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Farmer Participation in Supermarket Channels, Production Technology, and Efficiency: The Case of Vegetables in Kenya

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Abstract

Supermarkets are 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 productivity and efficiency have hardly been studied. We use a meta-frontier approach and combine this with propensity score matching to estimate treatment effects among vegetable farmers in Kenya. Participation in supermarket channels increases farm productivity in terms of meta-technology ratios by 45%. We also find positive and significant impacts on technical efficiency and scale efficiency. Supermarket expansion therefore presents opportunities for agricultural growth in the small farm sector, which is crucial for poverty reduction in Africa.

Keywords: supermarkets, technical efficiency, scale efficiency, meta-frontier, meta-technology ratio, sample selection, Kenya

Introduction

Domestic agri-food systems in many developing countries are experiencing increasing demand for high-value food products and a tendency towards supply chain modernization (Reardon et al. 2009; Swinnen 2007). In addition to market liberalization, these changes are largely motivated by rapid urbanization and rising living standards. The growing number of urban, middle-class consumers has preferences for higher levels of food quality, food safety, diversity, and convenience (Mergenthaler, Weinberger, and Qaim 2009; Pingali, Khwaja, and Meijer 2007). To meet these emerging preference structures, modern supply chains often adopt increased vertical coordination, with super- and hypermarkets rapidly gaining importance (Boselie, Henson, and Weatherspoon 2003; Neven and Reardon 2004; Reardon et al. 2003).

Participation in such modern supply chains can provide new income opportunities for farmers (Neven et al. 2009). Yet, there are also new challenges. Food quality and safety can be associated with informational uncertainties and high transaction costs, which could potentially limit participation possibilities for resource-poor farmers (Balsevich et al. 2003; Okello and Swinton 2007; Pingali, Khwaja, and Meijer 2007). Recent studies have analyzed the determinants of farmer participation in modern supply chains, including supermarket and export channels, and impacts on farm and household incomes (Hernández, Reardon, and Berdegué 2007; Maertens and Swinnen 2009; Rao and Qaim 2011). There are also studies that have looked into effects for more traditional markets and spillovers on land use and rural employment (Minten, Randrianarison, and Swinnen 2007; Schipmann and Qaim 2010; Maertens, Colen, and Swinnen 2011).

However, modernization of supply chains involves structural changes that may also affect farm productivity – an aspect that has received less attention in the available literature. While a few studies have analyzed productivity effects of supermarket or export channel participation (e.g., Hernández, Reardon, and Berdegué 2007; Minten, Randrianarison, and Swinnen 2007; 2009; Neven et al. 2009), we are not aware of any research that has taken a disaggregated view on different potential sources of productivity growth, such as changes in technology, technical efficiency, or scale efficiency. As productivity growth in smallholder agriculture can be an important avenue for poverty reduction (World Bank 2007), a better understanding of the sources and mechanisms for realizing the same is important from a development policy perspective.

Participation in modern supply chains may affect the farmers' choice of production technology. For instance, stricter requirements in terms of quality, food safety, and consistency in supply may necessitate the use of reliable irrigation equipment, improved seeds, and other modern inputs. At the same time, market assurance may also increase the farmers' ability and willingness to invest in technical innovation. Participation in modern supply chains may also influence technical efficiency in a positive way, in so far as it facilitates access to production and market related information. This is particularly so in cases where agri-business firms provide extension services to contract farmers (e.g., Schipmann and Qaim 2010; Masakure and Henson 2005). In other cases, development organizations may be involved in linking smallholders to high-value markets through technical and institutional support (e.g., Ngugi, Gitau, and Nyoro 2007). And finally, assured markets and more stable prices in modern supply chains (Michelson, Reardon, and Perez 2011) may entail scale efficiency gains. Largely due to risk considerations, smallholders often diversify their income sources. Therefore, reduced market risk may allow a higher degree of specialization on high-value commodities. On the other hand, Foster and Rausser (1991) showed that high risk may also lead to the overuse of some household resources, so that reduced risk may entail more scale-efficient resource allocation also in this respect.

Our study contributes to the literature on high-value markets in developing countries by developing a decomposition approach that allows us to estimate possible productivity effects due to differences in technology as well as gains due to technical and scale efficiency. The approach is used for empirical analysis in the Kenyan vegetable sector, where smallholder farmers have recently started supplying supermarket channels. We estimate separate group production frontiers for supermarket and traditional channel farmers, and a meta-production frontier, which enables us to derive meta-technology ratios, technical efficiency scores, and measures of scale efficiency. Finally, we use propensity score matching to account for possible selection bias in impact assessment.

The empirical analysis builds on a survey of vegetable farmers in central Kenya. The expansion of supermarkets in Sub-Saharan Africa is not yet as strong as in Asia and Latin America (Gulati et al. 2007; Reardon et al. 2003), but in Kenya supermarkets already account for about 6% of the national food retail sector and 20% of food retailing in urban areas (Planet Retail 2011; Ariga and Ngugi 2007). While the focus of supermarkets is largely on processed foods, they are also gaining shares in fresh product markets. In Nairobi, supermarkets now account for 4% of fresh fruit and vegetable sales (Olwande 2010). Supermarket procurement strategies have started to influence the horticultural sector around the capital city, and this phenomenon will likely spread to other parts of Kenya, when the modern retail sector expands.

The rest of this article is organized as follows. The next section presents the analytical framework and details of the econometric procedures. This is followed by presentation of the survey data and sample descriptive statistics. Subsequently, we show and discuss the estimation results, before closing with some concluding remarks.

Analytical framework

In order to get a first indication of the impacts of supermarket channel participation on farm productivity, we estimate a simple deterministic production function, including a participation dummy as treatment variable. Since this treatment variable may be endogenous due to self-selection, we use an instrumental variable (IV) approach. Yet, this approach does not allow us to differentiate between technology and efficiency effects. Hence, we use a frontier approach for the main part of the analysis.

Building on a single frontier for all farmers, regardless of whether they supply supermarkets or traditional channels, would be one option. This would assume that all farmers have access to the same technology, so that differences in production performance would be attributed to different levels of efficiency. However, we hypothesize that participation in supermarket channels may also improve farmer's access to better technology. Hence, we use the concept of a meta-production function as an envelope of neoclassical production functions (Hayami and Ruttan 1985). In our context, this assumes that farmers in supermarket and traditional channels are operating under different production technologies, which are represented in the form of group-specific frontiers. Battese, Rao, and O'Donnell (2004) and O'Donnell, Rao, and Battese (2008) developed a meta-frontier (MF) model, which enables the estimation of technology gaps for producers under different technologies relative to the potential technology available to the industry as a whole. The model also facilitates the interpretation of grand technical efficiency scores by decomposing them into group specific efficiency and technology differences.[1]

[1] Since the MF model has often been used for cross-country or cross-region studies, one could argue that it is only applicable if the group-specific frontiers cannot be breached. However, we also consider the framework useful when groups of farmers within the same region have differential access to technology due to institutional or related constraints. Compared to supermarket suppliers, smallholder households face higher marketing risks, and they are also more affected by credit and information constraints, making it much more difficult for them to access modern production technology.

Group-specific frontiers

We define separate stochastic production frontiers (SPFs) for farmers in supermarket and traditional channels as follows:

(1) $$Y_{ij} = f(\boldsymbol{x}_{ij}, \boldsymbol{\beta}_j) e^{v_{ij} - u_{ij}}; \quad i = 1, 2, \dots N; j = 1,2$$

where Y_{ij} denotes vegetable output of the *i*th farm for the *j*th group; $\boldsymbol{x}_{ij}$ denotes a vector of inputs and other explanatory factors; $\boldsymbol{\beta}_j$ denotes the parameter vector associated with the ***x***-variables for the stochastic frontier; v_{ij} is a random variable that is identically and independently distributed and independent of u_{ij}, which is a non-negative unobservable random error associated with technical efficiency. If we assume a log-linear functional form (such as the translog) as in Battese, Rao, and O'Donnell (2004), the SPF can be written as:

(2) $$Y_{ij} = f(\boldsymbol{x}_{ij}, \boldsymbol{\beta}_j) e^{v_{ij} - u_{ij}} \equiv e^{\boldsymbol{x}_{ij}\beta_j + v_{ij} - u_{ij}}.$$

Based on suitable distributional assumptions for the error terms *u* and *v*, data for farms in the *j*th group can be used to obtain maximum-likelihood (ML) estimates of the unknown parameters of the frontier defined by equation (2). Output-oriented technical efficiency (TE) estimates for farm *i* with respect to the frontier of group *j* can be computed as:

(3) $$TE_{ij} = \frac{Y_{ij}}{Y_{ij}^{max}} = \frac{e^{x_{ij}\boldsymbol{\beta}_j - u_{ij} + v_{ij}}}{e^{x_{ij}\boldsymbol{\beta}_j + v_{ij}}} = e^{-u_{ij}}.$$

In order to model the relationship between TE and those variables that might exert an impact on the level of TE, we follow Wang and Schmidt (2002) and Alvarez et al. (2006) by specifying a model for the *u* random variables which fulfills the scaling property, i.e., where the fundamental shape of the distribution remains constant for all observations. Specifically, we apply a heteroscedastic frontier model, which assumes heteroscedasticity of the one-sided error term. This error term reflects factors under the farmer's control, and since large farms have more factors under their control, the one-sided error term is likely subject to size-related heteroscedasticity (Caudill and Ford 1993). We therefore model inefficiency as follows:[2]

(4) $\sigma_{ui} = \exp(\boldsymbol{w_i}\boldsymbol{\delta}_{\mathbf{j}})$.

In equation (4), $\boldsymbol{w_i}$ is a vector of farm-specific variables and size-related input use (including a constant), where $\boldsymbol{w_i}$ and $\boldsymbol{x_i}$ are allowed to overlap (Alvarez et al. 2006; Wang and Schmidt 2002). Besides allowing for functions of inputs in the inefficiency model, the scaling property of the heteroscedastic model enables direct interpretation of inefficiency coefficients as semi-elasticities (Wang and Schmidt 2002). After estimating the group frontiers in equation (2), we perform a likelihood ratio (LR) test to verify if the technologies in the two market channels can be represented by a common technology. If the null hypothesis of a common technology is rejected, the estimation proceeds following the MF framework (Battese, Rao and O'Donnell 2004).

