Farmer Participation in Supermarket Channels, Production Technology and Technical Efficiency: The Case of Vegetables in Kenya[1]

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Abstract

Supermarkets 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. Productivity effects in previous studies are also estimated with respect to different frontiers. Using a survey of Kenyan vegetable growers and a meta-frontier approach, we control for self-selection using propensity score matching and show that participation in supermarket channels increases farm productivity by 35-38%. Effects on technical efficiency are, however, insignificant. Supermarket expansion therefore presents opportunities for realizing agricultural growth, thus enhancing poverty alleviation and rural development.

Keywords: supermarkets, meta-frontier, productivity, meta-technology ratio, sample selection, Kenya

Domestic agri-food systems in many developing countries are experiencing increasing demand for high-value food products and a tendency towards supply chain modernization (Swinnen 2007). These changes are motivated by rapid urbanization and rising living standards. In addition to dietary diversification, the growing number of urban middle-class consumers has preferences for higher levels of food quality, food safety, and convenience (Mergenthaler, Weinberger and Qaim 2009; Pingali, Khwaja and Meijer 2007). To fulfill these requirements, modern food supply chains often adopt tighter vertical coordination, with super- and hypermarkets rapidly gaining importance (Neven and Reardon 2004; Reardon et al. 2003). Consequently, there are increasing opportunities for farmers to integrate into modern supply chains.

Nevertheless, participation in modern supply chains comes with challenges. Food quality and safety standards demanded by high-value consumers are associated with informational uncertainties and higher transaction costs (Okello and Swinton 2006; Pingali, Khwaja and Meijer 2007). To minimize such costs, modern retailers often impose strict standards, which might potentially exclude resource-poor agricultural producers. However, there are potential gains to be realized by farmers who overcome these barriers to participate in modern supply chains (Hernandez, Reardon and Berdegue 2007; Minten, Randrianarison and Swinnen 2007; Neven et al. 2009).

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 (Hernandez, Reardon and Berdegue 2007; Neven et al. 2005; 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 (Maertens and Swinnen 2009; Minten, Randrianarison and Swinnen 2007; Schipmann and Qaim 2009). However, restructuring supply chains might also have impacts on technical efficiency and/or farm productivity.

Compared to traditional farming and spot-market sales, producing high-value foods for modern supply chains often entails more sophisticated planning and timing of input application. Improvement in output demand and better output prices can also influence input demand leading to higher input intensity (Hayami and Ruttan 1985) as well as higher output supply. These dynamics could have important effects on farm technical efficiency. Furthermore, fulfilling supermarket standards for consistent supply may require use of alternative production technology involving modern irrigation equipment. The resulting market assurance may also encourage investment in such fixed farm capital (Jayne et al. 1997). In addition, food quality and food safety requirements can affect the choice of inputs. Linkage to high-value chains may also involve provision of special extension and other agricultural support services (Masakure and Henson 2005). Such support services may include provision of better quality seeds and information on use of alternative inputs. We hypothesize that these mechanisms could lead to change in production technology thus contributing to productivity improvements. If this is the case, modern supply chains could contribute to agricultural productivity gains with substantial effect on poverty reduction and rural development (Irz et al. 2001; WorldBank 2007).

While some studies on supermarket effects have analyzed impacts on productivity, effects on technical efficiency have not been analyzed so far. Moreover, studies on productivity effects of supermarket participation employ approaches that do not measure productivity with respect to a common frontier. These studies also analyze individual factor productivity rather than overall farm productivity. This article applies a decomposition approach involving group frontiers and a meta-production frontier to estimate comparable technical efficiency scores and productivity ratios measured relative to a common frontier. We also subject productivity and efficiency estimates from meta-frontier analysis to statistical matching to account for self-selection. The study therefore contributes to the literature on emerging modern supply chains in developing countries and to the efficiency and productivity literature.

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 (Gulati et al. 2007; Reardon et al. 2003), but in Kenya supermarkets already account for 20% of food retailing in urban areas (Neven and Reardon 2004; Nyoro, Ariga and Ngugi 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 the section elaborating on the survey data and sample descriptive statistics. We then present and discuss the estimation results before giving some concluding remarks.

Analytical framework

The analytical approach adopted in this study follows the concept of a meta-production function as an envelope of neoclassical production functions (Hayami and Ruttan 1985). The concept assumes all producers in an industry have potential access to the same technology despite operating under different group-specific production technologies. Following this concept, Battese, Rao and O'Donnell (2004) and O'Donnell, Rao and Battese (2008) have developed a meta-frontier (MF) model for estimating productivity differences between groups of producers and comparable technical efficiency scores.

