A Meta-Frontier Approach for Causal Inference in Productivity Analysis: The Effect of Contract Farming on Sunflower Productivity in Tanzania

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Abstract

Due to changes in the global agricultural system and support from various organizations, contract farming has recently been significantly expanded in many developing countries. A considerable body of literature analyses the impact of contract farming on the welfare of smallholders, whereas its impact on efficiency and productivity is mostly overlooked. This study addresses this salient gap by combining the approaches suggested by Bravo-Ureta, Greene, and Solís (Empirical Economics 43:55–72, 2012) and Rao, Brümmer, and Qaim (American Journal of Agricultural Economics 94:891–912, 2012). We first use the approach of Bravo-Ureta, Greene and Solís (2012) to estimate two separate production frontiers (one for contract farmers and one for non-contract farmers) that account for potential biases due to self-selection on both observed and unobserved variables. Then, we follow Rao, Brümmer and Qaim (2012) and create a meta-frontier in order to estimate the effects of participation on the farms' meta-technology ratio, their group technical efficiency, and their meta-technology technical efficiency. The empirical analysis uses a cross-sectional data set from sunflower farmers in Tanzania, where some of the farmers participate in contract farming while others do not. We find a significant selection bias, which justifies the use of the sample selection framework. Our preliminary results indicate that contract farming significantly increases the yield potential (meta-technology ratio) but lowers the group technical efficiency. As the first effect is slightly larger than the second, we find a small positive effect of contract farming on productivity (meta-technology technical efficiency). The positive effects on the yield potential and the (average) productivity can be (at least partly) explained by the contractor's provision of (additional) extension service and seeds of high-yielding varieties to the contract farmers.

Keywords: Contract Farming, Sunflower, Technical efficiency, Productivity, Meta-Frontier, Sample selection, Tanzania

JEL codes: D24, Q12

1 Introduction

It has been recognized for many years that agriculture plays an important role in economic development of developing countries (e.g. Hayami and Ruttan, 1971). It is also well known that agriculture production in developing countries generally has a very low productivity compared to non-agricultural production in the same country or to agricultural production in developed countries. The low agricultural productivity often has many diverse reasons, e.g. limited knowledge about productivity-enhancing production methods and highly productive technologies, limited availability of or access to highly productive varieties and productivity-enhancing inputs, limited availability of liquidity and limited access to credit, and/or reluctance to invest in productivity-enhancing measures due to production risk, output price variability, and unreliable market access combined with (rational) risk aversion of poor farmers.

Contract farming is seen as a tool to increase agricultural productivity in developing countries, as it could solve some of the above-mentioned problems, e.g. by improving access to knowledge, better technologies (e.g. highly productive varieties), productivity-enhancing inputs, and credit and by providing more predictable output prices and guaranteed market access. In fact, contract farming in developing countries usually implies that contractors enter into a contract with farmers—either directly with the farmers or through farmers' associations—for just one year at the time, where the farmer produces a specific crop by following some guidelines and the contractor supplies production information and productivity-enhancing inputs on credit and guarantees to purchase the output at a premium price (e.g. Porter and Phillips-Howard, 1997). Vertical integration in production and marketing has often been a case for perishable products, products with technical requirements, and economically important products (Bijman, 2008). Over time however, this practice has been increasingly extended to several other mundane crops such as sunflowers (Guo, Jolly and Zhu, 2007).

There exists a considerable body of literature that analyses the impact of contract farming on the welfare of smallholders (e.g. Miyata, Minot and Hu, 2009; Prowse, 2012), whereas its impact on their efficiency and productivity is mostly overlooked. A few studies (e.g. Bravo-Ureta and Pinheiro, 1997; Begum et al., 2012) compare the productivity and efficiency of contract farmers and non-contract farmers in developing countries but most of these studies do not take into account that the farmers self-select into contract farmers and non-contract farmers.

Moreover, most studies on the effects of contract farming focus on crops that are considered to be ideal contract crops, i.e. crops with specific characteristics such as high perishability, requirements for product homogeneity, high hygiene, and food safety, or a complex production process. There are only very few studies that analyze the causal effects of contract farming in commercial production involving low-value crops like sunflower as it is done in this study.

The aim of this paper is to investigate the causal effect of participation in contract farming on the productivity and efficiency of small-scale sunflower farmers in Tanzania. We take into account the self-selection of farmers into contract farming by combining the approaches suggested by Bravo-Ureta, Greene and Solís (2012) and Rao, Brümmer and Qaim (2012). We first use the approach of Bravo-Ureta, Greene and Solís (2012) to estimate two separate production frontiers (one for contract farmers and one for non-contract farmers). This approach is based on a combination of a matching method and a stochastic frontier production function that accounts for sample selection (Greene, 2010) in order to correct for potential biases that arise from self-selection on both observed and unobserved variables. Then, we follow Rao, Brümmer and Qaim (2012) and create a meta-frontier in order to estimate the effects of participation on the farms' meta-technology ratio, their group technical efficiency, and their meta-technology technical efficiency.

The following section reviews the literature on contract farming and its impacts on technical efficiency, productivity, and income; section 3 presents the suggested econometric framework; section 4 describes the data and the empirical specification; section 5 presents and discusses the results, and the last section concludes.