Meta-frontier analysis

Battese, Rao, and O'Donnell (2004) define the MF as a deterministic parametric frontier of a specified functional form such that its values are no less than the deterministic part of the group-specific SPFs. Furthermore, the MF is assumed to be a smooth function and not a segmented

[2] An alternative functional form, $\sigma_{ui} = \sigma \exp(\boldsymbol{z_i}\boldsymbol{\delta}_{\mathbf{j}})$, assumes no intercept, so that the overall scale is set by a constant σ. Equivalently, we can eliminate the overall constant (σ) if we add an intercept to $\boldsymbol{w_i}\boldsymbol{\delta}_{\mathbf{j}}$ (Wang and Schmidt 2002). We use this latter option.

envelope of group frontiers. The deterministic MF model for all farms in the supermarket and traditional channels can therefore be expressed as follows:

(5) $$Y_i^* = f(\boldsymbol{x}_i, \boldsymbol{\beta}^*) = e^{\boldsymbol{x}_i\boldsymbol{\beta}^*}; i = 1, 2, \dots . N, N = \sum_{j=1}^{2} N_j$$

where $\boldsymbol{\beta}^*$denotes the vector of parameters of the MF function such that $\boldsymbol{x}_i\boldsymbol{\beta}^* \geq \boldsymbol{x}_i\boldsymbol{\beta}_j$ for all *i* observations. These parameters can be obtained by minimizing the sum of absolute deviations or the sum of the squared deviations of the distance between the MF and the *j*th group frontier evaluated at the observed input vector for a farm in the *j*th group. Estimating MF parameters therefore involves solving the following optimization problems:

(6) (a) $\min \mathrm{L1} \equiv \sum_{i=1}^{N} \left| \left(\ln f(\boldsymbol{x}_i, \boldsymbol{\beta}^*) - \ln f\left(\boldsymbol{x}_i, \widehat{\boldsymbol{\beta}}_j\right) \right) \right|$ or

(b) $\min \mathrm{L2} \equiv \sum_{i=1}^{N} \left(\ln f(\boldsymbol{x}_i, \boldsymbol{\beta}^{\sim}) - \ln f\left(\boldsymbol{x}_i, \widehat{\boldsymbol{\beta}}_j\right) \right)^2$

$s.t.$ $\ln f(\boldsymbol{x}_i, \boldsymbol{\beta}^*) \geq \ln f\left(\boldsymbol{x}_i, \widehat{\boldsymbol{\beta}}_j\right)$ or $\ln f(\boldsymbol{x}_i, \boldsymbol{\beta}^{\sim}) \geq f\left(\boldsymbol{x}_i, \widehat{\boldsymbol{\beta}}_j\right)$ for all *i*.

For these optimization problems, the $\widehat{\boldsymbol{\beta}}_j$ are treated as fixed, so that the second term in the summation is constant with respect to the minimization. Hence, equation (6a) can be equivalently solved by minimizing the objective function $L^* \equiv \overline{\boldsymbol{x}}\boldsymbol{\beta}^*$, subject to the linear restrictions as shown, where $\overline{\boldsymbol{x}}$ is the row vector of means of elements of the $\boldsymbol{x}$-vector for all observations in the dataset. Standard errors for the MF parameters can be derived by simulation, as outlined in Battese, Rao, and O'Donnell (2004).

In terms of the estimated MF, the observed output of the *i*th farm, defined by the SPF for the *j*th group in equation (2) can alternatively be expressed as follows:

(7) $$Y_i = e^{-u_{ij}} \times \frac{e^{x_i\beta_j}}{e^{x_i\beta^{*/\sim}}} \times e^{x_i\beta^{*/\sim}+v_{ij}}$$

where the first term on the right hand side is the technical efficiency with respect to group frontiers (TE), and the second term is the meta-technology ratio (MTR) for the particular sample farm involved:

(8) $$MTR_i = \frac{e^{x_i\beta_j}}{e^{x_i\beta^{*/\sim}}} = \frac{Y_i}{e^{x_i\beta^{*/\sim}}} / \frac{Y_i}{e^{x_i\beta_j}}.$$

MTR is a ratio of output for the frontier production function for the *j*th group relative to the potential output defined by the MF function, given the observed inputs (O'Donnell, Rao, and Battese 2008), or as the second equality in equation (8) illustrates, the ratio between the efficiency estimate against the group frontier and the efficiency estimate against the MF (TE_i^*). MTR lies between zero and one and captures productivity differences between the two technologies. Alternatively, equation (7) can be rearranged to decompose TE_i^* into the group TE estimate and MTR:

(9) $$TE_i^* = TE_{ij} \times MTR.$$

Scale efficiency

Differences in scale efficiency between supermarket and traditional channel farmers are estimated based on the group-specific frontiers shown in equation (2). We use the approach proposed by Ray (1998) for a translog functional form. Farm-specific estimates of an output-oriented measure of scale efficiency are obtained as:

(10) $$SE_i^o = exp\left[\frac{(1-E_i)^2}{2\beta}\right]$$

where E_i refers to the scale elasticity estimate from the translog, which is defined as the sum of the (farm specific) partial production elasticities.

The parameter $\beta = \sum_{j=1}^{n} \sum_{k}^{l} \beta_{jk} < 0$ should be negative in order to ensure that $0 < SE_i^o \leq 1$; this restriction will be fulfilled for any quasi-concave production frontier. Output-oriented scale efficiency can be interpreted as the relative output expansion by producing at optimal scale on the frontier for the observed factor proportions of a farm whose technical inefficiency has been eliminated (Førsund and Hjalmarsson 1979). Whenever an input bundle does not correspond to the optimal scale, the average productivity of its technically efficient correspondence is lower than what is maximally attainable at the optimal scale.

From equation (10) we see that scale elasticity and scale efficiency are related. Furthermore, scale elasticity and scale efficiency are both equal to unity only when constant returns to scale prevail, at which point production takes place at the optimal scale (Ray 1998). Scale efficiency increases with an increase in output when $E_i > 1$; this would indicate a sub-optimal scale of operation. On the other hand, $E_i < 1$ would indicate supra-optimal scale associated with decreasing returns to scale.

Potential selection bias

The group-specific and MF approaches can reveal differences in MTR, TE, and SE between farmers in supermarket and traditional channels. However, we cannot simply attribute these differences to participation in supermarket channels, because of a potential selection bias: some of the factors determining participation in supermarket channels may also influence farm efficiency and productivity. A common approach to address selectivity issues is the two-step Heckman (1976) procedure, which was recently used by Sipiläinen and Lansink (2005) and Solis, Bravo-Ureta, and Quiroga (2007). However, the two-step Heckman procedure is less suitable for non-linear functions such as the stochastic frontier. We therefore use matching techniques similar to Mayen, Balagtas, and Alexander (2010) in their stochastic frontier analysis. However, unlike their study we conduct matching after estimation to avoid losing information that is useful for constructing the frontiers.

We use a class of matching models known as propensity score matching (PSM) (Rosenbaum and Rubin 1983; Caliendo and Kopeinig 2008). Instead of simply comparing the outcome variables (i.e., MTR, TE, SE) between all supermarket and traditional channel farmers, PSM compares outcomes only between those supermarket ("treated") and traditonal ("control") farmers that are similar in terms of other observable characteristics, thus reducing the bias that would otherwise occur when the two groups are systematically different (Dehejia and Wahba 2002). In other words, PSM tries to imitate an experimental condition in which participation in the supermarket channel is randomly assigned, so that the difference can be interpreted as the treatment effect of supermarket participation.

PSM involves two stages. In the first stage, we generate propensity scores, $P(\boldsymbol{z})$, from a probit model, which indicate the probability of a farmer to participate in supermarket channels. $\boldsymbol{z}$ is a vector of observed conditioning variables, which may overlap with variables included in $\boldsymbol{x}$. Then we construct a control group by matching participants to non-participants according to their propensity scores. Participants for whom an appropriate match cannot be found, as well as non-participants not used as matches, are dropped. In the second stage, we calculate the average treatment effect on the treated (ATT) on outcome variable R, using matched observations of members and non-members. The PSM estimator of the ATT is the difference in outcomes between treatment and control group, appropriately matched by the propensity score:

(12) $$\tau_{ATT}^{PSM} = E_{P(\boldsymbol{z})|I=1}\{E[R_1|I = 1, P(\boldsymbol{z})] - E[R_0|I = 0, P(\boldsymbol{z})]\},$$

where R_1 and R_0 are the outcomes for the treated with treatment (supermarket participation) and control farmers without treatment, respectively, while $I = 1$ indicates treated farmers and $I = 0$ control farmers.

There are various matching techniques; the most common ones include nearest neighbor matching (NNM), kernel-based matching (KBM), stratified radius matching, and Mahalanobis matching (Caliendo and Kopeinig 2008). In this study, we apply the KBM and the NNM methods. NNM involves pairing farmers in supermarket and traditional channels who are closest in terms of $P(\boldsymbol{z})$ as matching partners. KBM, on the other hand, uses a weighted average of the outcome variable for all individuals in the control group (traditional channel suppliers) to construct a counterfactual outcome. Observations that provide better matches are given more weight. The weighted average is compared to the outcome for supermarket suppliers, and the difference provides an estimate of the treatment effect for each supermarket supplier. A sample average over all supermarket suppliers then provides an estimate of ATT.

One important aspect to mention is that PSM can only control for selection bias that is due to observed factors $\boldsymbol{z}$. That is, systematic differences between supermarket and traditional channel farmers may still exits even after conditioning, when part of the selection process is based on unobservables (Smith and Todd 2005). We make the standard assumption that the distribution of such unobservables is the same for the treatment and control group. However, Imbens (2004) states that this is ultimately an empirical question. We therefore apply the standard bounding test proposed by Rosenbaum (2002), which evaluates how strongly unobserved variables would have to influence the selection process to invalidate the implications of the matching process.