Group-specific frontiers and technical effects

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 values of inputs used by the *i*th farm for the *j*th group; $\boldsymbol{\beta}_j$ denotes the parameter vector associated with the *x*-variables for the stochastic frontier for the *j*th group involved; the v_{ij}s are assumed to be identically and independently distributed as random variables, independent of the u_{ij}, which is a non-negative unobservable random error associated with technical efficiency of the *i*th farm for the *j*th group. If we assume a log-linear functional form (e.g., Cobb-Douglas or Translog) as in Battese, Rao and O'Donnell (2004), the SPF can be written as:

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

Based on suitable distributional assumptions on the error terms u and v, input and output data for farms in the jth group can then 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 with respect to the group j frontier for the ith farm can also be computed from equation 2:

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

In order to model the relationship between TE and those variables which 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:

$$(4) \qquad \sigma_{ui} = \exp\,(\boldsymbol{w_i}\boldsymbol{\delta}_{\mathbf{j}})$$ [1]

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

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

In (5), $\boldsymbol{\beta}^*$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 (MAD) 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 problem:

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

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

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

For this optimization problem, the $\widehat{\boldsymbol{\beta}}_j$ is are treated as fixed so that the second term in the summation is constant with respect to the minimization. Hence, (6a) can be equivalently solved by minimizing the objective function $L^* \equiv \overline{\boldsymbol{x}}\boldsymbol{\beta}^*$, subject to the linear restriction of equation 6, where $\overline{\boldsymbol{x}}$ is the row vector of means of elements of the *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:

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

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 observation for the sample farm involved:

$$(8) \qquad MTR = \frac{e^{x_i \boldsymbol{\beta}_j}}{e^{x_i \boldsymbol{\beta}^{*/\sim}}} = \frac{Y_i}{e^{x_i \boldsymbol{\beta}^{*/\sim}}} \Big/ \frac{Y_i}{e^{x_i \boldsymbol{\beta}_j}}$$

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 (Battese, Rao and O'Donnell 2004), or as the second equality in (8) illustrates, the ratio between the efficiency estimate against the group frontier and the efficiency estimate against the MF (TE_i^*). It lies between zero and one and captures productivity differences between the two technologies. Alternative, (7) can be rearranged to decompose TE_i^* into the group TE estimate and MTR:

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

Potential selection bias

The MF approach above can reveal productivity and efficiency differences between farmers in supermarket and traditional channel. However, we cannot simply attribute these differences to participation in supermarket chains due to potential for selection bias - some of the unobserved factors determining participation in supermarket channels also influence farm efficiency and/or productivity. If participation in supermarket were randomized, the counterfactual situation would be observable, making it possible to derive causal inference. Unfortunately our data is cross-sectional, which rules out the possibility of observing counterfactual outcomes. The cross-sectional nature of our data also rules out possibility of addressing selection bias problem using panel data approaches. 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, Bravo-Ureta and Quiroga (2007). However, this approach is less suitable for non-linear functions such as the stochastic frontier. To address selection bias, we therefore use matching techniques, which have also been used in the context of stochastic frontier analysis by Mayen, Balagtas and Alexander (2010). Unlike their study, however, we conduct matching after estimation to avoid losing useful information for construction of the frontiers – thus improving the precision of our TE_i^* and MTR estimates.

Matching involves pairing farmers in supermarket and traditional channels who are similar in terms of their observable characteristics in order to eliminate selection bias

(Dehejia and Wahba 2002). The impact variable of interest in the matching model is the expected treatment effect for the treated population, which can be expressed as follows:

(10) $\tau_{I=1} = E(\tau I = 1) = E(R_1|I = 1) - E(R_0|I = 1)$

Here, τ is the average treatment effect for the treated (ATT), R_1 denotes the value of outcome for supermarket suppliers and R_0 denotes the value of the same for suppliers of traditional channels. Since the counterfactual $[E(R_0|I = 1)]$ is not observable, we use matching techniques to estimate this magnitude. Normally matching would be done on covariates that are correlated with selection into treatment and/or with the outcome variable. However, this can be challenging in the presence of a large set of covariates. Rosenbaum and Rubin (1983) therefore suggest matching on propensity scores to overcome the curse of "multidimensionality". Our matching approach is therefore based on predicted propensity scores (PS).

The PS is defined as the conditional probability that a producer participates in supermarket chain given covariates, Z $[PS = \hat{p}(I = 1|Z)]$ and is estimated using probit or logit function. The predicted PS is then used to estimate ATT through a matching process as follows:

(11) $\tau = E\{R_1 - R_0|I = 1\} = E\big\{E\{R_1 - R_0|I = 1, PS\}\big\}$

$= E\big\{E\{R_1|I = 1, PS\} - E\{R_0|I = 0, PS\}|I = 0\big\}$

There are various matching techniques, but the most common ones include nearest neighbor matching (NNM), kernel-based matching (KBM), stratified radius matching and Mahalanobis matching methods. 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 PS as matching partners.

The KBM method on the other hand uses a weighted average of the outcome variable for all individuals in the control group (suppliers to traditional channels) to construct a counterfactual outcome. Observations that provide better matches are given more weight. The weighted average is compared to the outcome for the supermarket suppliers, and the difference provides an estimate for treatment effect for the treated case. A sample average over all supermarket suppliers then provides an estimate of ATT. In both the NNM and the KBM, only observation in the common support region - area where the PS of the treated unit is not higher than the maximum or less than the minimum PS of the control units, are used in the calculation of ATT. Furthermore, we adopt matching "with replacement" in the NNM method.

To mimic the conditions of a randomized experiment, propensity score matching (PSM) assumes unconfoundedness or conditional independence assumption. This implies that once determinants of participation in supermarket channels are controlled for, supermarket participation is random and uncorrelated with the outcome variables (Wooldridge 2002). This is a rather strong assumption because systematic differences between farmers in the two channels may exits even after conditioning if selection is based on unmeasured characteristics (Smith and Todd 2005). Rosenbaum (2002) therefore suggests a bounding approach that evaluates how strongly unmeasured variables must influence the selection process to invalidate the implications of the matching process- thus providing a standard test for unconfoundedness.

