than older ones. Unsurprisingly, education has the opposite effect: each additional year of schooling increases the probability by 1.6 percentage points. Younger and better educated farmers are often more innovative, as they better understand how to acquire and process information, use new production techniques, and meet the standards required by supermarkets.

Participation in supermarket channels also necessitates irrigation, as supermarkets require farmers to supply vegetables continuously throughout the year. Producers unable to meet this requirement due to seasonality run the risk of losing their market. While both participants and non-participants in supermarket channels use irrigation, the descriptive statistics discussed above already revealed that more supermarket suppliers use advanced irrigation technology. The probit results in Table 2 confirm that advanced irrigation technology is a significant determinant of participation, which is also in line with findings by Neven *et al.* (2005) in Kenya and Hernandez *et al.* (2007) in Guatemala. Furthermore, access to reliable transportation is an important factor, as this is necessary for timely product delivery. Ownership of a vehicle increases the probability of being a supermarket supplier by 22 percentage points, while the availability of public transportation services in the village increase the probability by 14 percentage points. These results underscore the importance of physical infrastructure for market access in general, and participation in high-value markets in particular.

And finally, participation in the FCI market linkage program enhances farmers' access to supermarket channels. Ceteris paribus, participating in this program increases the probability of being a supermarket supplier by 36 percentage points. By negotiating with supermarkets on behalf of farmers, FCI reduces transaction costs. Furthermore, as explained above, technical training is provided and collective action encouraged, making smallholder farmers more reliable trading partners for supermarkets. Equally important is the invoice discounting service by FCI, which enables even relatively poor households with immediate cash needs to participate in supermarket channels, despite the lagged payment schedule. These are important findings from a policy perspective. Where no NGO like FCI is operating, public agencies might potentially take on such roles of institutional support.

4.2. Technical efficiency effects

We now analyze technical efficiency of vegetable production and impacts of supermarket channel participation, using a stochastic frontier model as described above. Our dependent variable is the value of vegetable output per farm. Value is preferred over output quantity for two reasons: First, data on output quantity is less precise and less reliable in our context and also not fully comparable across different types of vegetables grown. Second, in addition to yield effects we also expect improvements in product quality through participation in supermarket channels, which can be captured – at least partially – by using output value (also see Abdulai and Tietje, 2007). As independent variables we use agricultural inputs and production factors in the frontier, and a set of socioeconomic characteristics in the inefficiency model. Regional dummies are included in both model parts. These regions represent agroecological conditions; regional boundaries differ slightly from administrative divisions.

Before discussing the actual estimation results, we carry out standard tests for choice of functional form and justification of the inefficiency approach. The test results are reported in Table 3. A popular specification in production function analysis is the Cobb-Douglas model, which is easy to implement and interpret, yet building on restrictive assumptions. In our case, a likelihood ratio test rejects the null hypothesis that these assumptions hold, suggesting that the more flexible translog function is a better choice. Test results also reject the mean response model in favour of the stochastic frontier; dominance of the one-sided error over the random error is indicated by the value of λ, which is bigger than 1. Additional tests also confirm the presence of inefficiency in our sample of vegetable farmers.

Insert Table 3 here

Results of the stochastic frontier estimations are shown in Table 4. Following Battese (1997), we correct for zero values of inputs by including dummies for input use and interactions between these dummies and the continuous input variables. Furthermore, the continuous input variables are mean corrected $(x_i - \bar{x})$, so that the estimated coefficients of the first order terms can be interpreted directly as production elasticities. Table 4 shows different model specifications. While model I does not correct for sample selection, model II does so through regression on propensity scores. These two models have similar coefficient estimates for the production frontier, so that we only focus on model II for interpretation. The value of vegetable output increases significantly with the use of fertilizer, manure, and labour. A 1% increase in each of these inputs increases output by 0.21%, 0.15%, and 0.20%, respectively. Likewise, seed cost – which we use as a proxy for seed quality – and plot size have a significantly positive impact on output value, whereas the effect of pesticide is insignificant. The latter might potentially be due to an endogeneity problem, as farmers use pesticide as a response to pest pressure, which is unobserved.

Insert Table 4 here

Looking at the determinants of inefficiency (lower part of Table 4), the differences in results between model I and model II are more pronounced. In model I, only the share of vegetable area is significant at the 10% level. The negative sign of the coefficient indicates that the variable contributes to reduced inefficiency, which makes sense, as specialized vegetable farmers are expected to be more efficient. Of particular interest here is the supermarket channel participation dummy, whose coefficient is negative but insignificant in model I. Yet the coefficient is highly significant in model II. In addition, the propensity score coefficient is significant; the negative propensity score coefficient indicates a positive selection bias, which is controlled for in model II. We conclude that participation in supermarket channels reduces inefficiency in the Kenyan vegetable sector; in other words, participation increases technical efficiency, which confirms our main research hypothesis.