Data and descriptive statistics

Farm survey

Data for this study were collected in 2008 in Kiambu District, Central Province of Kenya. Kiambu is located in relative proximity to Nairobi; even before the spread of supermarkets, this district has been one of the main vegetable-supplying regions for the capital city. The two biggest supermarket chains now sourcing vegetables from Kiambu are Nakumatt and Uchumi, which are both Kenyan owned. Foreign owned retail chains so far play a much smaller role in Kenya (Planet Retail 2011).

Based on information from the Kiambu 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, stratifying between supermarket and traditional channels. Since farmers who 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 traditional channel suppliers. 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.

Vegetable marketing channels

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] 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.

Traditional market 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 traditional 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 in supply (Ngugi, Gitau, and Nyoro 2007). Price agreements are made before delivery. Payments are usually only once a week or every two weeks. Some farmers also supply supermarkets through special traders. Based on similar 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.

[3] Recently, African indigenous vegetables have received renewed attention from upper and middle income consumers in Kenya (Ngugi, Gitau, and Nyoro 2007).

All agreements with farmers are verbal; written contracts are uncommon. Supermarkets do not directly provide inputs or extension, but they refuse delivery from farmers who are not supplying regularly or who do not meet the stated requirements. Since the agreed prices are usually higher and more stable than prices in traditional vegetable markets, farmers have a strong incentive to upgrade their production technology (Rao and Qaim 2011). There are also various organizations in Kenya trying to link smallholders to supermarkets through special support programs. One such organization active in Kiambu is the NGO Farm Concern International (FCI). FCI trains farmers and farmer groups on production of indigenous vegetables before linking them to various supermarkets in Nairobi (Ngugi, Gitau, and Nyoro 2007). FCI also promotes collective action and – through training efforts – helps farmers to meet the strict delivery standards imposed by supermarkets.

Descriptive statistics

Table 1 compares selected variables between supermarket and traditional channel suppliers in our sample. On average, farmers supplying supermarkets own more land.[4] They are also better educated and have significantly higher farm, non-farm, and per capita 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 traditional channel 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

[4] 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, as compared to the national average of 54% (Ndeng'e, Opiyo, and Kristjanson 2003).

technology such as drip irrigation and sprinklers, 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 the share of vegetable area under irrigation and experience in vegetable farming.

Insert table 1 here

In the lower part 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. From the interviews it became clear that this is due to both higher yields and higher prices. However, since different types of vegetables are produced, which are measured in different units, output quantities are not easily comparable. Unfortunately, farmers were not able to report exact quantity measures for each vegetable type, which would have enabled us to construct output indices. The reason is that farmers sell most of their vegetables in bundles, which are not always of equal size.

With respect to inputs, the groups differ in terms of chemical fertilizer, farmyard manure, and labor use. Famers in supermarket channels use significantly more purchased farmyard manure and hired labor. Manure adds organic matter to the soil and – according to farmers' own statements – entails a quicker regeneration of the vegetable leaves after harvest. This is important, because in supermarket channels vegetables have to be supplied on a regular basis. On the other hand, supermarket suppliers use significantly less chemical fertilizer and family labor.

There are also significant differences in terms of sources and cost of seeds. The majority of the traditional channel suppliers obtain their seeds from informal sources, such as other farmers or traditional wet markets. While these are relatively cheap seeds, they are not cleaned and treated against pests and diseases. And, due to improper storage, the germination rate may be significantly reduced. In contrast, about two-thirds of the farmers supplying supermarkets buy seeds from formal sources, in particular from the Kenya Seed Company. These seeds are cleaned, treated, and stored under controlled conditions. Hence, the observed differences in seed sources and costs reflect differences in quality. FCI has also identified poor quality of indigenous vegetable seeds as an important constraint; the NGO now supplies cleaned and treated seeds to supermarket farmers.

These comparisons suggest that production practices and technologies differ between supermarket and traditional channel farmers. Whether these differences also affect productivity and efficiency will be analyzed in the following.

Results and discussion

We begin the analysis by estimating an average production function for vegetables. We use a translog functional form, which turned out to be statistically superior to the more restrictive Cobb-Douglas specification. The dependent variable is the value of vegetable output (revenue) per plot. As explained, we do not know exact output quantities, which is a drawback, because variations in values can reflect variations in both vegetable yields and prices. Hence, changes in productivity, as measured here, combine quantity, quality, and harvest timing components, which has to be kept in mind for the interpretation of our results.

As independent variables, we include inputs such as quantities of labor, fertilizer, farmyard manure and pesticide as well as the cost of seeds, besides various other covariates. 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. Supermarket participation is included as a treatment dummy. Since this is endogenous, we employ a treatment effects IV model. We use farm size (total area owned) and the availability of public transportation in the village as instruments, which are exogenous, correlated with supermarket participation, but uncorrelated with the value of vegetable output per plot. Estimation results are shown in table 2. The first column reports estimates of the outcome equation. Supermarket participation has a large, positive, and significant effect on the value of output, which underscores the sizeable productivity impacts that are worthwhile to be further analyzed.

Insert table 2 here

Group-specific frontiers

Since we are interested in decomposing technology and efficiency effects, we now use the stochastic frontier framework, as described above. We begin with the estimation of group-specific SPFs. Before discussing the estimation results, we carry out standard tests for choice of functional form and justification of the inefficiency approach. These test results are shown in table 3. Concerning the structure of production, hypotheses tests reveal that the Cobb-Douglas functional form is an inadequate restriction in comparison to the translog production frontier for both groups. The more flexible translog is therefore preferred.

Insert table 3 here

A second test in table 3 tests the null hypothesis that there are no technical inefficiency effects. This is also rejected for both groups, implying that the majority of vegetable producers in the two channels operate below the production frontier. Hence, the average production frontier is not an adequate specification. Finally, the hypothesis of identical technology across supermarket and traditional channels is rejected at a high level of significance. The application of the meta-frontier approach is therefore more appropriate in our context.

Results for the group frontiers are shown in table 4. Again, we use the method proposed by Battese (1997) to correct for zero input values. Furthermore, the continuous input variables are mean corrected $(\log x_i - \log \bar{x})$, so that the estimated coefficients of the first order terms can be interpreted directly as production elasticities at the sample mean.[5] For supermarket suppliers, the value of vegetable output is significantly influenced by all inputs except chemical fertilizer. For traditional channel suppliers, among the input variables only fertilizer and plot size have statistically significant effects. There are also considerable differences in the magnitude of the input production elasticities across the two channels. We include region dummies as explanatory variables, some of which have large and significant effects. This is not surprising, because these dummies are proxies for environmental conditions, such as rainfall, slope, and soil quality, which are known to affect productivity (Sherlund, Barrett and Adesina 2002). Interestingly, some of these effects differ remarkably between the two channels.

Insert table 4 here

With respect to efficiency effects, which are shown in the lower part of table 4, farmyard manure, labor, gender, and experience in vegetable farming play significant roles. Use of farmyard manure by supermarket suppliers increases technical efficiency (reduces inefficiency). On the other hand, use of labor as well as increasing share of family labor reduces their technical efficiency. Strikingly, female suppliers of supermarket channels are more technically efficient than male suppliers. For farmers in traditional channels, increasing use of labor improves

[5] We also calculated average production elasticities for inputs by taking the mean of the elasticities for individual farm observations, which are similar in magnitude. These additional results can be made available upon request.

efficiency, while share of family labor is insignificant. Experience in vegetable farming also increases efficiency of traditional channel suppliers.

Meta-frontier estimates and technical efficiency

Differential parameter estimates in the two group frontiers are indicative of differences in production technology between farmers supplying supermarket and traditional channels. This was already confirmed by the test shown in table 3. The next task is to investigate whether these differences are responsible for productivity effects. We therefore proceed with the MF analysis. Using parameter estimates from the group frontiers, both a linear and a quadratic programming optimization model (see equations 6a and 6b) are solved for the entire sample. Since the group frontiers favor the use of a translog model, the meta-frontier is also specified as a translog. Estimation of group frontiers and the meta-frontier were done using Ox version 6.10 (Doomik 2007). Parameter estimates for the two meta-frontiers (L1 and L2) and the simulated standard errors are shown in table 5. Since we find only minor differences between the two meta-frontiers, the following discussion is based on the L1 coefficients.

Insert table 5 here

Results reveal positive and significant effects of chemical fertilizer, farmyard manure, labor, and plot size on the value of vegetable output. The parameters of the MF are used in the estimation of MTR and TE, as shown in equations (8) and (9), respectively. A summary of these two measures is shown in table 6, alongside scores for TE with respect to the group frontiers. However, the group-specific scores cannot be compared across groups since they are estimated with respect to different frontiers. Comparisons of TE across groups should therefore only be based on estimates from the MF.

Insert table 6 here

As can be seen from table 6, farmers in supermarket and traditional channels show significant differences in MTR and TE. On average, supermarket farmers exhibit a productivity level that is 15 percentage points (27%) higher than farmers in traditional channels. Given the technology potentially available to all vegetable farms in Kiambu, supermarket farmers produce 71% of potential output, whereas traditional channel farmers produce 56% of potential output on average. The group frontier for supermarket suppliers is tangential to the meta-frontier since the maximum value of the MTR is achieved, while this is not the case for traditional channel suppliers.

While supermarket farmers achieve higher TE on average, the efficiency levels are relatively low for farmers in both channels. This holds true for both the meta-frontier TE and the group TE. On the one hand, this indicates substantial scope for efficiency improvements. On the other hand, it should also be noted that we probably do not perfectly control for environmental and biophysical factors, which may influence both the estimated production function and technical efficiency estimates (Sherlund, Barrett, and Adesina 2002). While the regional dummies used may capture some of these effects, they are hardly able to control for micro-level environmental variations. Hence, the absolute MTR and TE levels should be interpreted with some caution. However, we have no reason to believe that such micro-level environmental variations are correlated with supermarket participation, so that we do not expect a systematic bias in the impact assessment.

Scale efficiency

As discussed above, higher price stability and market assurance in supermarket channels reduce marketing risk and can thus encourage more optimal production decisions and scales of operation. We estimate scale efficiency scores for farmers in the two market channels as explained in the analytical framework section. Results are shown in table 7. On average, supermarket suppliers are more scale-efficient than their counterparts supplying traditional channels. But these results are with respect to the group-specific frontiers. The optimal scale of operation differs between the two channels; in terms of the value of output it is 49% larger for supermarket than for traditional channel farmers. It should be stressed that this only refers to farmers' vegetable business, and not the farm as a whole. Therefore, these results do not imply that the growth of supermarkets will inevitably lead to larger farm sizes.