Data collection and overview

In this section, we first present details of farm household survey and then describe the data used in the study.

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.[2] 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

Traditional 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 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 and regularity in supply (Ngugi, Gitau and Nyoro 2007) Price agreements are made before delivery, and prices are relatively stable. Payments 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.[3]

Descriptive statistics

Table 1 compares selected variables between supermarket and spot market 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 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 drip irrigation and sprinklers,[5] 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

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 labor use. Famers in supermarket channels use significantly more purchased farmyard manure and hired labor. However, they use significantly less fertilizer and family labor. The two groups of farmers also show significant differences in terms of source and cost of seeds. These differences are an indication of differences in quality of seeds used. The comparisons suggest that production practices and technologies differ considerably. Whether these differences also affect productivity and technical efficiency, as we have hypothesized, will be analyzed in the next section.

Results and discussion

The analysis begins with the estimation of groups-specific SPFs and technical effects. We then proceed to the meta-frontier analysis and estimate technology gap ratios and technical efficiency with respect to the MF.

Group-specific technology and technical effects

We analyze technical effects using group-specific SPFs. Our dependent variable in the frontier analysis is the value of vegetable production, which is preferred in our case due to non-comparability of quantity measurements. Furthermore we also expect quality differences which are appropriately captured using value of output. Before discussing our results we carry out standard tests for choice of functional forms and justification for the inefficiency approach. These results are shown in table 2. In both supermarket and traditional channel sub-samples, the likelihood ratio test rejects the more restrictive Cobb-Douglas functional form in favor of the more flexible translog model. Additional tests also confirm presence of inefficiency effects in both sub-samples.

Insert table 2 here

Results for the group frontiers are shown in table 3. 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 $(\log x_i - \log \bar{x})$, so that the estimated coefficients of the first order terms can be interpreted directly as production elasticities at the sample mean.

Insert table 3 here

The value of vegetable output for supermarket suppliers is significantly affected by pesticides, farmyard manure, labor and plot size. Labor has the highest elasticity of 0.31 indicating that a 1% increase in labor quantity would lead to a 0.31% increase in value of vegetable output. Value of vegetable output for traditional channels is, however, insignificantly affected by labor. This is most likely due to larger share of the redundant family labor among traditional channel suppliers. Farmyard manure has the least effect on the value of vegetable output for supermarket suppliers. An increase in manure use by 1% yields a 0.1% increase in value of vegetable output. The effect is, however, much higher for farmers in traditional channels. This confirms observation in table 1 that traditional channel farmers use significantly less farmyard manure. Similarly, plot size has higher positive and significant effect on value of output for farmers in traditional channels. Expenditure on seeds also affects vegetable output significantly but only for supermarket suppliers. This is probably due use of better quality seeds as revealed by higher expenditure on seeds by supermarket suppliers. A larger proportion of supermarket suppliers also obtain seeds from formal seed outlets – another indication of superior seed quality. Fertilizer has a positive and significant effect on value of output for farmers in traditional channels but is insignificant for supermarket farmers. Use of irrigation technology also has positive and significant effect on value of output for farmers in traditional channels. The differences in response of value of output to respective variables are indicative of potential differences in technology which we explore later.

With regards to efficiency effects, farmyard manure, labor, gender differences and experience in vegetable farming are shown to play significant roles. Use of farmyard manure by supermarket suppliers increases technical efficiency. On the other hand, increasing use of labor as well as increasing share of family labor reduces technical efficiency among supermarket farmers. Vegetable producers in supermarket channels would therefore benefit from reduced use of labor, more so the use of family labor. For farmers in traditional channels, increasing use of labor improves farm efficiency. Yet increasing share of family labor has insignificant effect on technical efficiency. Technical efficiency improvements due to labor use by these farmers are therefore likely to come from increasing use of hired labor, which as shown in table 1, are significantly lower for this group of farmers. Experience in vegetable farming also increases efficiency of spot market farmers. Finally, female suppliers of supermarket channels are shown to be more technically efficient.

Meta-technology ratio and technical efficiency with respect to meta-frontier

Differential effects of variables exhibited by group frontiers in the previous section are indicative of differences in production technology by farmers in the two market channels. These differences are confirmed by results of the likelihood ratio test shown in the last row of table 2. Test results confirm our earlier hypothesis of technological differences between farmers in the two channels. The next task is therefore to investigate if these differences could lead to productivity differences. We therefore proceed with the MF analysis as outlined in the analytical framework. Using parameter estimates from the group frontiers, both a linear and a quadratic programming optimization model specified in equation 6 is solved for the entire sample. Since the group frontiers favor the use of translog model, the meta-frontier is also specified as a translog function. Estimation of group frontiers and the meta-frontier were done using Ox version 6.10 (see Doornik, 2007). Parameter estimates for the two meta-frontier and the simulated standard errors are shown in table 4. Since we find only minor differences between the two meta-frontiers, the following discussion is based on the results obtained by minimizing the absolute sum of deviations as in equation (6a).