2 Review of the Literature

Contract farming is an agreement between farmers and buyers about the production and the supply of agricultural products under pre-established conditions, and often at pre-determined prices (e.g. Eaton and Shepherd, 2001; Andri and Shiratake, 2003; FAO, 2012). It is an institutional arrangement which—according to microeconomic theory—develops in response to missing or imperfect markets (e.g. Grosh, 1994; Glover, 1994; Key and Runsten, 1999). In theory, contracts improve the access of the smallholder farmers to resources; e.g. yield-enhancing inputs, credit, information, services, and product markets. Non-price factors involved in the contracts, such as technical assistance, training and education could further help farmers to improve their efficiency, productivity, and profitability (e.g. Ruben and Sáenz-Segura, 2008; Chakraborty, 2009). And with pre-determined prices, farmers are eventually able to have more stable farm incomes. Earning additional income is a primary motivation for farmers to enter contracts (Bijman, 2008; Little and Watts, 1994). Smallholders enter the contract if their expected gain of contracting is greater than their reservation utility (Barrett et al., 2011; da Silva, 2005). Even though earning additional income is the primary motivation for farmers to engage in contract farming, farmers may also contract for other reasons (Prowse, 2012). Contract farming can also be used to allocate risk between the smallholders and the contracting firm (Bogetoft and Olesen, 2004). Smallholders usually take the production risk, whereas the contracting firms usually face the marketing risk (Carr and Banco, 1993; Glover, 1994; Bogetoft and Olesen, 2004). Bogetoft and Olesen (2004) argue that most of the smallholders use contract farming to diversify the risk rather than to maximize the production volume.

2.1 Contract Farming in Developing Countries

Although contract farming is still a debatable form of institutional arrangement in the agribusiness sector of developing countries, it is becoming more common. The change in global economic climate and the need for market access facilitate its rapid spread (Oya, 2012). Contract farming plays a crucial role in the development of better market institutions that foster small scale agriculture (Masakure and Henson, 2005), particularly in Sub Saharan Africa (UNCTAD, 2009). For instance, in Kenya, contract farming accounts for 60 percent of tea and sugar production and almost 100 percent of cut flowers production; in Mozambique, 400,000 smallholders are engaged in contract farming; and in Zambia, contract farming accounts for 100 per cent of cotton and paprika production (UNCTAD, 2009). Birthal et al. (2008) outlines three reasons for the expansion of contract farming in developing counties: namely, the reduction of the government's role in service provision, the increase in the number of supermarkets, and the increase in attention of donors.

Depending on the economic environment, there are generally about five applicable models in contract farming that are practiced in different places and countries (Bijman, 2008). (a) The centralized model; this entails conditions under which a buyer buys from many smallholder farmers contracted on individual basis or farmer groups. (b) The Nucleus Estate Model; this refers to a situation where a contractor has his own farm on which to produce the commodity but, in addition, the contractor outsources additional produce from other independent farmers. (c) The Multipartite Model; this refers to a situation where joint venture in contract farming exists between public and the private partners. (d) The informal model; this refers to a situation where small contractors, usually local traders or processors, work with the farmers on the basis of informal relations that are generally oral and loose in their specifications. A farmer is only assured of market for his produce at a price rate that is slightly higher than the market price, in certain cases contractors do not even assure farmers of purchasing the produce. (e) Lastly, there is the Intermediary Model; this involves processors as end buyers, while traders act as middlemen between smallholder farmers (producers) and the processor (Bijman, 2008).

2.2 Contract farming and sunflower production in Tanzanian

Agriculture and particularly farm activities still constitute the major component of the Tanzanian economy. The sector provides livelihood to more than 70% of the population. It accounts for about 24% of the GDP, 30% of total exports and about 65% of raw materials for domestic industries. It provides significant linkages, both backward and forward linkages with other non-farm sectors. Agriculture thus, constitutes the back bone of the Tanzanian economy, and the advancement of the agricultural sector can contribute to the economic development of the country.

Contract farming has existed in Tanzania for decades, but it has largely confined itself to few traditional cash crops such as tobacco, tea, sisal and coffee. The National Strategy for Growth and Reduction of Poverty (2010–2014) recognizes the development of the private sector as the vehicle for economic growth and poverty reduction. Contract farming is underlined as the appropriate strategy of involving the private sector in facilitating and sustaining smallholder farming not only in few traditional cash crops but also in many other crops including ordinary crops which may be produced commercially to enhance economic growth and reduction of poverty at household level (TNBS, 2009; URT, 2009). Recently, there is a growing interest in contract farming from both the government and farmers. The government considers contract farming as one of the means of solving farmers' production and marketing problems. On the other hand, interest in contract farming is growing because of the failure of many traditional farmers' cooperatives. Cooperatives were once the reliable form of farmer organization in Tanzania, but following their failure to address and safeguard the pertinent interests, farmers have lost faith in them. Besides cooperatives and contract farming, other forms of producer organizations have emerged such as farmer groups, Saving and Credit Cooperative Societies (SACCOS), and small scale farmers networks, e.g. Muviwata (URT and FAO, 2008).

Sunflower is a hardy crop that is tolerant to low rainfall and suited even to regions with moderate rainfall (Mayhew and Penny, 2005). In Tanzania, sunflower grows well in many parts of the country but the largest amounts of sunflower are produced in Dodoma and Singida regions. The total amount produced in Tanzania has steadily increased over time, from an average of 80,000 tons per year in 2000/2001 to about 489,387 tons per year by 2010/2011 (URT, 2011), and the crop accounts for about 36 per cent of all oil seeds produced in the country (RLDC, 2008). Other major oil seeds produced in the country include groundnuts, oil palm, simsim and soya (URT, 2008).