Insert table 7 here

Further analyzing the group-specific levels of scale efficiency, table 7 shows that a substantial proportion of supermarket farmers are still operating sub-optimally, so that there is scope to further expand vegetable production before reaching the optimal scale. Others are already producing at supra-optimal scale. Interestingly, traditional channel suppliers are above the most productive scale size on average, given their conditions and technology. This supports the finding by Foster and Rausser (1991) that high risk can lead to the overuse of some resources.

Insert table 8 here

Further differences between the two channels can be identified when we take a look at the average input endowment for the scale efficient farmers in table 8. The scale efficient traditional channel suppliers, although their most productive scale size in terms of value of output is substantially smaller, they use close to 50% more fertilizer, and employ 30% more labor than the scale efficient farmers in the supermarket channel. For pesticides, the differences are less marked, while for farmyard manure, traditional farmers utilize only about one-third of the manure that supermarket farmers use. These patterns deviate from the overall average input endowments shown in table 1, in particular for manure, where the total quantity did not differ between the channels in this order of magnitude. The group of scale-efficient farmers also shows differences in expenditure on seeds.

Average treatment effects

In order to establish if the estimated differences in meta-technology ratio (MTR), technical efficiency (TE), and scale efficiency (SE) can really be attributed to participation in supermarket channels, we use PSM, as described above. The matching process begins with the estimation of propensity scores, $P(\boldsymbol{z})$, using a probit model. In the specification of this probit we avoid the use of potentially endogenous variables, as this could cause problems in result interpretation (Caliendo and Kopeinig 2008). The probit estimation results are shown in table 9. Farmer age and education, availability of public transport in the village, land ownership, and regional characteristics determine participation in supermarket channels.

Insert table 9 here

The estimated propensity score are now used to derive average treatment effects of supermarket participation on the three outcome variables of interest. We use the KBM and NNM methods and impose the common support condition to ensure proper matching. The matching procedure was conducted with STATA 11 software, following steps described by Leuven and Sianesi (2003).

Table 10 shows the average treatment effects. Both matching methods reveal significant impacts on MTR. Participation in supermarket channels leads to a 23-26 percentage point (41-46%) improvement in productivity, thus confirming that there is a significant technological jump. Figure 1 shows the cumulative distribution function (CDF) of MTR before and after matching. Kolmogorov-Smirnov (KS) tests confirm that the CDF of supermarket suppliers statistically dominates that of traditional suppliers in both cases, but the dominance is more pronounced when we control for selection bias.

Insert table 9 here

Insert figure 1 here

Our results also show that supermarket participation leads to significant improvements in meta-frontier TE (table 10 and figure 2). Yet, in absolute terms the impact on TE is lower than the MTR effect. This is not surprising, since many of the supermarket farmers are relatively young entrants into this new marketing channel. As was shown, entry into supermarket channels entails technological upgrading and changes in the input mix, which is reflected in the MTR. However, technological change may lead to lower TE in the short run, as farmers have to adjust to the new situation, which may be followed by a rise in the medium and long run due to learning effects. To some extent, this is confirmed in table 11, where we disaggregate meta-frontier TE of supermarket farmers by the period of entry into this new channel. TE seems to decrease within the first three years and rise again afterwards. Obviously, this disaggregation can only be suggestive of a possible time path. A more comprehensive analysis of TE dynamics would require panel data.

Insert table 11 here

Insert figure 2 here

Table 10 also shows that supermarket participation significantly improves scale efficiency by 21–23 percentage points (30-33%). Figure 3 confirms that the CDF for supermarket suppliers is statistically dominant. These results confirm that greater price stability and market assurance in supermarket channels contribute to more scale-efficient resource allocation and gains from specialization.

Insert figure 3 here

Validity of the matching assumptions

Despite the general ability of PSM to control for selection bias, the estimates are only valid subject to two conditions: (i) balancing in covariates is achieved, and (ii) there is no systematic farmer heterogeneity due to unobservables (Caliendo and Kopeinig 2008; Dehejia and Wahba 2002). The objective of estimating the propensity scores is to balance the distribution of variables relevant to the matching process. Balancing tests are therefore necessary after matching to determine if the matching process has reduced the bias by eliminating differences in covariates, in which case the matched comparison group can be considered as a plausible counterfactual (Caliendo and Kopeinig 2008). We evaluate the balancing condition and bias reduction following Rosenbaum and Rubin (1985). Table 12 shows indicators of covariate balancing before and after matching. The results reveal substantial reduction of bias for both matching methods. The pseudo R^2 and *p*-values of the likelihood ratio tests before and after matching are also presented in table 12. The joint significance of regressors is rejected after matching, while it is not rejected before matching. This underlines that systematic differences that are due to observable factors are properly eliminated. Distributions of propensity scores and regions of common support are shown in figure 4.

Insert table 12 here

Insert figure 4 here

But what about potential hidden bias due to unobservables? We test for this using Rosenbaum bounds (Rosenbaum 2002; Hujer, Caliendo and Thomsen 2004). Assuming two individuals have the same observed covariates $\boldsymbol{z}$ (as implied by the matching procedure), the two matched observations would differ in their odds of participating in supermarket channels only by the difference in unobserved covariates, which is measured by the parameter Γ. The test procedure involves changing the level of Γ and deriving the bounds on the significance levels of the ATT under the assumption of endogenous self-selection into supermarket participation. This allows for identification of the critical levels of Γ at which the estimated ATT would become insignificant.

Results of this test are shown in table 10. Using the example of MTR, the critical values for hidden bias (Γ) are 5.55-5.60 with KBM and 4.20-4.25 with NNM. The lowest value of Γ=4.2 implies that individuals that have the same $\boldsymbol{z}$-vector would have to differ in their odds of supermarket participation by a factor of 4.2 (320%), in order to render the ATT for MTR insignificant. Concerning the other two outcome variables and always using the lowest values for Γ, farmers would have to differ in their odds of supermarket participation by 125% and 260%, in order to overturn the significant impacts on technical efficiency and scale efficiency, respectively. Even though unobservables may play a certain role, it is very unlikely that they would influence the odds of supermarket participation to such a big extent.

Supermarket and traditional channel farmers do not only differ in terms of the technology used, but also in terms of their input use (table 1). Since we estimate non-constant returns, our ATT estimates implicitly assume that all differences in input use are due to supplying different marketing channels. While we expect supermarket participation to influence input use, other factors may also play a role. Therefore, we carried out another robustness check for the ATTs, by matching on the sub-vector of input use intensities. This assumes the extreme case that supermarket participation does not at all influence input use. Results of this alternative matching exercise are shown in table A2 in the appendix. As one would expect, the ATTs for MTR, TE, and SE are lower than the ones shown in table 9, but all of them remain positive and significant.

Overall, the various tests show that some caution is warranted with respect to interpreting the exact numerical ATTs, but they also underline that the general findings of positive treatment effects are quite robust, and especially so for the MTR and SE.

Conclusion

Agri-food systems in many developing countries are currently undergoing a transformation towards modern high-value supply chains, with supermarkets and their new procurement systems gaining in importance. Recent research has studied what types 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 more explicit analysis of productivity and efficiency effects.

Using survey data of vegetable growers in Kiambu District, central Kenya, we have shown that participation in supermarket channels has a positive impact on farm productivity. We have also used a meta-frontier approach to analyze different potential sources of productivity growth, namely technology gaps, and changes in technical and scale efficiency. Finally, we have employed propensity score matching to derive net treatment effects. We are not aware of any previous study that has combined meta-frontier estimates with statistical matching techniques for impact assessment.

Participation in supermarket channels improves the meta-technology ratio by about 45%. Higher output prices in supermarket channels and better market assurance increase the farmers' ability and willingness to upgrade their technology. In the study region, this is supported by an international NGO that provides technical advice and improved access to high-quality seeds. The treatment effect on technical efficiency is also positive and significant, but it is somewhat lower in absolute terms. This is not surprising, as many farmers are relatively new suppliers of supermarkets, so that they first need to adjust to the new situation. Moreover, we have found that supermarket participation increases scale efficiency by 30%. This is mainly attributed to reduced marketing risk, which allows farmers to specialize and to operate closer to the most productive scale size.

It should be stressed that our analysis has a couple of limitations, which are mostly due to the nature of the data used. First, since exact measures of output quantity are not available, we have used output value (revenue) as dependent variable in the production function. Hence, the productivity and efficiency impacts combine quantity and quality components, which we are not able to separate. Second, using a revenue frontier makes relatively strong assumptions about the separability of household consumption and production choices, which can make interpretation of efficiency parameters difficult (Barrett 1997). Even though farmers in Kiambu grow vegetables almost exclusively for commercial purposes, this general issue has to be kept in mind. Third, the regional dummies included as explanatory variables are probably imperfect controls of micro-level variability in environmental conditions. While we do not expect this to affect supermarket impacts systematically, it may explain the relatively low mean technical efficiency levels detected in our sample. Fourth, controlling for possible selection bias due to unobserved heterogeneity is difficult with cross-section data. Therefore the exact numerical results should be interpreted with caution. Yet we carried out a number of additional tests, results of which suggest that the general findings of positive treatment effects are fairly robust.

Kenya is only one example where supermarkets are transforming agricultural supply chains in developing countries. Kiambu District may be a special case, because of its proximity to Nairobi. Supermarkets do not decide on procurement regions randomly, but they usually choose the more productive regions first (Neven et al. 2009). Therefore, the treatment effects observed in Kiambu are expected to be higher than in other regions from which supermarkets may procure in the future, when developments gradually spread to a wider geographical area. Nonetheless, also in other regions supermarkets may contribute to productivity and efficiency gains among smallholders, which are crucial for poverty reduction and rural development. This does not preclude the possibility that particularly disadvantaged farmers are bypassed or that transforming agri-food systems may also entail problems associated with increasing industry concentration. However, since supermarkets will spread anyway, it is important to understand the development potentials and implement policies to harness these potentials while avoiding undesirable social consequences. Such policies should particularly include improved credit, extension, and input delivery systems, which can help farmers in the process of upgrading their production technology.