Model III in Table 4 also corrects for sample selection but uses the natural logarithm of output quantity instead of output value as dependent variable. As argued above, we prefer output value as the more reliable measure. And indeed, compared to models I and II the performance of model III is somewhat inferior. Nonetheless, the main result of a significant increase in technical efficiency through participation in supermarket channels is robust, suggesting that this effect has both a quantity and product quality component.

Building on estimation results of model II, Table 5 shows a summary of efficiency scores for the whole sample, and disaggregated by marketing channel and region. Vegetable farmers in our sample only reach a mean technical efficiency score of 61%, underlining large scope for improvement. On average, supermarket suppliers have an efficiency score that is 10.9 percentage points (18.8%) higher than that of farmers selling in traditional spot markets. The difference between marketing channels is statistically significant in all four agroecological regions, although it varies in magnitude. With almost 20 percentage points, the efficiency gain of participating in supermarket channels is highest in the Kikuyu/Westland & Dagoreti and Githunguri and Lower Lari regions, while it is lowest in Lari.

Insert Table 5 here

How can these differences be explained? Strikingly, all farmers in Lari, including supermarket and spot market suppliers, are technically more efficient than their colleagues in the other regions, as indicated by high mean efficiency scores and low standard deviations. This can partly be explained by favourable agroecological conditions. Hence, it appears that efficiency gains of supermarket channel participation are higher in situations where farmers start from a lower efficiency base, either due to agroecological or other disadvantages. Our sub-sample size for Lari is small, so regional differences should not be over-interpreted. Yet the same finding is also supported by Figure 2, which shows the entire distribution of efficiency scores for the two marketing channels across the four regions. As can be seen, the distribution of supermarket suppliers consistently dominates the distribution of spot market suppliers, except for high levels of efficiency. An implication is that more disadvantaged farms – if specifically targeted – could benefit over-proportionally from participating in high-value supply chains, potentially entailing positive income distribution effects.

Insert Figure 2 here

5. Conclusion

Agri-food systems in many developing countries are currently undergoing a transformation towards modern high-value supply chains, with supermarkets and their procurement systems gaining in importance. Recent research has studied what type of farmers participate in such high-value supply chains and what the impacts are in terms of farm and household income. Our research contributes to this literature through analysis of technical efficiency effects and the role of institutional support programs aimed at linking smallholder farmers to high-value markets.

Using primary survey data of vegetable growers in Kenya, we showed that participants in supermarket channels tend to be younger and better educated farmers, who are more capable of meeting the strict quality standards and delivery requirements. Likewise, access to irrigation technology and transportation are crucial factors that determine participation. Another important finding is that institutional support through Farm Concern International – an NGO active in the Kenyan vegetable sector – facilitates the link between smallholder farmers and supermarkets significantly. Innovative NGO interventions include specific training efforts in production and marketing, invoice discounting, and the promotion of farmer collective action. The analysis revealed that these interventions increase the probability of farmer participation in supermarket channels by 36 percentage points. Using stochastic frontier analysis and controlling for sample selection, we also showed that participation in supermarket channels increases technical efficiency of vegetable production by 19% on average. This is due to improvements in product quality as well as more productive use of inputs and technologies.

Kenya is only one example where supermarkets and other high-value market developments are transforming agricultural supply chains in developing countries. Therefore, this research has wider policy implications. Understanding both the potentials and risks of the agri-food system transformation is crucial, as developments gradually spread to a wider geographical area. Our results suggest that high-value chains can contribute to agricultural efficiency gains and thus to innovation and sustainable growth in the small farm sector, which are important preconditions for poverty reduction and rural development. The findings even suggest that efficiency gains are higher for disadvantaged farms with lower initial technical efficiency scores than for farms that are more efficient anyway. Thus, modernizing supply chains could potentially also contribute to positive income distribution effects. However, disadvantaged farms might face access problems to high-value markets, which have to be overcome through targeted institutional support. Initiatives such as those by Farm Concern International are a step in the right direction. Such programs should be scaled up, in order to harness the growth and development potentials and avoid undesirable social outcomes. Possibly, public extension services could also play a certain role in this regard.