The use of contracts in the production of sunflower in the Kongwa district (Dodoma region) began in the 2007/08 crop season. Contract farming was introduced in the sunflower sector in Kongwa district as a way of improving business related to sunflower production and marketing. It was introduced separately by two private firms: Uncle Milo Investment Company Limited and RIG Investment Company Limited, both based in Dodoma urban district (Salisali, 2012). The contract farming arrangement meant to address major problems that smallholder farmers often face in the area, the most critical ones being lack of seeds of high-yielding varieties and lack of a reliable and profitable market for sunflower produce. It also aimed at improving access of farmers to extension services and better agronomics specific to sunflower production. It was envisaged that provision of training and assistance to farmers by contracting firms would increase the quality and quantity of produced sunflower seeds, and would enhance commercialization of smallholder production for increased incomes at household level (Salisali, 2012). In practice however, the current contracts arrangements only include the provision of a single input, i.e. seeds of high-yielding varieties, although other inputs and services such as fertilizers, pesticides, credit, training, and extension service are as well important for improving the productivity of sunflower farming.

2.3 Effect of contract farming on technical efficiency, productivity, and income

There is abundant literature that finds considerable technical inefficiencies and low returns of smallholder farming business in developing countries (e.g. Koopmans, 1951; Farrell, 1957; Schultz, 1964; Timmer, 1971; Bravo-Ureta and Evenson, 1994). It is argued that in small-scale agricultural production, inefficiency is often associated with factors related to demographic characteristics of household, farm characteristics and the structure of organization and management for which farmers are accustomed to (Forsund, Lovell and Schmidt, 1980; Battese and Coelli, 1993). Furthermore, low levels of technical efficiency may be caused by failures in the credit, insurance, information and product markets. Key and Runsten (1999) argue that these market failures even prevent farmers from optimally using the resources that they have in abundance such as land and labor. The gap between what is actually produced and the potential output level remains hugely wide and the income remains low. Improving technical efficiency of smallholders has the potential to increase their productivity, total output, and incomes without requiring increase in inputs or change of technology.

Several studies analyse the effect of contract farming on farmers' income (e.g. Little, 1994; Key and Runsten, 1999; Singh, 2002; Warning and Key, 2002; PingSun, Sununtar and Adam, 2008; Miyata, Minot and Hu, 2009) and most of these studies find a significant positive effect. However, studies that analyze the effect of contract farming on efficiency and/or productivity are rare. Several empirical studies find that contract farmers have a higher technical efficiency and/or productivity than non-contract farmers (e.g. Warning and Key, 2002; Ramaswami, Birthal and Joshi, 2006; Ruben and Sáenz-Segura, 2008; Chakraborty, 2009), while other studies find no (significant) differences (e.g. Glover and Kusterer, 1990; Miyata, Minot and Hu, 2009; Little and Watts, 1994). However, these studies do not take self-selection into contract-farmers and non-contract farmers into account. To our knowledge, the only study that analyzes the causal effect of contract farming on technical efficiency and productivity has been done by Rao, Brümmer and Qaim (2012) who find that participation in supermarket contracts leads to substantial productivity gains for Kenyan vegetable farmers.

3 Econometric Framework

In economics the terms efficiency and productivity are widely used and many times interchangeably. Despite their similarity, linkages and interchangeable usage, efficiency and productivity have important differences (e.g. Coelli et al., 2005). Productivity is the ratio of the amount of output produced to the amount of resources used, whereas large values of this ratio indicate higher productivity. Efficiency refers to both technical efficiency and allocative efficiency. Our empirical analysis focuses on output-oriented technical efficiency, which is measured by comparing the observed output with the maximum feasible (frontier) output under the assumption of fixed input quantities. Through non-price factors, contract farming may increase the yield per unit of inputs, which in turn may enhance farmers' technical efficiency, productivity, and incomes.

To evaluate the impact of contract farming on the technical efficiency and productivity of sunflower farmers, we suggest and use a new multi-step procedure for causal inference in efficiency and productivity analysis that is a combination of the two frameworks introduced by Bravo-Ureta, Greene and Solís (2012) and Rao, Brümmer and Qaim (2012), respectively.

Bravo-Ureta, Greene and Solís (2012) apply Propensity Score Matching (PSM) (Rosenbaum and Rubin, 1983; Imbens, 2000; Caliendo and Kopeinig, 2008) to create two matched samples of contract farmers and non-contract farmers with similar characteristics in order to remove (or at least reduce) observable differences between contract farmers and non-contract farmers. As matching based on propensity scores does not necessarily improve the covariate balance (Diamond and Sekhon, 2013), we obtain the matched samples by genetic matching instead of propensity score matching. Genetic matching is based on a genetic search algorithm that directly maximizes the covariate balance (Diamond and Sekhon, 2013). In this study, we use 1-to-1 genetic matching without replacement, which matches each contract farmer with exactly one non-contract farmer.

We further follow Bravo-Ureta, Greene and Solís (2012) and estimate two stochastic frontier models, one for contract farmers and one for non-contract farmers. To deal with biases from unobserved differences between contract farmers and non-contract farmers, we use the stochastic frontier model proposed by Greene (2010) that accounts for non-random sample selection. This model assumes that the unobserved characteristics in the selection equation are correlated with the noise in the stochastic frontier model. The specification of this model is as follows:

$$y_i = \beta^{c\prime} x_i + \epsilon_i \text{ for } d_i = 1 \tag{1}$$

$$y_i = \beta^{n\prime} x_i + \epsilon_i \text{ for } d_i = 0 \tag{2}$$

$$d_i = 1[\alpha' z_i + w_i > 0] \tag{3}$$

$$\epsilon_i = v_i - u_i \tag{4}$$

$$u_i \sim N^+(0, \sigma_u^c) \text{ for } d_i = 1 \tag{5}$$

$$u_i \sim N^+(0, \sigma_u^n) \text{ for } d_i = 0 \tag{6}$$

$$(w_i, v_i) \sim N_2\left((0,0), (1, \rho^c\, \sigma_v^c, \sigma_v^{c2})\right) \text{ for } d_i = 1 \tag{7}$$