References

Alvarez, A., C. Amsler, L. Orea and P. Schmidt. 2006. Interpreting and Testing the Scaling Property in Models Where Inefficiency Depends on Firm Characteristics. *Journal of Productivity Analysis25*(3): 201-212.

Balsevich, F., J. A. Berdegué, L. Flores, D. Mainville and T. Reardon. 2003. Supermarkets and Produce Quality and Safety Standards in Latin America. *American Journal of Agricultural Economics85*(5): 1147-1154.

Barrett, C. B. 1997. How Credible Are Estimates of Peasant Allocative Scale, or Scope Efficiency? A Commentary. *Journal of International Development9*(2): 221-229.

Battese, G. E. 1997. A Note on the Estimation of Cobb Douglas Production Functions When Some Explanatory Variables Have Zero Values. *Journal of Agricultural Economics48*(1 3): 250-252.

Battese, G. E., D. S. P. Rao and C. J. O'Donnell. 2004. A Metafrontier Production Function for Estimation of Technical Efficiencies and Technology Gaps for Firms Operating under Different Technologies. *Journal of Productivity Analysis21*(1): 91-103.

Boselie, D., S. Henson and D. Weatherspoon. 2003. Supermarket Procurement Practices in Developing Countries: Redefining the Roles of the Public and Private Sectors. *American Journal of Agricultural Economics85*(5): 1155-1161.

Caliendo, M. and S. Kopeinig. 2008. Some Practical Guidance for the Implementation of Propensity Score Matching. *Journal of Economic Surveys22*(1): 31-72.

Caudill, S. B. and J. M. Ford. 1993. Biases in Frontier Estimation Due to Heteroscedasticity. *Economics Letters41*(1): 17-20.

Dehejia, R. H. and S. Wahba. 2002. Propensity Score-Matching Methods for Nonexperimental Causal Studies. *Review of Economics and tatistics84*(1): 151-161.

Doomik, J. 2007. *Object-Oriented Matrix Programming Using Ox, 3rd ed*. London: Timberlake Consultants Press and Oxford.

Førsund, F. R. and L. Hjalmarsson. 1979. Generalised Farrell Measures of Efficiency: An Application to Milk Processing in Swedish Dairy Plants. *The Economic Journal89*(354): 294-315.

Foster, W. E. and G. C. Rausser. 1991. Farmer Behavior under Risk of Failure. *American Journal of Agricultural Economics73*(2): 276-288.

Gulati, A., N. Minot, C. Delgado and S. Bora. 2007. "Growth in High-Value Agriculture in Asia and the Emergence of Vertical Links With." In " *Global Supply Chains, Standards and the Poor*. MA, Cambridge: CAB International**:** 91-108.

Hayami, Y. and V. W. Ruttan. 1985. *Agricultural Development: An International Perspective*: Baltimore, MD: Johns Hopkins University Press.

Heckman, J. 1976. The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for Such Models. *Annals of Economics and Social Measurement5*(4): 475 - 492.

Heckman, J. and S. Navarro-Lozano. 2004. Using Matching, Instrumental Variables, and Control Functions to Estimate Economic Choice Models. *Review of Economics and statistics86*(1): 30-57.

Hernández, R., T. Reardon and J. Berdegué. 2007. Supermarkets, Wholesalers, and Tomato Growers in Guatemala. *Agricultural Economics36*(3): 281-290.

Hujer, R., M. Caliendo, and S. L. Thomsen. 2004. New Evidence on the Effects of Job Creation Schemes in Germany--a Matching Approach with Threefold Heterogeneity. *Research in Economics58*(4): 257-302.

Imbens, G. W. 2004. Nonparametric Estimation of Average Treatment Effects under Exogeneity: A Review. *Review of Economics and Statistics86*(1): 4-29.

Jayne, T. S., T. Yamano, M. T. Weber, D. Tschirley, R. Benfica, A. Chapoto and B. Zulu. 2003. Smallholder Income and Land Distribution in Africa: Implications for Poverty Reduction Strategies. *Food Policy28*(3): 253-275.

Leuven, E. and B. Sianesi. 2003. PSMATCH2: Stata Module to Perform Full Mahalanobis and Propensity Score Matching, Common Support Graphing, and Covariate Imbalance Testing, http://ideas.repec.org/c/boc/bocode/s432001.html (accessed on 14 July 2011).

Maertens, M. and J. F. M. Swinnen. 2009. Trade, Standards, and Poverty: Evidence from Senegal. *World Development37*(1): 161-178.

Maertens, M., L. Colen, and J.F.M. Swinnen. 2011. Globalization and Poverty in Senegal: A Worst Case Scenario? *European Review of Agricultural Economics* 38(1): 31-54.

Masakure, O. and S. Henson. 2005. Why Do Small-Scale Producers Choose to Produce under Contract? Lessons from Nontraditional Vegetable Exports from Zimbabwe. *World Development33*(10): 1721-1733.

Mayen, C. D., J. V. Balagtas and C. E. Alexander. 2010. Technology Adoption and Technical Efficiency: Organic and Conventional Dairy Farms in the United States. *American Journal of Agricultural Economics92*(1): 181-195.

Mergenthaler, M., K. Weinberger and M. Qaim. 2009. The Food System Transformation in Developing Countries: A Disaggregate Demand Analysis for Fruits and Vegetables in Vietnam. *Food Policy34*(5): 426-436.

Michelson, H., T. Reardon, and F. Perez. 2011. Small Farmers and Big Retail: Trade-Offs of Supplying Supermarkets in Nicaragua. *World Development* (in press).

Minten, B., L. Randrianarison, and J. Swinnen. 2009. Global Retail Chains and the Poor: Evidence from Madagascar. *World Development* 37(11): 1728-1741.

Minten, B., L. Randrianarison, and J. Swinnen. 2007. Spillovers from High Value Agriculture for Exports on Land Use in Developing Countries: Evidence from Madagascar. *Agricultural Economics37*(2 3): 265-275.

Ndeng'e, G., C. Opiyo and P. Kristjanson. 2003. Geographic Dimension of Well Being in Kenya - Where Are the Poor? From District to Locations. M. o. P. a. N. D. CBS, Kenya. Nairobi, Kenya.

Neven, D., M. M. Odera, T. Reardon and H. Wang. 2009. Kenyan Supermarkets, Emerging Middle-Class Horticultural Farmers, and Employment Impacts on the Rural Poor. *World Development37*(11): 1802-1811.

Neven, D. and T. Reardon. 2004. The Rise of Kenyan Supermarkets and the Evolution of Their Horticulture Product Procurement Systems. *Development Policy Review22*(6): 669-699.

Ngugi, I. K., R. Gitau and J. Nyoro. 2007. *Access to High Value Markets by Smallholder Farmers of African Indigenous Vegetables in Kenya*. London: International Institute for Environment and Development (IIED)

Nyoro, J. K., J. Ariga and I. K. Ngugi. 2007. "Countries with Emerging Modern Supply Chains: Kenya." In B. Vorley, A. Fearne and D. Ray, Eds." *Regoverning Markets: A Place for Small-Scale Producers in Modern Agrifood Chains?* Hampshire, UK: Gower Publishing Limited**:** 163 - 171.

O'Donnell, C. J., D. S. P. Rao and G. E. Battese. 2008. Metafrontier Frameworks for the Study of Firm-Level Efficiencies and Technology Ratios. *Empirical Economics34*(2): 231-255.

Okello, J. J. and S. M. Swinton. 2007. Compliance with International Food Safety Standards in Kenya's Green Bean Industry: Comparison of a Small-and a Large-Scale Farm Producing for Export. *Applied Economic Perspectives and Policy29*(2): 269.

Olwande, J. 2010. Consumption and Purchasing Patterns of Fresh Fruits and Vegetables in Urban Kenya: Agenda for Incestment Priorities in Fresh Produce Supply Chains. Nairobi, Tegemeo Institute.

Pingali, P., Y. Khwaja and M. Meijer. 2007. "The Role of the Public and Private Sectors in Commercializing Small Farms and Reducing Transaction Costs." In J. F. M. Swinnen, Ed." *Global Supply Chains, Standards and the Poor*. Cambridge, MA: CAB International**:** 267-280.

Planet Retail. 2011. Retail sales in Kenya. http://www.planetretail.net/Markets/Country/91 (accessed on 14 August 2011).

Rao, E.J.O. and M. Qaim. 2011. Supermarkets, Farm Household Income, and Poverty: Insights from Kenya. *World Development* 39(5): 784-796.

Ray, S. C. 1998. Measuring Scale Efficiency from a Translog Production Function. *Journal of Productivity Analysis11*(2): 183-194.

Reardon T., C. B. Barrett, J. A. Berdegué, and J. F. M. Swinnen. 2009. Agrifood Industry Transformation and Small Farmers in Developing Countries. *World Development* 37(11): 1717-1727.

Reardon, T., C. P. Timmer, C. B. Barrett and J. Berdegué. 2003. The Rise of Supermarkets in Africa, Asia, and Latin America. *American Journal of Agricultural Economics85*(5): 1140-1146.

Rosenbaum, P. R. 2002. *Observational Studies*: Springer Verlag.

Rosenbaum, P. R. and D. B. Rubin. 1983. The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika70*(1): 41.

Rosenbaum, P. R. and D. B. Rubin. 1985. Constructing a Control Group Using Multivariate Matched Sampling Methods That Incorporate the Propensity Score. *The American Statistician39*(1): 33-38.

Schipmann, C. and M. Qaim. 2010. Spillovers from Modern Supply Chains to Traditional Markets: Product Innovation and Adoption by Smallholders. *Agricultural Economics41*(3 4): 361-371.

Sherlund, S. M., C. B. Barrett and A. A. Adesina. 2002. Smallholder Technical Efficiency Controlling for Environmental Production Conditions. *Journal of Development Economics69*(1): 85-101.