Insert table 4 here

Results show positive and significant effects of fertilizer, farmyard manure and plot size on the value of vegetable output. Use of advanced irrigation technology also leads to positive increase in the value of output. The parameters of the MF are also used in the estimation of MTR and technical efficiency with respect to the MF as shown in equations 8 and 9 respectively. A summary of these two measures is shown in table 5 alongside scores for technical efficiency with respect to group frontiers. The group-specific scores of technical efficiency, however, cannot be compared across groups since they are estimated with respect to different frontiers. It seems more appropriate to compare the efficiency scores with respect to the common MF across the two groups.

Insert table 5 here

As can be seen from table 5, farmers in supermarket and traditional channels show significant differences in MTR and technical efficiency with respect to MF. On average supermarket farmers exhibit a productivity level that is 18 percentage points (33%) higher than farmers in traditional channels. Given the technology potentially available to all vegetable farms in Kiambu district, supermarket farmers produce 72% of potential output which is way above the 54% of the potential output produced by farmers in traditional channels on average. In both cases, however, the group frontiers are tangent to the meta-frontier since the maximum value of technology gap ratio is achieved. Nevertheless as figure 2(a) illustrates, more supermarket famers achieve the maximum MTR as compared to farmers in traditional channels.

Insert figure 2 here

With regards to technical efficiency measured relative to the meta-frontier, supermarket farmers have higher technical efficiency on average. Relatively more farmers in supermarket channels also score higher levels of technical efficiency. Indeed there are relatively more supermarket farmers who score more than 80% level of technical efficiency as can be seen in figure 2(b).

Productivity and efficiency effect of participation in supermarket channels

In order to establish if the estimated differences in technical efficiency and technology gap ratio can be attributed to farmer participation in supermarket channels, we carry out treatment effect analysis using matching technique as outlined in the analytical framework. The matching process begins by estimation of propensity scores using a probit model. Results of the propensity score model shown in table 6 indicate that the age of the farmer, education level and use of advanced irrigation technology positively determine participation in supermarket channels.

Insert table 6 here

Predicted propensity scores from the probit model are used in subsequent steps to estimate productivity and efficiency effects of supermarket participation. We use the KBM and NNM methods and impose the common support condition on the matching process to ensure proper matching. Common support condition ensures that matching is only done in the region of common support. The matching procedure was conducted in STATA software following steps by Leuven and Sianesi (2003). Distributions of PS and the region of common support are shown in figure 4. The distributions reveal the significance of proper matching and the need for imposing common support condition in order to avoid bad matches.

Insert figure 4 here

In table 7 we present the average treatment effects estimated by KBM and NNM methods. Both methods reveal significant effects of supermarket participation on productivity. The results suggest that participation in supermarket chains leads to 19-20 percentage point (35% - 38%) improvement in productivity, thus confirming our main research hypothesis. These gains are higher for supermarket farmers with middle range of productivity scores as can be seen from figure 3. Participation in supermarket chains, however, does not have significant effect on technical efficiency.

Insert figure 3 here

We therefore conclude that participation in supermarket channels leads to substantial productivity gains for Kenyan vegetable farmers. The findings are particularly important given the role of agriculture in the Kenyan economy and the recent expansion of supermarkets in the country. Modernization of food supply chains in Kenya thus present great potential for agricultural development and a crucial opportunity to enhance poverty reduction in the country.

Insert table 7 here

Assessing validity of the matching assumptions

Despite the relative ability of matching techniques in addressing potential selection bias, the estimates are only valid subject to two conditions - balancing in covariates and unconfoundedness (Caliendo and Kopeinig 2008; Dehejia and Wahba 2002). The objective of estimating the PS used in matching is to balance the distribution of variables relevant to the matching process rather than obtaining precise selection into treatment. Balancing tests are therefore necessary after matching to determine if matching process has reduced bias by eliminating differences in covariates. We evaluate balancing condition and bias reduction following suggestions by Rosenbaum and Rubin (1985). Table 8 show indicators of matching quality for the matching model. Results in the fifth column reveal substantial reduction of bias through matching. The pseudo R^2 and *p-value* of the likelihood ratio tests before and after matching are also presented in table 8. The joint significance of regressors is rejected after matching while it is not rejected before matching. This is evidence of non-systematic difference in the distribution of covariates between farmers in supermarket and traditional channels after matching.

Insert table 8 here

We also test for unconfoundedness by evaluating the sensitivity of ATT estimates to hidden bias, the results of which are also presented in table 7. Since sensitivity of insignificant effects are not meaningful, Rosenbaum bounds are only calculated for treatment effects that are significantly different from zero (Hujer, Caliendo and Thomsen 2004). The critical values of Γ for MTR is 2.25 – 3.00 (KBM) and 2.12 – 2.20 (NNM). These values imply that at the level of Γ=2.12, the causal inference of significant impact of supermarket participation on productivity would have to be viewed critically. In other words, if individuals that have same **Z**-vector differ in their odds of participation in supermarket channels by 112%, the significance of supermarket effect on farm productivity may be questionable. Our results of productivity effects of supermarket participation are therefore quite robust to unobserved heterogeneity.

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 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 analysis of productivity and technical efficiency effects.