$$(w_i, v_i) \sim N_2\left((0,0), (1, \rho^n\, \sigma_v^n, \sigma_v^{n2})\right) \text{ for } d_i = 0, \tag{8}$$

where y_i denotes the logarithmic output quantity of producer $i = 1, \ldots, N$, x_i is a vector of logarithmic input quantities (and potentially interaction terms and quadratic terms thereof), d_i is a binary dummy variable that is one for contract farmers and zero otherwise, z_i is a vector of covariates in the sample selection equation, ϵ_i is the error term of the stochastic frontier model that takes into account noise (v_i) and inefficiency (u_i), w_i is the error term of the selection equation, and α, β^c and β^n are parameter vectors to be estimated. It is assumed that the inefficiency term u_i follows a half-normal distribution with dispersion parameter σ_u^c (σ_u^n) and that w_i and v_i follow a bivariate normal distribution with variances 1 and σ_v^{c2} (σ_v^{n2}), respectively, and a correlation coefficient of ρ^c (ρ^n) for (non-)contract farmers. Non-zero values of ρ^c and ρ^n indicate self-selection so that the estimates of standard stochastic frontier models would be inconsistent. The log-likelihood function of this model and a two-stage estimation procedure are described in Greene (2010).

From the two estimated stochastic frontier models, we can derive the group-specific technical efficiency estimates ($TE_i = E[e^{-u_i}]$) both for contract farmers and non-contract farmers. By comparing these technical efficiency estimates, we can assess whether the sunflower production of contract farmers or of non-contract farmers is closer to the production frontier of the respective group of farmers. However, as the two groups of farmers are compared to two different benchmarks, the comparison of the technical efficiency estimates does not allow us to compare the productivity of the two groups of farmers. Therefore, we follow Rao, Brümmer and Qaim (2012) and obtain a meta-frontier that envelopes the production frontiers of the two groups of farmers (see also Battese, Rao and O'Donnell, 2004; O'Donnell, Rao and Battese, 2008). We estimate the parameters of the meta-frontier function (β^*) by minimizing the sum of the absolute differences between the meta-frontier and the respective group-specific frontier at all observations, while the meta-frontier may not be below any of the group-specific frontiers at any observation:

$$\min_{\beta^*} \sum_{i=1}^{N} |\beta^{*\prime} x_i - \beta^{c\prime} x_i \, d_i - \beta^{n\prime} x_i \, (1 - d_i)|, \tag{9}$$

$$\text{s.t. } \beta^{*\prime} x_i \geq \beta^{c\prime} x_i \; \forall \; i \tag{10}$$

$$\beta^{*\prime} x_i \geq \beta^{n\prime} x_i \; \forall \; i. \tag{11}$$

As β^c and β^n are treated as fixed, the above minimization can be solved by linear programming:

$$\min_{\beta^*} \beta^{*\prime} \bar{x}, \tag{12}$$

$$\text{s.t. } \beta^{*\prime} x_i \geq \max(\beta^{c\prime} x_i, \beta^{n\prime} x_i) \; \forall \; i, \tag{13}$$

where $\bar{x} = N^{-1} \sum_{i=1}^{N} x_i$ is a vector containing the mean values of each element of x_i in the entire sample (Rao, Brümmer and Qaim, 2012). Based on the parameters of the meta-frontier function (β^*), we can calculate the meta-technology ratios (MTRs) of the two groups of farmers:

$$MTR_i = \begin{cases} \dfrac{\beta^{c\prime} x_i}{\beta^{*\prime} x_i} & \text{if } d_i = 1 \\ \dfrac{\beta^{n\prime} x_i}{\beta^{*\prime} x_i} & \text{if } d_i = 0. \end{cases} \tag{14}$$

The MTRs indicate how close the group-specific frontiers are to the meta-frontier, where an MTR of one indicates that the group-specific frontier is equal to the meta-frontier. The meta-frontier technical efficiency (TE_i^*) is composed of the group-specific technical efficiency and the MTR:

$$TE_i^* = TE_i \cdot MTR_i. \tag{15}$$

The meta-frontier technical efficiencies indicate the technical efficiency with respect to the meta-frontier.

4 Data and Empirical Specification

This study uses data from a cross sectional farm household survey conducted in the Kongwa district, located in the Dodoma region in central agricultural zone of Tanzania, between September and October 2012. The Dodoma region is the most important region for sunflower production in Tanzania, e.g. in the year 2008, this region accounted for 22.5% of total sunflower production in Tanzania (RLDC, 2008). A two-stage sample design was used to collect the data. First, eight villages from four wards were purposefully selected because of the presence of sunflower contract farming in these villages. Then, the contract farmers were randomly selected from the list of contracted farmers, and non-contract farmers were randomly selected from the village households list (after removing the contract farmers). The data collection was carried out by face to face interviews with the household heads using a structured questionnaire. In total, the data set includes 396 small-scale sunflower farmers, 201 contract farmers and 195 non-contract farmers.

The variables that are used in the production model, in the sample selection model, and as covariates for the genetic matching are described in Table 1. The input and output quantities are not used in the sample selection model and in the genetic matching, because they may depend on the participation in the contract scheme. Descriptive statistics of these variables are presented in Table 2 in the next section.