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Table 1. Summary statistics

Variables	**Supermarket (133)**	**SD**	**Spot market (269)**	**SD**
Household and farm characteristics				
Total area owned *(acres)*	2.692**	5.607	1.870	2.485
Total vegetable area cultivated *(acres)*	1.168***	1.457	0.697	0.992
Share of vegetable area *(%)*	68.8*	31.9	62.8	32.5
Access to reliable water source *(%)*	19.5	39.8	21.6	41.2
Use of advanced irrigation technology *(%)*	87.9***	32.7	71.4	45.3
Share of vegetable area irrigated *(%)*	76.7	38.7	77.0	39.1
Age of operator *(years)*	47	12	49	15
Education of operator *(years of schooling)*	10.3***	3.14	8.72	4.05
General farming experience *(years)*	16.16**	11.60	17.89	13.33
Vegetable farming experience *(years)*	14.01	11.73	15.18	12.14
Household labour endowment *(no. of people)*	1.89	1.06	2.07	1.20
Own means of transportation *(%)*	24.06***	42.91	8.92	28.56
Total crop income *(Ksh)*	185,578***	228,973	86,078	129,123
Livestock income *(Ksh)*	98,366	351,568	69,944	130,510
Total farm income *(Ksh)*	283,944***	379,823	156,022	189,333
Non-farm income *(Ksh)*	151,589***	235,460	59,115	134,945
Household income per capita *(Ksh)*	167,155***	251,363	76,839	93,710
Plot level variables for vegetables				
Sales revenue per acre *(Ksh/acre)*	499,005***	400,508	370,865	335,877
Dummy for farming of exotic vegetables *(%)*	76***	43	88	32
Fertilizer use *(kg/acre)*	362.56**	548.76	494.21	640.19
Pesticide use *(ml/acre)*	2,251.22	4,083.44	2,745.51	4,382.22
Purchased manure use *(kg/acre)*	15,926**	28,107	11,108	19,329
Own manure use *(kg/acre)*	5,550	15,693	6,107	14,473
Hired labour use *(labour days/acre)*	215.36**	296.29	164.28	276.98
Family labour use *(labour days/acre)*	307***	395	489	632
Total labour use *(labour days/acre)*	522**	472	653	734

*, **, *** Mean differences between supermarket and spot market suppliers are significant at the 10%, 5%, and 1% level, respectively.
Note: 1 US dollar = 75 Ksh.

Table 2. Determinants of participation in supermarket channels (probit results)

Variable	Marginal effect[a]	SE
Total area owned *(acres)*	0.006	0.007
Livestock income *(Ksh)*	1.68^{-08}	1.05^{-07}
Gender of operator *(dummy)*	0.118	0.075
Age of operator *(years)*	-0.005**	0.002
Education of operator *(years)*	0.016**	0.008
Own means of transportation *(dummy)*	0.224***	0.080
Access to public agricultural extension *(dummy)*	-0.053	0.056
Household labour endowment *(no. of people)*	-0.036	0.023
Experience in vegetable farming *(years)*	0.001	0.003
Use of advanced irrigation equipment *(dummy)*	0.172***	0.052
Availability of public transportation in village *(dummy)*	0.141**	0.056
Participation in FCI market linkage program *(dummy)*	0.358***	0.066
Number of observations		*402*
Pseudo R-squared		*0.1524*
Log likelihood		*-216.29485*

*, **, *** Significant at the 10%, 5%, and 1% level, respectively.
[a] *Results can be interpreted as marginal effects on the probability to participate (evaluated at mean values for continuous variables).*

Table 3. Hypothesis testing for stochastic production frontier model

Test type	Null hypothesis	Test-statistics	Critical value	Test results
Choice of functional form (χ-value)				
	H_0: $\beta_{ij} = 0; i,j=1,\ldots,6$	33.632	32.671	Translog is appropriate
Frontier vs. mean response model				
	$H_0 : \lambda \leq 1$	1.633		Frontier is appropriate
Test for presence of inefficiency (p-value)				
	$u_i = 0$	0.041	0.1	Inefficiency exists
Test for inefficiency effects (χ-value)				
	H_0: $\delta_{0i} = \delta_{2i} = 0;$	45.916	19.675	Model inefficiency
Test for constant returns to scale (CRS) (based on p-value): Returns to scale = 0.993				
	H_0: $\sum_{i=1}^{6} \beta_i = 1$	0.921	0.05	CRS exist

Note: The test statistics refer to model II of Table 4, which is our preferred specification, as detailed in the text.