Using primary survey data of vegetable growers in Kenya, we show that participation in supermarket channels has a positive impact on farm productivity. First we show evidence of differences in technology between farmers in supermarket and traditional channels. We then use meta-frontier analysis to estimate comparable productivity and efficiency scores. Finally we control for self-selection through statistical matching and show that participation in supermarket channels improves farm productivity by 35-38%. We thus also contribute to the efficiency and productivity literature by applying matching techniques to address problems of selection bias, more so in the meta-frontier framework. Analyses of group-specific frontiers also show that use of farmyard manure improves technical efficiency of farmers in supermarket channels. Increasing use of labor, however, reduces efficiency of supermarket suppliers. Farmers in traditional channels, on the other hand would benefit from increased use of labor, particularly hired ones. Holding other factors constant, however, participation in supermarket channels has insignificant effect on farm efficiency.

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 the implications of the agri-food system transformation is crucial, as supermarket developments gradually spread to a wider geographical area. Our results suggest that high-value chains can contribute to agricultural productivity gains and agricultural growth thus enhancing poverty reduction and rural development. This does not preclude the possibility that the long-term impact of the transformation of the agri-food system in Kenya might also entail problems for agricultural producers, e.g. because of market power which highly concentrated supermarket value chains could exert against small producers. However, since this transformation in favor of a larger role of supermarkets seems to take place in any case, it is particularly important to reap the potential benefits from the process as soon as possible, and to develop a framework in which smallholders can profit from having access to supermarket value chains as much as possible.

[1] An alternative functional form; $\sigma_{ui} = \sigma \exp(\boldsymbol{z_i \delta_j})$ 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 $\boldsymbol{w_i \delta_j}$ (Wang and Schmidt 2002). We use this latter option.

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

[3] 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.

[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 (Ndeng'e et al. 2003).

[5] 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.

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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 *(%)*	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
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
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% levels, respectively.

Note: 1 US dollar = 75 Ksh.

Table 2: Hypothesis Testing for Stochastic Production Frontier Model

Null hypothesis H_0	χ^2 Statistics	χ^2 Critical	Conclusion
Choice of functional form: $\beta_{ij} = 0$			
Supermarket model	84.34	32.67	Translog is appropriate
Spot market model	39.18	32.67	Translog is appropriate
No inefficiency [a]: $\gamma = 0$			
Supermarket model	83.73	14.07	Stochastic frontier appropriate
Spot market model	15.91	14.07	Stochastic frontier appropriate
No technical effects: $\delta_1 = \ldots\ldots = \delta_8 = 0$			
Supermarket model	23.48	15.51	Inefficiency model appropriate
Spot market model	15.96	15.51	Inefficiency model appropriate
Test for same technology	149.12	48.60	MF is appropriate

[a] *This test is subject to 9 restrictions;* $\sigma_u = 0$ *and* $\delta_1 = \ldots\ldots = \delta_8 = 0$. *This results into a mixed* χ^2 *distribution with an upper bound of* 16.27 at $\alpha = 0.05$ or 14.07 *at* $\alpha = 0.1$ *for 9 restrictions* (Kodde and Palm 1986).

Table 3: Parameter Estimates of the Stochastic Production Frontier (Translog Model)

	Supermarket		Spot market	
	Coefficient	SE	Coefficient	SE
Production frontier model: Dependent variable is log value of output				
Dummy for use of fertilizer	-0.101	0.083	-0.264**	0.134
Dummy for use of pesticide	0.371***	0.075	-0.295*	0.169
Dummy for use of manure	-0.584	0.366	-0.394**	0.198
log seed cost	0.116***	0.033	0.004	0.065
log fertilizer	0.066	0.050	0.333***	0.069
log pesticide	0.164***	0.043	0.055	0.073
log manure	0.101***	0.022	0.299**	0.146
log labor	0.311***	0.058	0.009	0.114
log plot size	0.165**	0.073	0.256***	0.074
0.5 × (*log* seed cost)^2	0.129***	0.022	-0.037	0.080
0.5 × (*log* fertilizer)^2	0.153***	0.054	0.151	0.098
0.5 × (*log* pesticide)^2	0.140**	0.068	0.075	0.062
0.5 × (*log* manure)^2	-0.282***	0.023	0.105	0.094
0.5 × (*log* labour)^2	-0.507***	0.054	0.215	0.147
0.5 × (*log* plot size)^2	0.023	0.060	-0.025	0.127
Advanced irrigation technology *(dummy)*	-0.027	0.033	0.176*	0.094
Githunguri & Lower Lari region[a] (*dummy*)	-0.361***	0.138	-0.359*	0.194
Kikuyu/Westland region[a] (*dummy*)	0.710***	0.199	-0.174	0.180
Limuru region[a] (*dummy*)	0.402	0.299	-0.346*	0.183
Exotic vegetable *(dummy)*	0.520***	0.057	0.290**	0.144
Constant	0.036	0.178	0.143	0.231
Inefficiency model				
Experience in vegetable farming (*years*)	0.004	0.005	-0.014**	0.007
Gender of operator (*male dummy*)	0.896***	0.301	-0.230	0.222
Education of operator (*years*)	-0.014	0.019	-0.030	0.021
Access to agricultural extension (*dummy*)	-0.055	0.159	0.230	0.167
Share of vegetable area	0.210	0.245	-0.222	0.234
log manure	-0.298**	0.117	0.272	0.171
log labour	0.379**	0.153	-0.517***	0.115
Share of family labour	0.522***	0.163	0.133	0.200
Constant	-1.320***	0.343	-0.155	0.366
Number of observations	*133*		*265*	
Log likelihood	*-71.527*		*-237.470*	