Table 1: Variables and their descriptions

Variable	Unit	Definition
Output quantity		
YIELD	kilograms	sunflower seeds harvested
Input quantities		
LAND	acres	land planted with sunflower
LABOR	person days	labor used for sunflower production
SEED	kilograms	sunflower seeds used as seed
IMPLE	Tanzanian Shilling	other inputs used for sunflower production
Further explanatory variables in the production function		
WARD	categorical	the ward in which the household resides
Dependent variable of the selection equation		
PARTIC	dummy	1 indicates participation in contract farming
Covariates for matching and explanatory variables in the selection equation		
FSIZE	acres	total farm size
HSIZE	number	number of people in the household
AGE	years	age of the household head
GENDER	dummy	1 indicates a female household head
EDUC	ordinal	highest educational attainment of the household head (1: no formal; 2: primary; 3: secondary; 4: diploma)

5 Results

In this section, we present and discuss *preliminary* results of the genetic matching, of the sample-selection stochastic frontier models, and of the meta-frontier analysis. Most calculations and estimations were done within the statistical software environment "R" (R Core Team, 2015) using the add-on packages "MatchIt" (Ho et al., 2011), "Matching" (Sekhon, 2011), and "rgenoud" (Mebane, Jr. and Sekhon, 2011) for genetic matching and the add-on package "lpSolve" (Berkelaar and others, 2015) for linear programming, while the sample-selection stochastic frontier models were estimated by LIMDEP 10.

5.1 Genetic Matching

In order to remove (or at least reduce) observable differences between contract farmers and non-contract farmers, we use 1-to-1 genetic matching without replacement, which matches each contract farmer with exactly one non-contract farmer. From this, we obtain one sample of contract farmers and one sample of non-contract farmers with similar characteristics. The matching algorithm found 190 matching pairs of contract farmers and non-contract farmers, while for 11 contract farmers and for 5 non-contract farmers no corresponding farmer of the other group could be found. Descriptive statistics of the original sample and of the matched sample are presented in Table 2.

Table 2: Summary statistics for the matched and unmatched sample

Variables	Pooled		Contract farmers		Non-contract far.		t-ratio[a]
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unmatched Sample							
YIELD	378.54	406.16	430.35	428.20	325.13	375.78	2.6***
LAND	3.56	3.20	3.68	2.94	3.44	3.45	0.77
LABOR	22.87	17.57	22.95	18.12	22.79	17.04	0.09
SEED	11.50	11.79	11.24	11.37	11.77	12.22	-0.44
IMPLE	50467	60199	52722	56009	48144	64294	0.76
FSIZE	8.44	7.41	8.60	5.92	8.28	8.69	0.42
HSIZE	2.86	1.73	2.76	1.50	2.97	1.94	-1.20
AGE	42.43	12.71	43.47	13.24	41.37	12.07	1.65
GENDER	0.20	0.40	0.17	0.38	0.24	0.43	-1.78*
EDUC[b]			40975		37631		1.24
Observations	396		201		195		
Matched Sample							
YIELD	363.58	376.48	415.84	407.86	311.32	335.24	2.7***
LAND	3.48	3.15	3.58	2.90	3.39	3.39	0.58
LABOR	22.92	17.80	22.90	18.45	22.94	17.18	-0.02
SEED	11.38	11.77	11.04	11.36	11.72	12.18	-0.56
IMPLE	48984	59476	50695	54895	47274	63830	0.56
FSIZE	8.05	5.53	8.46	5.83	7.64	5.19	1.45
HSIZE	2.84	1.67	2.79	1.51	2.89	1.83	-0.61
AGE	42.48	12.84	43.61	13.39	41.36	12.19	1.7*
GENDER	0.20	0.40	0.16	0.37	0.24	0.43	-1.92*
EDUC[b]			36804.5		35585.5		0.75
Observations	380		190		190		

Notes: $^{*}P$ = <0.10 ; $^{**}P$ = <0.05 ; $^{***}P$ = <0.01

[a] A t-test for testing whether the mean values of the variables are the same for contract farmers and non-contract farmers.

[b] As EDUC is an ordinal variable, the table reports rank sums and the last column presents the results of a Mann-Whitney U test.

As described above, the matching is done based on the variables that are unlikely to be affected by participation in contract farming but which may affect participation in contract farming and/or productivity, i.e. FSIZE, HSIZE, AGE, GENDER, and EDUC. In the original unmatched sample, the mean values of none these variables significantly differ between contract farmers and non-contract farmers at the 5% level, and only the proportion of female household heads significantly differs at the 10% level. As contract farmers and non-contract farmers have very similar observable characteristics, it is questionable whether the application of a matching method is indeed necessary in our application.

In the matched sample, the household size (HSIZE) and the household head's education (EDUC) are more similar between contract farmers and non-contract farmers than in the original unmatched sample. However, the other three variables are slightly less similar after matching. In our on-going work on this analysis, we will take a closer look at the matching algorithm, e.g. to check whether better matching results can be obtained.

On average, the input quantities used for sunflower production do not significantly differ between contract-farmers and non-contract farmers, neither in the original unmatched sample nor in the matched sample. However, in spite of using similar input quantities, the contract farmers produce on average significantly more sunflower seeds than non-contract farmers (32% more in the original unmatched sample, 33.5% more in the matched sample). This indicates that contract farmers have a higher productivity than non-contract farmers both in the original unmatched sample and in the matched sample. However, these comparisons do not take into account unobserved differences between contract farmers and non-contract farmers.