Table 4. Parameter estimates of the stochastic production frontier (translog model)

	Model I		**Model II**		**Model III**	
Variables	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Production frontier model[a]						
Dummy for use of fertilizer	-0.147	0.117	-0.133	0.112	0.115	0.126
Dummy for use of pesticide	-0.041	0.119	-0.022	0.106	-0.048	0.117
Dummy for use of manure	-0.398**	0.174	-0.383**	0.170	-0.261	0.177
ln Seed cost	0.132**	0.055	0.121**	0.050	-0.014	0.059
ln Fertilizer	0.211***	0.062	0.207***	0.059	0.199***	0.066
ln Pesticide	0.054	0.059	0.049	0.057	-0.049	0.064
ln Manure	0.183***	0.056	0.154***	0.054	0.129**	0.065
ln Labour	0.217***	0.064	0.203***	0.060	0.295***	0.070
ln Plot size	0.255***	0.059	0.259***	0.057	0.407***	0.068
0.5 × (ln Seed cost)^2	0.144**	0.061	0.146**	0.059	0.013	0.071
0.5 × (ln Fertilizer)^2	0.100	0.077	0.104	0.073	0.253***	0.081
0.5 × (ln Pesticide)^2	0.082	0.067	0.059	0.063	0.057	0.066
0.5 × (ln Manure)^2	0.103	0.086	0.053	0.079	-0.045	0.082
0.5 × (ln Labour)^2	0.031	0.106	0.010	0.102	0.034	0.109
0.5 × (ln Plot size)^2	-0.066	0.099	-0.057	0.095	-0.166	0.107
Advanced irrigation technology *(dummy)*	0.078	0.094	0.884	0.086	0.119	0.091
Githunguri & Lower Lari region[b] (*dummy*)	-0.124	0.372	0.039	0.338	-0.596	0.369
Kikuyu/Westland region[b] (*dummy*)	0.499	0.320	0.708**	0.339	0.402	0.361
Limuru region[b] (*dummy*)	0.096	0.300	0.294	0.346	-0.003	0.371
Exotic vegetable *(dummy)*	0.374***	0.107	0.353***	0.101	0.310***	0.116
Constant	-0.641**	0.316	-0.670*	0.373	-0.143	0.376
Inefficiency model						
ln Age of operator (*years*)	1.122	0.888	0.455	0.515	0.505	0.638
Experience in vegetable farming (*years*)	-0.025	0.024	-0.018*	0.010	-0.009	0.012
Supermarket channel participation (*dummy*)	-1.476	1.330	-0.913***	0.300	0.999**	0.400
Propensity score *(PS)*			-3.421**	1.662	-6.246*	3.514
Supermarket participation × $(PS - \overline{PS})$			-2.567	2.178	3.608	2.854
Gender of operator (*male dummy*)	-0.339	0.443	-0.332	0.344	0.724	0.631
Education of operator (*years*)	-0.017	0.040	0.068	0.044	0.087	0.060
Access to agricultural extension (*dummy*)	0.278	0.331	0.228	0.249	0.081	0.311
Share of vegetable area	-1.203*	0.724	-1.105***	0.420	-0.098	0.504
Githunguri & Lower Lari region[b] (*dummy*)	3.271	3.277	6.668	12.83	3.695	4.396
Kikuyu/Westland region[b] (*dummy*)	3.716	3.233	6.440	12.79	3.762	4.278
Limuru region[b] (*dummy*)	2.855	3.265	5.728	12.79	2.933	4.294
Constant	-6.778	4.737	-6.511*	12.55	-5.913	4.600
Number of observations	402		402		402	

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

[a] *The dependent variable in models I and II is ln value of output, whereas in model III it is ln quantity of output.*

[b] *The reference region is Lari.*

Note: Interaction terms were included in estimation, but are not shown here for reasons of space.

Table 5. Differences in efficiency scores by marketing channel and region

	Number of farmers	Mean efficiency
Whole sample		
Mean	402	0.613 (0.201)
Minimum		0.032
Maximum		0.972
By marketing channel		
Supermarket suppliers (mean)	133	0.687 (0.154)
Spot market suppliers (mean)	269	0.578 (0.211)
Mean difference		0.109***
By region and market channel		
Kikuyu/Westland & Dagoreti		
All farmers in that region (mean)	180	0.587 (0.196)
Supermarket suppliers (mean)	82	0.695 (0.141)
Spot market suppliers (mean)	98	0.496 (0.190)
Mean difference		0.197***
Githunguri & Lower Lari		
All farmers in that region (mean)	93	0.586 (0.195)
Supermarket suppliers (mean)	43	0.644 (0.171)
Spot market suppliers (mean)	50	0.536 (0.202)
Mean difference		0.108***
Limuru		
All farmers in that region (mean)	107	0.613 (0.170)
Supermarket suppliers (mean)	6	0.790 (0.055)
Spot market suppliers (mean)	101	0.602 (0.168)
Mean difference		0.188***
Lari		
All farmers in that region (mean)	22	0.955 (0.011)
Supermarket suppliers (mean)	2	0.967 (0.006)
Spot market suppliers (mean)	20	0.954 (0.011)
Mean difference		0.014*

*, **, *** Differences are significant at the 10%, 5%, and 1% level, respectively.
Note: Standard deviations are shown in parentheses.