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

[a] *The reference region is Lari.*

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

Table 4: Parameter Estimates for the Meta-frontier

Variable	Coefficient estimate L1	SE	Coefficient estimate L2	SE
Dependent variable is log value of output				
Dummy for use of fertilizer	-0.186	0.094	-0.198	0.086
Dummy for use of pesticide	0.289**	0.114	0.249**	0.100
Dummy for use of farmyard manure	-0.447	0.193	-0.485	0.175
log seed cost	0.064	0.064	0.080	0.061
log fertilizer	0.189***	0.07	0.160***	0.056
log pesticide	0.031	0.063	0.032	0.057
log manure	0.316***	0.082	0.290***	0.079
log labor	0.114	0.093	0.142*	0.085
log plot size	0.230***	0.08	0.218***	0.076
0.5 × (*log* seed cost)^2	0.217***	0.06	0.216***	0.053
0.5 × (*log* fertilizer)^2	0.176**	0.079	0.144**	0.063
0.5 × (*log* pesticide)^2	0.122*	0.07	0.088	0.066
0.5 × (*log* manure)^2	0.14*	0.081	0.091	0.07
0.5 × (*log* labour)^2	0.052	0.146	0.013	0.14
0.5 × (*log* plot size)^2	0.004	0.091	-0.037	0.081
log seed cost × *log* fertilizer	0.157**	0.076	0.139**	0.071
log seed cost × *log* pesticides	-0.128	0.043	-0.115	0.038
log seed cost × *log* manure	-0.012	0.055	-0.007	0.051
log seed cost × *log* labour	-0.065	0.068	-0.061	0.064
log seed cost × *log* plot size	-0.157	0.062	-0.136	0.054
log fertilizer × *log* pesticide	-0.033	0.051	-0.017	0.039
log fertilizer × *log* manure	-0.118	0.054	-0.131	0.047
log fertilizer × *log* labour	0.046	0.064	0.07	0.057
log fertilizer × *log* plot size	-0.146	0.064	-0.147	0.058
log pesticide × *log* manure	0.011	0.066	0.023	0.06
log pesticide × *log* labour	0.028	0.068	0.028	0.06
log pesticide × *log* plot size	-0.01	0.064	-0.017	0.053
log manure × *log* labour	-0.112	0.094	-0.092	0.088
log manure × *log* plot size	0.133*	0.07	0.133**	0.062
log labor × *log* plot size	0.051	0.086	0.055	0.078
Advanced irrigation technology (*dummy*)	0.092	0.057	0.113*	0.058
Githunguri & Lower Lari region [a] (*dummy*)	-0.265	0.183	-0.276	0.185
Kikuyu/Westland region [a] (*dummy*)	0.619***	0.201	0.51**	0.204
Limuru region [a] (*dummy*)	-0.238	0.219	-0.291	0.222
Exotic vegetable	0.378***	0.093	0.358***	0.083
Constant	0.372	0.233	0.517**	0.233
Number of observations		*398*		

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

[a] *The reference region is Lari.*

Table 5: Meta-technology Ratio (MTR) and Technical Efficiency for Group SPFs and Meta-frontier

	Supermarket suppliers			Traditional channel suppliers		
	Group TE	MTR	Meta-frontier TE	Group TE	MTR	Meta-frontier TE
Mean	0.61	0.72***	0.42 *	0.70	0.54	0.37
Minimum	0.09	0.16	0.07	0.12	0.07	0.01
Maximum	0.99	1.00	0.99	0.91	1.00	0.86
Std. deviation	0.30	0.24	0.19	0.17	0.24	0.24

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

Table 6: Propensity Score for Participation in Supermarket Channels (Probit Estimates)

	Coefficient	SE
Variables		
Education of operator (years)	0.180**	0.075
Education of operator squared *(years)*	-0.008*	0.010
Own means of transportation *(dummy)*	0.433**	0.201
Age of operator *(years)*	-0.008	0.006
Household labour endowment *(no. of people)*	-0.035	0.062
Share of family labor	-0.515**	0.210
Off farm employment *(dummy)*	0.276*	0.142
Use of advanced irrigation equipment *(dummy)*	0.296**	0.148
Household access to electricity *(dummy)*	0.196	0.185
Lari region *(dummy)*	-0.738*	0.424
Githunguri and Lower Lari region *(dummy)*	0.584***	0.188
Constant	-1.151**	0.539
Number of observations	*398*	
Pseudo R-squared	*0.126*	
Log likelihood	*-221.532*	

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

Table 7: Average Treatment Effects and Results of Sensitivity Analysis

Matching algorithm	Outcome	ATT	Critical level of hidden bias (Γ)	Number of treated	Number of control
Kernel-based matching	Meta-technology ratio	0.19*** (6.75)	2.25 – 3.00	129	207
	Meta-frontier TE	0.04 (1.62)		129	207
Nearest neighbor matching	Meta-technology ratio	0.20*** (5.70)	2.12 – 2.20	129	207
	Meta-frontier TE	0.05 (1.64)		129	207