5.2 Sample-Selection Stochastic Frontier Model

The first stage of the sample-selection stochastic frontier model is the estimation of equation (3) as a standard probit model. The estimation results of this model, using both the original unmatched data set and the matched data set, are presented in Table 3. These results indicate that smaller households and older household heads are, ceteris paribus, more likely to enter a contract scheme than larger households and younger household heads. The total farm size and the gender and education of the household head do not have a significant effect (at 5% level) on the adoption of the contract scheme. When using the matched data set, the entire model is no longer statistically significant (at 5% level). This indicates that the matching has significantly reduced observable differences between the samples of contract farmers and non-contract farmers.

We estimated the sample-selection stochastic frontier models both with the Cobb-Douglas and the Translog functional form. In all cases, a likelihood ratio test revealed that the fit of the Translog functional form was not significantly better than the fit of the Cobb-Douglas functional form. Therefore, we use the Cobb-Douglas functional form in

Table 3: Estimates of the Sample-Selection Equation

Parameters	Unmatched Sample		Matched Sample	
	Coef.	Std. Err.	Coef.	Std.Err.
CONSTANT	-0.816**	0.345	-0.709*	0.371
FSIZE	0.044*	0.024	0.022	0.038
FSIZE^2	-0.001	0.001	-0.0002	0.001
HSIZE	-0.089**	0.042	-0.078*	0.044
AGE	0.016***	0.006	0.015**	0.006
GENDER	-0.230	0.161	-0.276*	0.165
EDUC:PRIMARY	0.269	0.170	0.252	0.172
EDUC:SECONDARY	0.943*	0.502	0.706	0.556
EDUC:DIPLOMA	0.048	0.891	0.032	0.888
Log likelihood	-262.58		-256.67	
LR chi2(8)	19.58**		13.44*	
Observations	393		380	

Note: $^*P$ = <0.10 ; $^{**}P$ = <0.05; $^{***}P$ = <0.01

our analysis. The estimation results for contract farmers and non-contract farmers based on the matched sample are presented in Table 4.

Table 4: Estimates of the Sample-Selection Stochastic Frontier Models for the Matched Sample

	Contract farmers		Non-contract far.	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Constant	4.19***	0.585	3.81***	1.014
log(LAND)	0.401**	0.171	0.578***	0.149
log(LABOR)	0.247**	0.102	0.298**	0.138
log(SEED)	0.261**	0.104	0.073	0.135
log(IMPLE)	0.049***	0.014	0.027	0.017
WARD: Chamkoloma	0.049	0.121	0.358	0.228
WARD: Sagala	0.314*	0.173	0.216	0.299
WARD: Mlali	0.256	0.243	0.408	0.339
σ_u	1.01***	0.106	0.221	1.031
σ_v	0.34***	0.081	0.75***	0.154
ρ	-0.086	1.325	0.667**	0.327
Log likelihood	-362.83		-289.82	
Observations	190		190	

Note: $^*P$ = <0.10 ; $^{**}P$ = <0.05; $^{***}P$ = <0.01

The estimated coefficients of the logarithmic input quantities are all positive so that the monotonicity condition is (globally) fulfilled. Elasticities of scale of 0.958 and 0.976 for contract farmers and non-contract farmers, respectively, indicate that both groups of farmers operate under slightly decreasing returns to scale.

The dispersion parameter of the inefficiency term (σ_u) is much larger for the contract farmers than for the non-contract farmers, which indicates that the contract farmers are more affected by inefficiency than the non-contract farmers. In contrast, the standard deviation of the noise term (σ_v) is much larger for the non-contract farmers than for the contract farmers, which indicates that the non-contract farmers are more affected by noise than the contract farmers.

The estimated correlation parameter (ρ) is small (in absolute terms) and statistically insignificant for the contract farmers. This indicates that unobserved factors that affect the participation in contract farming are not correlated with the noise term of the stochastic frontier model. In contrast, the estimated correlation parameter (ρ) is significantly positive for the non-contract farmers. This indicates that unobserved factors that negatively (positively) affect the participation in contract farming also negatively (positively) affect the noise term of the stochastic frontier model. As the predictive power of the selection model is low, the error terms of the selection model w_i are negative for all non-contract farmers so that the positive correlation coefficient (ρ) implies that the noise terms of the stochastic frontier model for non-contract farmers have a tendency to be negative. Hence, there is a significant sample selection bias due to unobserved factors, which justifies the use of the sample-selection stochastic frontier model at least for estimating the stochastic frontier model of the non-contract farmers.

The distributions of the technical efficiency estimates of the contract farmers and the non-contract farmers are illustrated in Figure 1. While the technical efficiency estimates of the contract farmers have a very large variation with an average value of 0.516, the technical efficiency estimates of the non-contract farmers are all close to its mean value of 0.839. The much higher (average) technical efficiencies of the non-contract farmers compared to the contract farmers is a consequence of the much smaller value of σ_u and the predominantly negative noise terms of the frontier model (v_i) due to the negative noise term of the selection model (w_i) in combination with the significantly positive value of ρ.

Having controlled for biases arising from both observable and unobserved differences between contract farmers and non-contract-farmers, we can conclude that participation in contract farming has a strong negative causal effect on technical efficiency. This means that farmers who become contract farmers will be on average much further away from their new production frontier (i.e. the contract farmers' production frontier) than they were away from their previous production frontier (i.e. the non-contract farmers' production frontier).