Sipiläinen, T. and A. Oude Lansink. 2005. "Learning in Organic Farming–an Application on Finnish Dairy Farms". Paper presented at the XIth Congress of the EAAE (European Association of Agricultural Economists), Copenhagen, Denmark, August 24-27.

Smith, A. J. and E. P. Todd. 2005. Does Matching Overcome Lalonde's Critique of Nonexperimental Estimators? *Journal of Econometrics125*(1-2): 305-353.

Solis, D., B. E. Bravo-Ureta and R. E. Quiroga. 2007. Soil Conservation and Technical Efficiency among Hillside Farmers in Central America: A Switching Regression Model. *Australian Journal of Agricultural and Resource Economics51*(4): 491-510.

Swinnen, J. F. M., (Ed). 2007. *Global Supply Chains, Standards and the Poor*. Cambridge, MA: CAB International.

Wang, H. J. and P. Schmidt. 2002. One-Step and Two-Step Estimation of the Effects of Exogenous Variables on Technical Efficiency Levels. *Journal of Productivity Analysis18*(2): 129-144.

World Bank. 2007. *World Development Report 2008: Agriculture for Development*. Washington DC: World Bank.

Table 1. Summary Statistics

Variables	Supermarket (n = 133)		Traditional (n = 269)	
	Mean	SD	Mean	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
Use of advanced irrigation technology *(%)*	52.6***	50.1	35.3	47.9
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
Gender of operator (%)	93*	25	88	32
Vegetable farming experience *(years)*	14.01	11.73	15.18	12.14
Own means of transportation *(%)*	24.06***	42.91	8.92	28.56
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
Seed cost *(Ksh/acre)*	6,823.60*	9,485.90	5,490.80	6,105.70
Seed from formal channels *(%)*	65***	48	45	50
Chemical 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 labor use *(labor days/acre)*	215.36**	296.29	164.28	276.98
Family labor use *(labor days/acre)*	307***	395	489	632
Total labor use *(labor days/acre)*	522**	472	653	734

*, **, *** Mean differences between supermarket and traditional channel suppliers are significant at the 10%, 5%, and 1% levels, respectively.

Table 2. Estimates of the Deterministic Production Function (Translog Treatment Effects Model)

	Production function (second stage)		Supermarket participation (first stage)	
	Coefficient	SE	Coefficient	SE
Supermarket participation (IV)	1.048***	0.339		
Dummy for use of fertilizer	-0.321**	0.135	0.503*	0.267
Dummy for use of pesticide	-0.272*	0.139	0.671***	0.252
Dummy for use of farmyard manure	-0.255	0.195	-1.174*	0.623
log seed cost	0.127**	0.057	0.129	0.113
log fertilizer	0.195***	0.071	0.209	0.156
log pesticide	0.083	0.068	-0.128	0.149
log manure	0.140**	0.068	0.319**	0.139
log labor	0.252***	0.070	-0.070	0.163
log plot size	0.298***	0.075	-0.346**	0.144
Advanced irrigation technology (*dummy*)	0.050	0.083	0.250	0.166
Exotic vegetable	0.360***	0.109	0.020	0.225
Age of operator (years)	-0.004	0.003	-0.021***	0.007
Availability of public transport in village			0.392*	0.219
Total area owned (acres)			0.093**	0.041
Constant	-0.180	0.269	-0.666	0.565
athrho	*-0.653**	*0.359*		
lnsigma	*-0.344****	*0.076*		
LR test of independent equations	*3.01**			
Number of observations	*402*			

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

Note: Regional dummies as well as all input interaction and square terms were included in the estimation, but are not shown here for brevity.

Table 3. Hypothesis Testing for Stochastic Production Frontier Model

Null hypothesis H_0	χ^2 Statistics	Deg. of freedom	χ^2 Critical	p-value
Cob-Douglass functional form is more appropriate: $\beta_{ij} = 0$				
Supermarket model	84.34	21	32.67	0.000
Traditional channel model	30.00	21	32.67	0.092
No technical inefficiency effects: $\gamma = 0 = \delta_1 = \dots\dots = \delta_8 = 0$				
Supermarket model	83.73	9	14.07	0.000
Traditional channel model	15.91	9	14.07	0.069
Homogenous technology across channels	149.12	46	48.60	0.000

Table 4. Estimates of the Stochastic Production Frontier (Translog Models)

	Supermarket		Traditional	
	Coefficient	SE	Coefficient	SE
Production frontier model				
Dummy for use of chemical fertilizer	-0.101	0.083	-0.238*	0.134
Dummy for use of pesticide	0.371***	0.075	-0.286	0.179
Dummy for use of manure	-0.584	0.366	-0.407**	0.207
log seed cost	0.116***	0.033	0.012	0.064
log chemical fertilizer	0.066	0.050	0.330***	0.068
log pesticide	0.164***	0.043	0.069	0.069
log manure	0.101***	0.022	0.142	0.113
log labor	0.311***	0.058	0.017	0.098
log plot size	0.165**	0.073	0.265***	0.073
0.5 × (*log* seed cost)^2	0.129***	0.022	-0.021	0.082
0.5 × (*log* chemical fertilizer)^2	0.153***	0.054	0.152	0.100
0.5 × (*log* pesticide)^2	0.140**	0.068	0.073	0.060
0.5 × (*log* manure)^2	-0.282***	0.023	0.053	0.087
0.5 × (*log* labor)^2	-0.507***	0.054	0.232	0.151
0.5 × (*log* plot size)^2	0.023	0.060	-0.096	0.140
Advanced irrigation technology *(dummy)*	-0.027	0.033	0.192**	0.094
Githunguri& Lower Lari region [a] (*dummy*)	-0.361***	0.138	-0.383**	0.194
Kikuyu/Westland region [a] (*dummy*)	0.710***	0.199	-0.142	0.183
Limuru region [a] (*dummy*)	0.402	0.299	-0.273	0.177
Exotic vegetable *(dummy)*	0.520***	0.057	0.247*	0.135
Constant	0.036	0.178	0.199	0.222
Inefficiency model				
Experience in vegetable farming (*years*)	0.004	0.005	-0.012**	0.005
Gender of operator (*male dummy*)	0.896***	0.301	-0.142	0.195
Education of operator (*years*)	-0.014	0.019	-0.019	0.015
Access to agricultural extension (*dummy*)	-0.055	0.159	0.152	0.133
Share of vegetable area	0.210	0.245	-0.345	0.217
log manure	-0.298**	0.117	-0.026	0.137
log labor	0.379**	0.153	-0.438***	0.091
Share of family labor	0.522***	0.163	0.171	0.180
Constant	-1.320***	0.343	-0.161	0.320
Number of observations	*133*		*269*	
Log likelihood	*-71.527*		*-251.732*	

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

[a] The reference region is Lari.

Note: Input interaction terms are shown in table A1 in the appendix.

Table 5. Parameter Estimates for the Meta-Frontier

	Coefficient estimates L1	SE	Coefficient estimates L2	SE
Dummy for use of chemical fertilizer	-0.157	0.098	-0.171*	0.089
Dummy for use of pesticide	0.211*	0.111	0.179*	0.097
Dummy for use of manure	-0.466**	0.190	-0.478***	0.172
log seed cost	0.076	0.060	0.089	0.058
log chemical fertilizer	0.187***	0.072	0.164***	0.059
log pesticide	0.063	0.062	0.064	0.055
log manure	0.224***	0.069	0.201***	0.062
log labor	0.160*	0.084	0.184**	0.073
log plot size	0.208***	0.079	0.202***	0.074
0.5 × (*log* seed cost)^2	0.232***	0.061	0.225***	0.055
0.5 × (*log* chemical fertilizer)^2	0.200**	0.079	0.166**	0.067
0.5 × (*log* pesticide)^2	0.116*	0.067	0.086	0.062
0.5 × (*log* manure)^2	0.088	0.085	0.046	0.071
0.5 × (*log* labor)^2	0.095	0.145	0.059	0.135
0.5 × (*log* plot size)^2	0.009	0.093	-0.031	0.082
log seed cost ×*log* chemical fertilizer	0.131*	0.073	0.119*	0.068
log seed cost ×*log* pesticides	-0.122***	0.041	-0.106***	0.037
log seed cost × *log* manure	-0.005	0.055	-0.006	0.049
log seed cost × *log* labor	-0.045	0.071	-0.039	0.067
log seed cost ×*log* plot size	-0.160**	0.066	-0.135**	0.056
log chemical fertilizer × *log* pesticide	-0.036	0.049	-0.013	0.037
log chemical fertilizer × *log* manure	-0.105**	0.051	-0.113**	0.044
log chemical fertilizer × *log* labor	-0.010	0.065	0.015	0.058
log chemical fertilizer × *log* plot size	-0.132**	0.066	-0.139**	0.061
log pesticide × *log* manure	0.018	0.059	0.023	0.054
log pesticide × *log* labor	0.045	0.065	0.038	0.058
log pesticide × *log* plot size	0.003	0.061	-0.005	0.052
log manure × *log* labor	-0.061	0.085	-0.048	0.080
log manure × *log* plot size	0.073	0.064	0.082	0.057
log labor × *log* plot size	0.041	0.093	0.047	0.083
Advanced irrigation technology *(dummy)*	0.086	0.057	0.092	0.056
Githunguri& Lower Lari region [a] (*dummy*)	-0.283	0.173	-0.267	0.182
Kikuyu/Westland region [a] (*dummy*)	0.585***	0.189	0.519***	0.193
Limuru region [a] (*dummy*)	-0.184	0.198	-0.200	0.207
Exotic vegetable *(dummy)*	0.344***	0.088	0.325***	0.076
Constant	0.411*	0.219	0.525**	0.214
Number of observations	*402*		*402*	

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

[a] The reference region is Lari.

Table 6. Meta-Technology Ratio (MTR) and Technical Efficiency (TE) for Group Frontiers and Meta-Frontier

	Supermarket suppliers			Traditional channel suppliers		
	Group TE	MTR	Meta-frontier TE	Group TE	MTR	Meta-frontier TE
Mean	0.61	0.71***	0.41**	0.64	0.56	0.36
Minimum	0.09	0.19	0.06	0.03	0.08	0.01
Maximum	1.00	1.00	1.00	0.89	1.00	0.86
Std. deviation	0.30	0.23	0.23	0.19	0.23	0.18

*, **, *** Mean values for supermarket suppliers are significantly different from mean values for traditional channel suppliers at the 10%, 5%, and 1% levels, respectively.