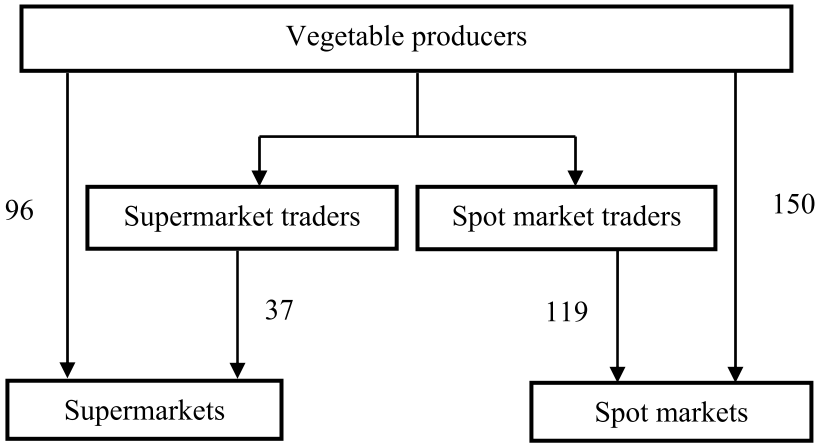

Figure 1. Vegetable marketing channels among Kenyan sample farmers

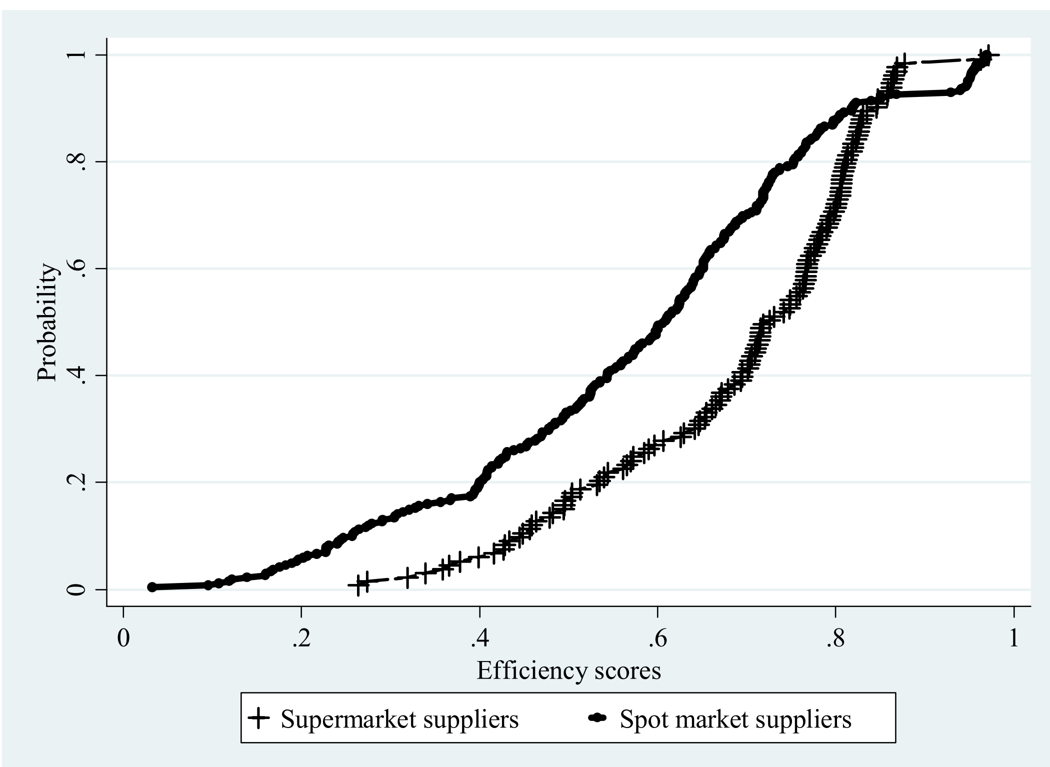

Figure 2. Cumulative distribution of technical efficiency by marketing channel