5.3 Meta-Frontier

The coefficients of the meta-frontier are presented in Table 5. In order to facilitate the comparison with the coefficients of the coefficients of the group-specific production fron-

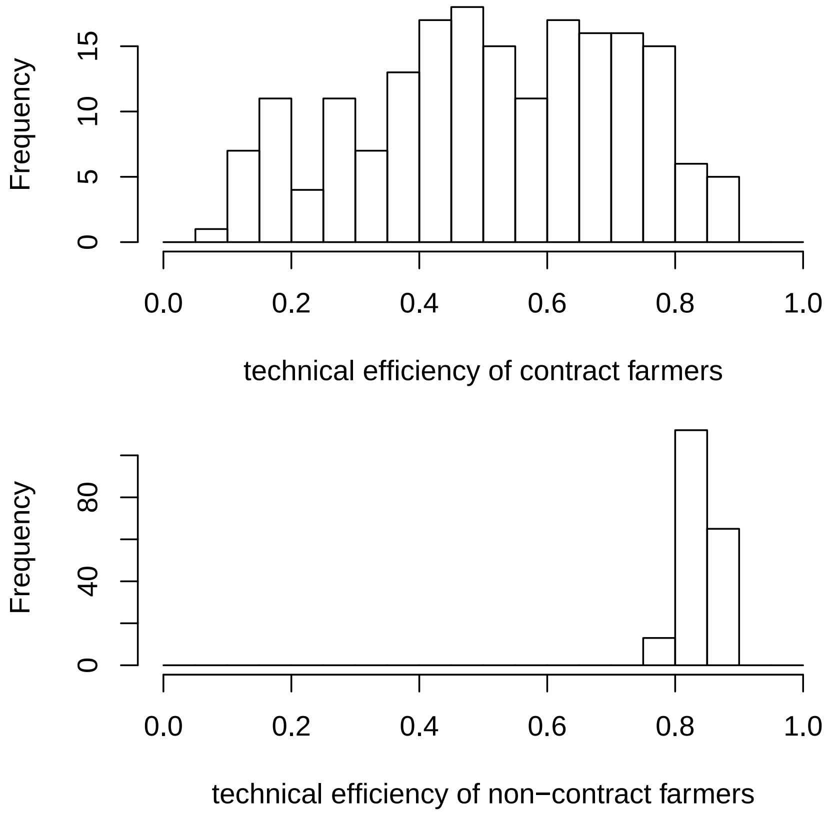

Figure 1: Distributions of Technical Efficiency Estimates

tiers, these coefficients are presented again in this figure along with coefficients of the meta-frontier. Most coefficients of the meta-frontier are very similar to the coefficients of the contract farmers' frontier, which indicates that the meta-frontier is similar to the contract farmers' frontier.

Table 5: Coefficients of the Meta-Frontier

	Contract farmers	Non-contract far.	Meta-frontier
Constant	4.19	3.81	4.28
log(LAND)	0.401	0.578	0.408
log(LABOR)	0.247	0.298	0.248
log(SEED)	0.261	0.073	0.262
log(IMPLE)	0.049	0.027	0.040
WARD: Chamkoloma	0.049	0.358	0.050
WARD: Sagala	0.314	0.216	0.312
WARD: Mlali	0.256	0.408	0.255

This is confirmed by the meta-technology ratios, which are presented in Figure 2. Almost all contract farmers have a meta-technology ratio that is close to one (on average 0.982), which indicates that the meta-frontier is mainly defined by the contract farmers' frontier. In contrast, many non-contract farmers have a quite low meta-technology

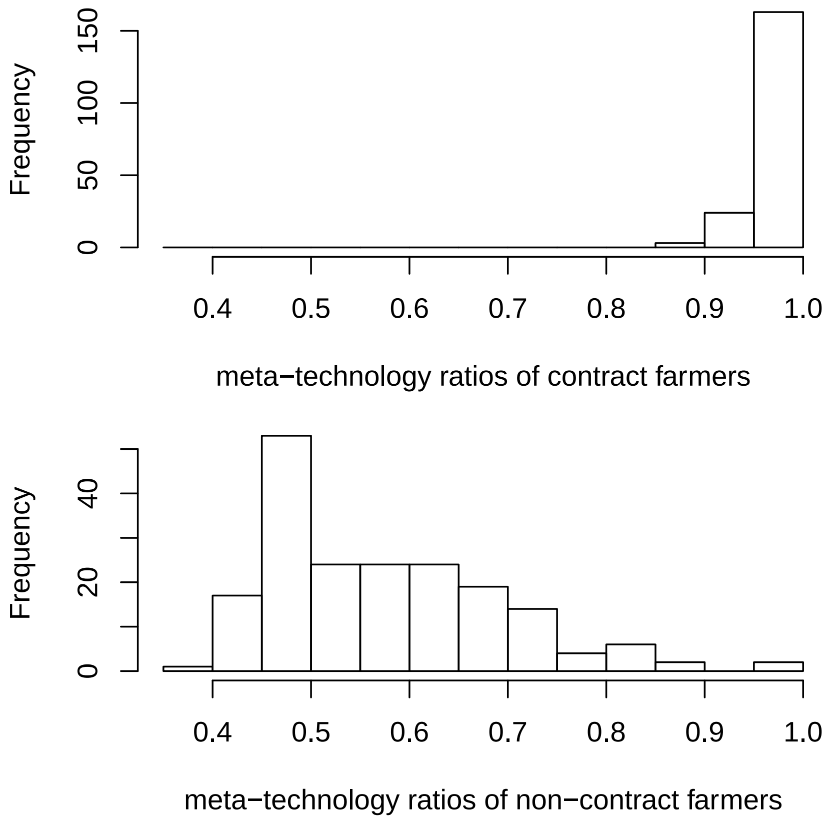

Figure 2: Distributions of Meta-Technology Ratios

ratio (on average 0.574), which means that the non-contract farmers' frontier is considerably below the meta-frontier.