Table 8: Indicators of Covariate Balancing, Before and After Matching

Matching algorithm	Outcome	Median absolute bias		% bias reduction	Pseudo R^2		p-value of LR	
		Before matching	After matching		Unmatched	Matched	Unmatched	Matched
Kernel-based matching	Meta-technology ratio	34.18	4.26	87.54	0.126	0.027	0.000	0.354
	Meta-frontier TE	34.18	4.26	87.54	0.126	0.027	0.000	0.354
Nearest neighbor matching	Meta-technology ratio	34.13	8.20	75.97	0.114	0.031	0.000	0.142
	Meta-frontier TE	34.13	8.20	75.97	0.114	0.031	0.000	0.142

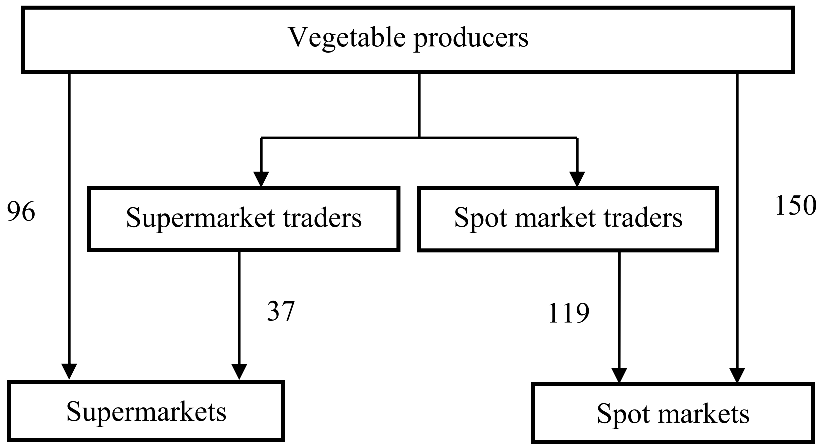
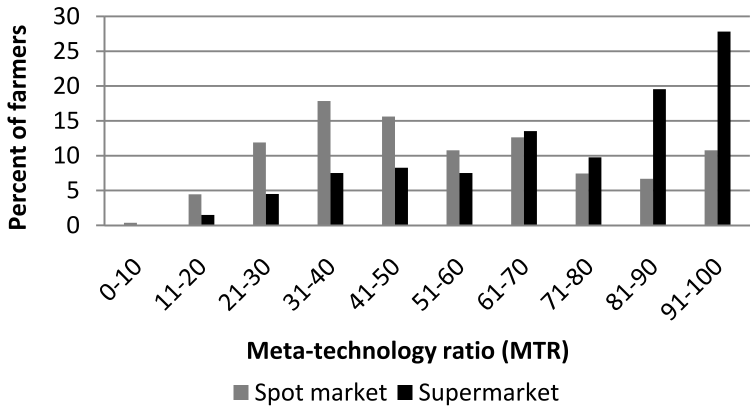
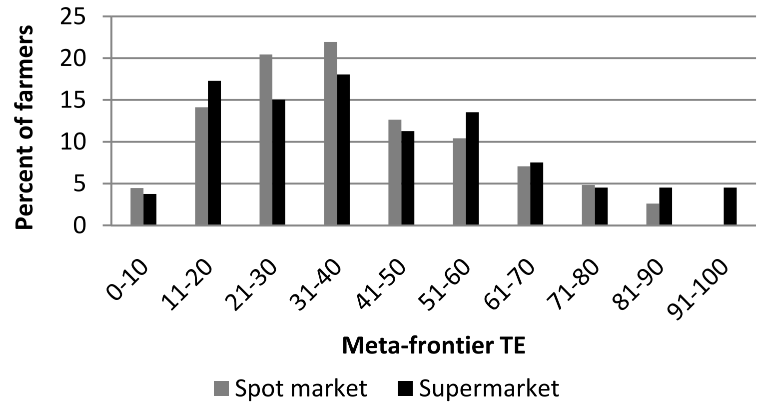


Figure 1: Vegetable marketing channels among Kenyan sample farmers



a) Distribution of meta-technology ratio (MTR)



b) Distribution of meta-frontier TE

Figure 2: Distribution of meta-technology ratios and meta-frontier technical efficiency according to market channels