Table 7. Scale Efficiency Scores by Market Channel and Scale of Operation

	No. of farms	Mean scale elasticity	Mean scale efficiency
All farms			
Supra-optimal scale	260	0.79	0.66
Optimal scale	65	1.00	1.00
Sub-optimal scale	77	1.26	0.79
All	402	0.91	0.75
Supermarket			
Supra-optimal scale	57	0.76	0.88
Optimal scale	22	1.00	1.00
Sub-optimal scale	54	1.32	0.80
All	133	1.02	0.87
Traditional channels			
Supra-optimal scale	203	0.80	0.62
Optimal scale	43	1.00	1.00
Sub-optimal scale	23	1.14	0.78
All	269	0.86	0.69

Note: Farmers are considered to operate under optimal scale when their scale elasticity falls into the range of 0.95-1.05.

Table 8. Average Input Endowment of Scale-Efficient Farms by Market Channel

	Supermarkets *n = 43*	Traditional channels *n = 22*
Fertilizer	25.1	37.6
Farmyard manure	1660	608
Pesticide	153.4	130.2
Labor	33.3	43.2
Seed cost	296.80	166.40

Note: Scale efficient farms are defined as explained in Table 7.

Table 9. Propensity Score for Participation in Supermarket Channels (Probit Estimates)

	Coefficient	SE
Education of operator (years)	0.058**	0.024
Age of operator *(years)*	0.076**	0.036
Age of operator squared*(years)*	-0.001**	0.000
Availability of public transport in village*(dummy)*	0.405*	0.207
Land area owned (*acres*)	0.082**	0.039
Household labor endowment *(no. of people)*	-0.097	0.067
Gender of operator (*male dummy*)	0.275	0.264
Lari region *(dummy)*[a]	-1.049**	0.421
Githunguri and Lower Lari region *(dummy)*[a]	0.065	0.181
Limuru region *(dummy)*[a]	-1.551***	0.231
Constant	-2.680***	0.948
Number of observations	*402*	
Pseudo R^2	*0.210*	
Log likelihood	*-201.588*	

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

[a] The reference region is Kikuyu/Westlands.

Table 10. Average Treatment Effects and Results of Sensitivity Analysis

Matching algorithm	Outcome	ATT (z-values)	Critical level for hidden bias (Γ)	Number of treated	Number of control
Kernel-based matching	Meta-technology ratio (MTR)	0.23*** (8.10)	5.55 – 5.60	132	211
	Meta-frontier TE	0.13*** (5.14)	2.25 – 2.30	132	211
	Scale efficiency (SE)	0.23*** (8.51)	10.3 – 10.4	132	211
Nearest neighbor matching	Meta-technology ratio (MTR)	0.26*** (6.20)	4.20 – 4.25	132	211
	Meta-frontier TE	0.16*** (4.98)	2.60 – 2.65	132	211
	Scale efficiency (SE)	0.21*** (4.88)	3.60 – 3.65	132	211

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

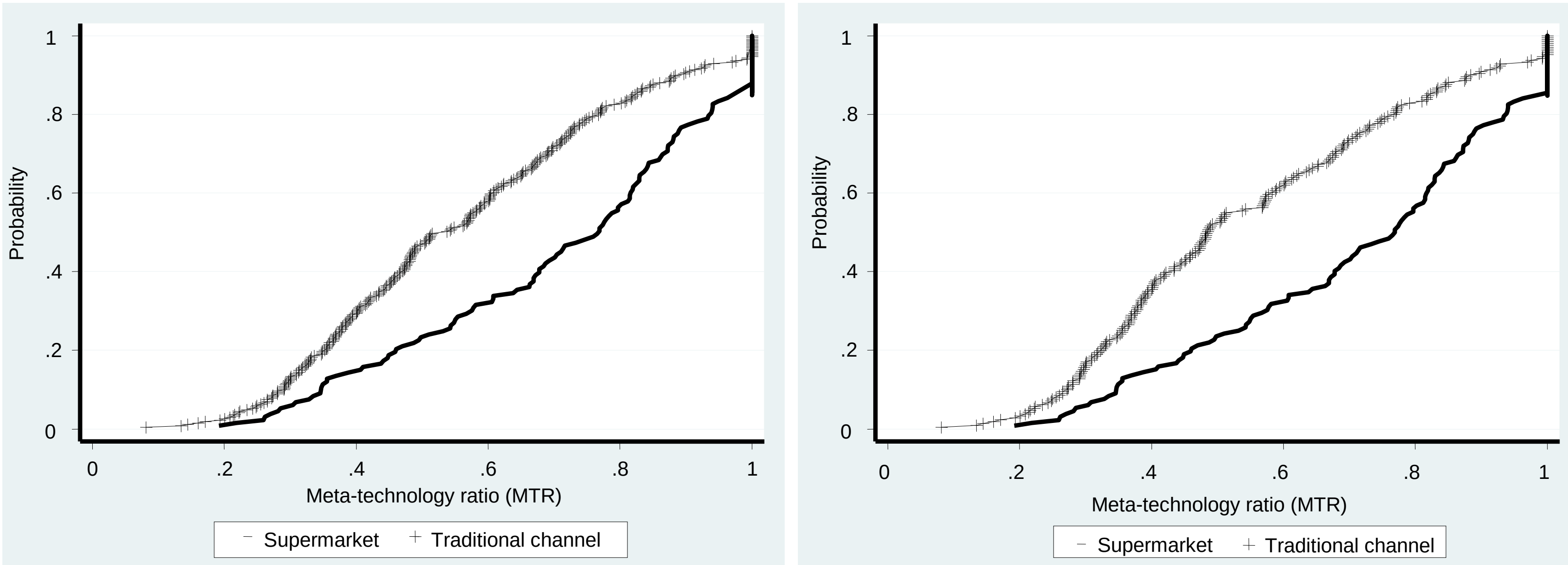
Note: The z-values for the ATTs are based on bootstrapped standard errors with 500 replications.

Table 11. Technical Efficiency Scores Disaggregated According to Experience in Supplying Supermarkets

Experience supplying supermarket	Number of observations	Average meta-frontier TE
Less than 6 months	20	0.46
6 months to 1 year	13	0.43
1 – 2 years	27	0.37
2 – 3 years	16	0.35
More than 3 years	57	0.43

Table 12. Indicators of Covariate Balancing Before and After Matching

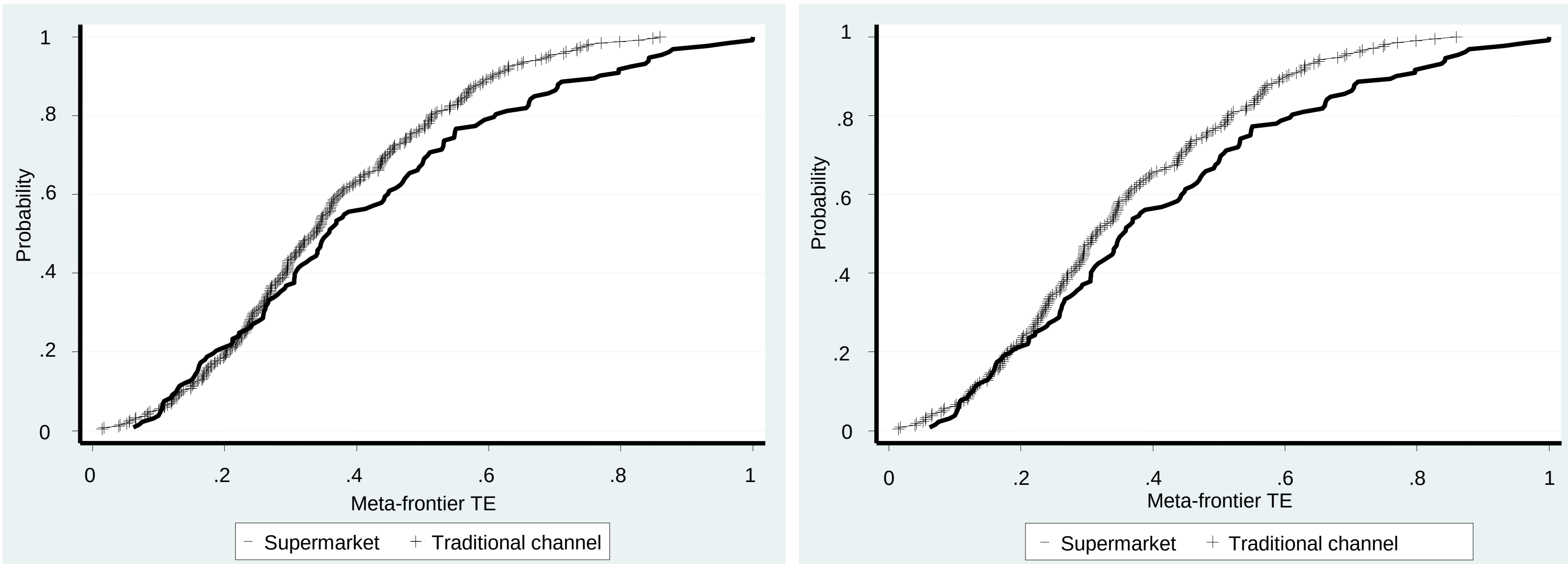
Matching algorithm	Outcome	Median absolute bias		% bias reduction	Pseudo R^2		*p*-value of LR	
		Un-matched	Matched		Un-matched	Matched	Un-matched	Matched
Kernel-based matching	Meta-technology ratio	23.01	3.17	86.22	0.210	0.002	0.000	1.000
	Meta-frontier TE	23.01	3.17	86.22	0.210	0.002	0.000	1.000
	Scale efficiency	23.01	3.17	86.22	0.210	0.002	0.000	1.000
Nearest neighbor matching	Meta-technology ratio	23.01	6.84	70.26	0.210	0.023	0.000	0.577
	Meta-frontier TE	23.00	6.84	70.26	0.210	0.023	0.000	0.577
	Scale efficiency	23.00	6.84	70.26	0.210	0.023	0.000	0.577



a) Without adjustment for selection bias
(KS-statistic = 0.314 (p=0.000))

b) With adjustment for selection bias
(KS-statistic = 0.319 (p=0.000))