Based on these results, we can conclude that participation in contract farming has a strong positive causal effect on the meta-technology ratio. This means that participation in contract farming has a strong positive causal effect on the yield potential that the farmer can obtain. This effect could be caused by the provision of (additional) extension service or the provision of seeds of high-yielding varieties to contract farmers.

The distributions of the obtained meta-technology technical efficiencies are illustrated in Figure 3. While the meta-technology technical efficiency estimates of the contract farmers have a very large variation with an average value of 0.507, the meta-technology technical efficiency estimates of the non-contract farmers have a much smaller variance and a slightly lower mean value of 0.482.

As the meta-technology technical efficiency estimates of the contract farmers and non-contract farmers are measured against the same production frontier (benchmark), we can directly compare the meta-technology technical efficiency estimates between contract farmers and non-contract farmers. Hence, we can conclude that participation in contract farming increases the productivity of some farmers and decreases the productivity of other farmers. As the positive effects slightly outweigh the negative effects, we find on average a small positive effect of contract farming on productivity.

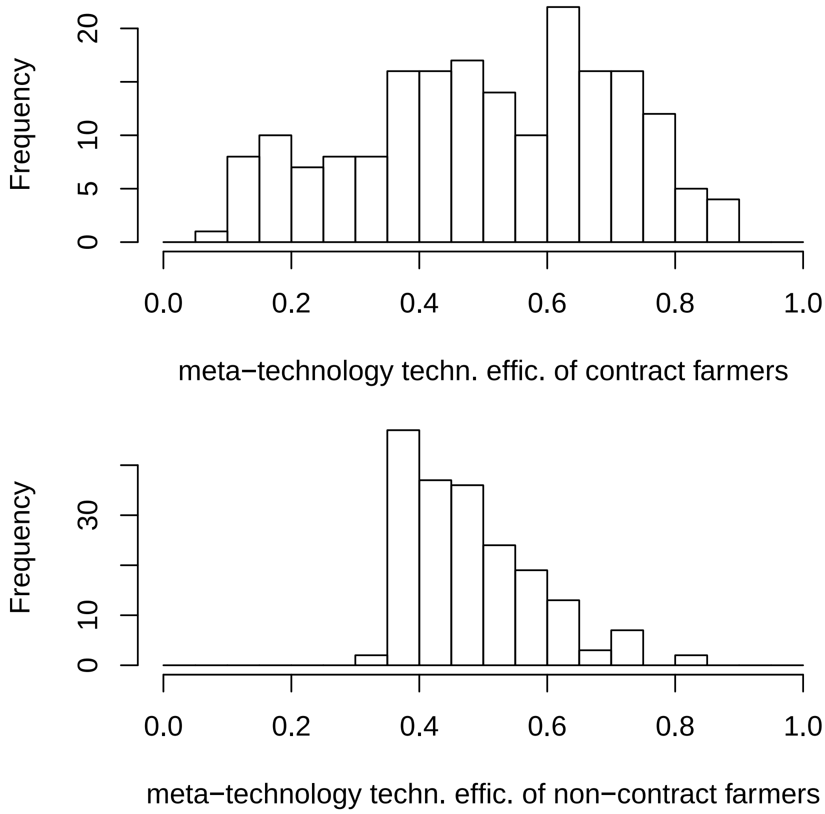

Figure 3: Distributions of Meta-Technology Technical Efficiencies

6 Conclusions

Smallholder farmers in developing countries are characterized by remarkably low levels of productivity and efficiency, which can be attributed to lack of market access, low technical knowledge, underdeveloped insurance and financial markets, and so forth. Contract farming has the potential to alleviate some of these constraints and thus, could improve the productivity of smallholders, which in turn could increase food-security and income.

In this study, we analyze the effect of contract farming on the technical efficiency and productivity of small-scale sunflower farmers in the Kongwa district of the central agricultural zone of Tanzania. of small-scale sunflower farmers in Tanzania. We suggest an econometric framework for causal inference in efficiency and productivity analysis that is a combination the approaches suggested by Bravo-Ureta, Greene and Solís (2012) and Rao, Brümmer and Qaim (2012). This framework takes into account the self-selection of the farmers into contract farming due to both observed and unobserved characteristics and separates the effect in three components: the technical efficiency within the group, the meta-technology ratio. and the meta-technology technical efficiency.

Our estimation results indicate that there is significant self-selectivity into contract farming, which justifies the use of our approach. Furthermore, our results show that participation in contract farming significantly increases the yield potential (meta technology ratio) but lowers the technical efficiency (measured to the respective frontier). As the first effect is slightly larger than the second, we find a small positive effect of contract farming on productivity (meta-technology technical efficiency). The positive effects of contract farming on the yield potential and the (average) productivity can be (at least partly) explained by the contractor's provision of (additional) extension service and seeds of high-yielding varieties to the contract farmers.

The results have two policy implications: (a) as contract farming increases the yield potential and average productivity, contract farming arrangements may be an adequate tool to improve the productivity of sunflower farmers, particularly if the contract arrangement improves the farmers access to (additional) extension service and seeds of high-yielding varieties; and (b) our result that inefficiency is even more widespread among contract farmers than among non-contract farmers, indicates that not all farmers benefit from participating in contract farming, which may be caused by insufficient provision of seeds of high-yielding varieties and/or extension services to some of the contract farmers.

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