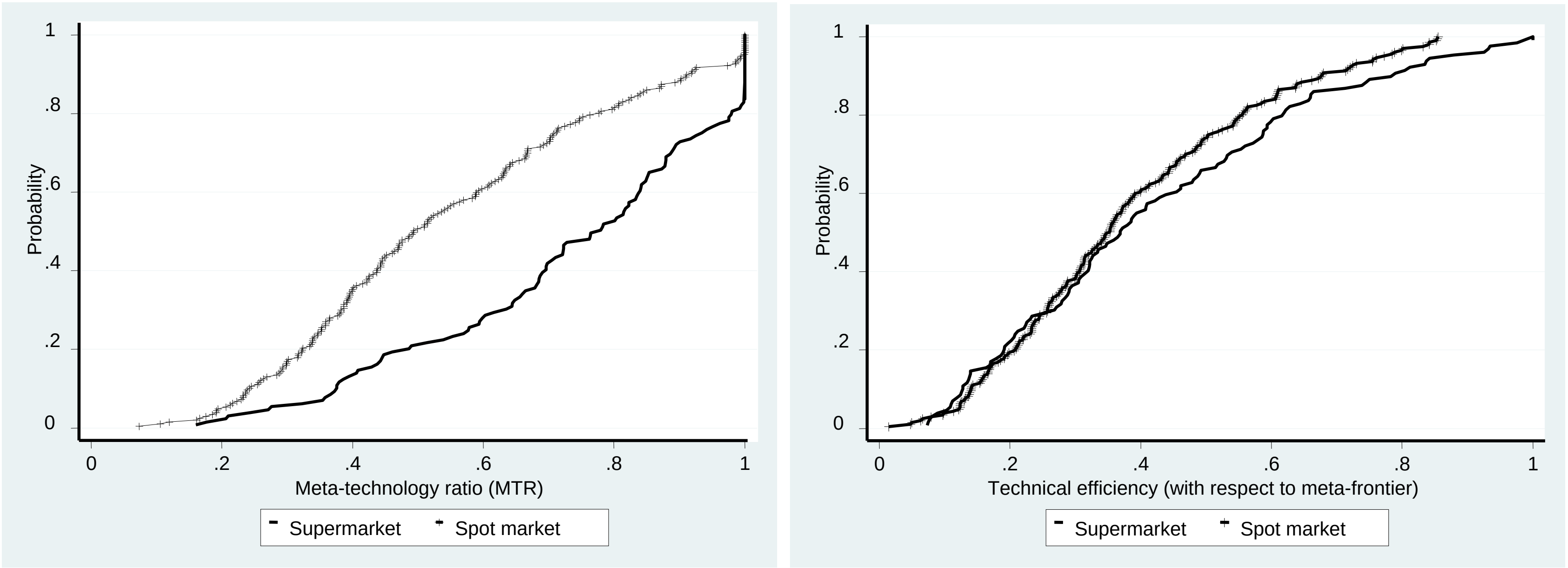
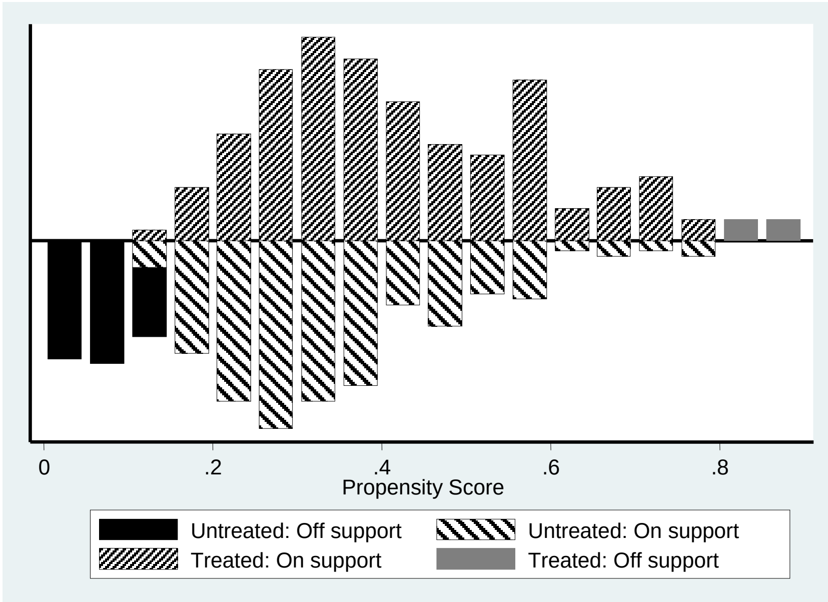
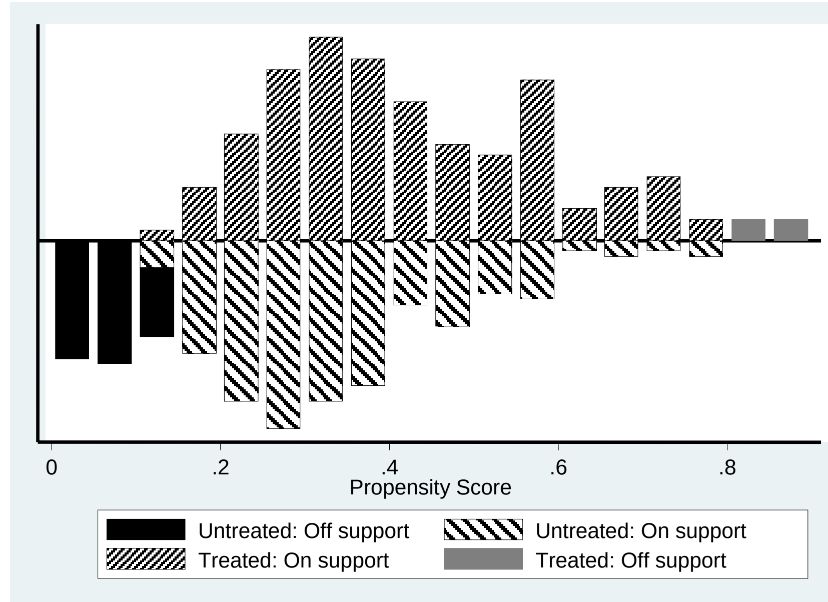


Figure 3: Cumulative distribution of meta-technology ratio (MTR) and meta-frontier TE by market channel – adjusted for selection bias.





Effects on meta-technology ratio (MTR)

Effects on meta-frontier TE

Note: On support refer to observations in respective categories that find suitable matches, while off support indicate observations that do not find suitable matches.

Figure 4: Propensity score distribution and common support for propensity score estimation.