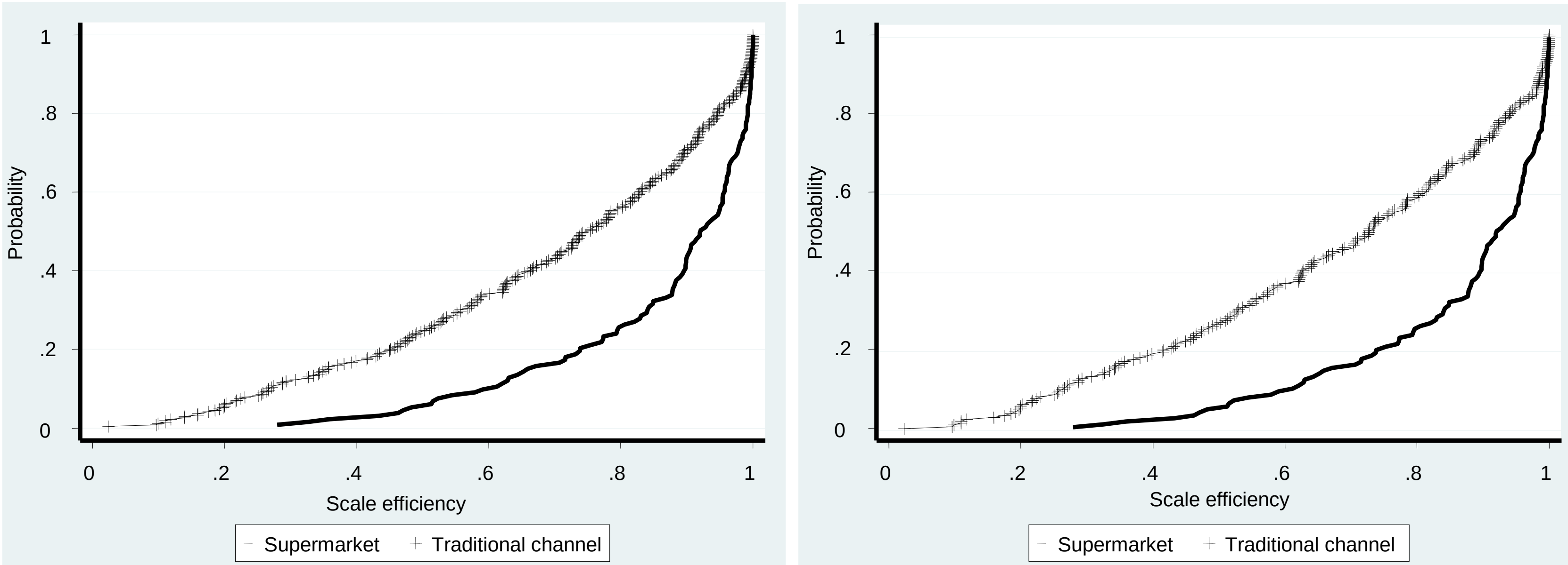
Figure 1. Cumulative distribution of MTR by market channel (with and without adjustment for selection bias)



a) Without adjustment for selection bias
(KS-statistic = 0.125 (p=0.101))

b) With adjustment for selection bias
(KS-statistic = 0.133 (p=0.090))

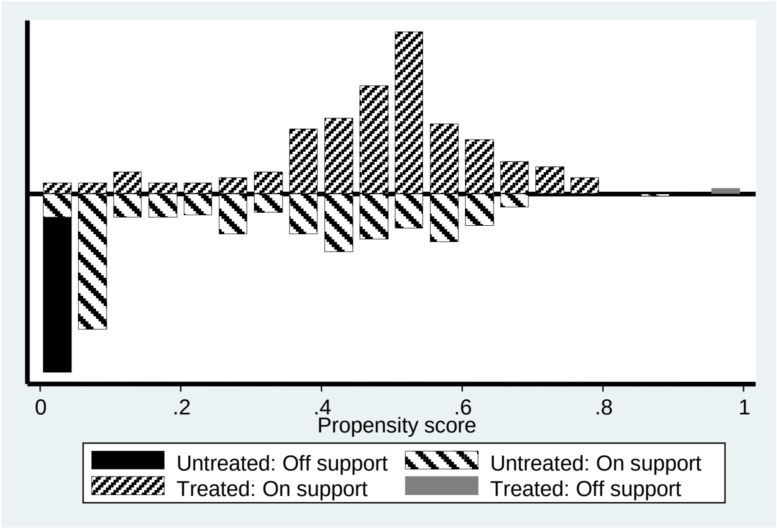
Figure 2. Cumulative distribution of meta-frontier TE by market channel (with and without adjustment for selection bias)



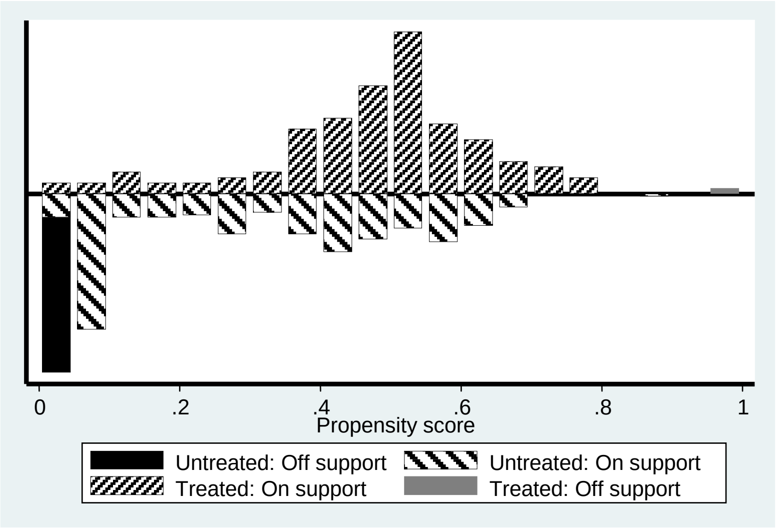
a) Without adjustment for selection bias
(KS-statistic = 0.328 (p=0.000))

b) With adjustment for selection bias
(KS-statistic = 0.358 (p=0.000))

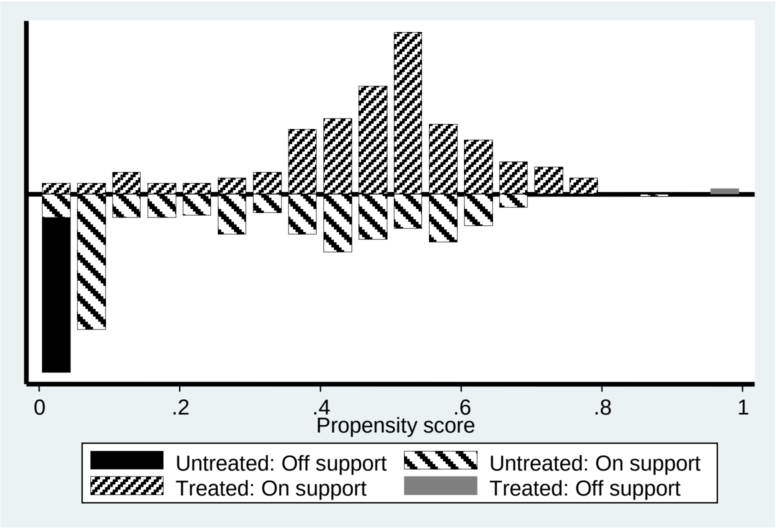
Figure 3. Cumulative distribution of SE by market channel (with and without adjustment for selection bias)



a) Meta-technology ratio (MTR)



b) Meta-frontier technical efficiency (TE)



c) Scale efficiency (SE)

Note: On support refers to observations that find suitable matches, off support indicates observations that do not find suitable matches.

Figure 4. Distribution and common support for propensity score estimation for effects on MTR, TE, and SE

Appendix

Table A1. Input Interaction Terms for Group Stochastic Frontiers (Translog Models)

	Supermarket		Traditional	
	Coefficient	SE	Coefficient	SE
log seed cost ×*log* chemical fertilizer	0.275***	0.082	-0.049	0.057
log seed cost ×*log* pesticides	-0.252***	0.045	-0.035	0.055
log seed cost × *log* manure	0.132**	0.052	-0.009	0.062
log seed cost × *log* labor	-0.298***	0.066	0.085	0.076
log seed cost ×*log* plot size	-0.120***	0.038	0.049	0.085
log chemical fertilizer × *log* pesticide	0.007	0.039	0.016	0.052
log chemical fertilizer × *log* manure	-0.294***	0.027	-0.126	0.057
log chemical fertilizer × *log* labor	0.181***	0.069	0.030	0.076
log chemical fertilizer × *log* plot size	-0.158*	0.082	0.050	0.082
log pesticide × *log* manure	0.168*	0.088	0.041	0.060
log pesticide × *log* labor	-0.162***	0.037	-0.001	0.060
log pesticide × *log* plot size	0.136**	0.068	-0.153**	0.073
log manure × *log* labor	0.312***	0.052	-0.146*	0.088
log manure × *log* plot size	0.019	0.102	0.138**	0.069
log labor × *log* plot size	0.099	0.091	-0.107	0.088
Number of observations	*133*		*269*	
Log likelihood	*-71.527*		*-251.732*	

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

Table A2. Average Treatment Effects with Matching on Sub-Vector of Input Intensities

Matching algorithm	Outcome	ATT (*z*-values)	Number of treated	Number of control
Kernel-based matching	Meta-technology ratio	0.18***(7.04)	126	268
	Meta-frontier TE	0.08***(3.34)	126	268
	Scale efficiency	0.19*** (8.26)	126	268
Nearest neighbor matching	Meta-technology ratio	0.18***(4.70)	132	211
	Meta-frontier TE	0.09***(2.62)	126	268
	Scale efficiency	0.20*** (4.65)	126	268

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

Note: The *z*-values for the ATTs are based on bootstrapped standard errors with 500 replications.