Does commercialisation drive technical efficiency improvements in Ethiopian subsistence agriculture?

Wondmagegn Tirkaso
Department of Economics, Swedish University of Agricultural Sciences (SLU), Uppsala, Sweden. E-mail: wondmagegn.tafesse@slu.se

Sebastian Hess*
Dairy and Food Industry Economics, Department of Agricultural Economics, Christian-Albrechts-University, Kiel, Germany. E-mail: shess@ae.uni-kiel.de

* Corresponding author

Abstract

The conditions in which increased market participation leads to improved technical efficiency are still not adequately understood. This study therefore investigated farmers' market participation rates and their predicted technical efficiency scores by performing a two-stage least squares (2SLS) regression analysis using household-level data obtained from the 2009 Ethiopian rural household survey. The predicted efficiency score from the stochastic frontier production function showed that the farmers had a mean technical efficiency score of 40.2%, implying that their output could be increased substantially if improvements were made to existing input mixes. The variables related to educational level and radio and mobile telephone access were positively linked to a farmer's technical efficiency. The estimated results also indicated that farmers with a higher degree of commercialisation were technically more efficient compared to those with lower market participation. The overall results suggest the importance of increasing the market participation rate of smallholders in order to improve agricultural productivity in rural Ethiopia.

Key words: technical efficiency; commercialisation; smallholders; stochastic frontier; Ethiopia

1. Introduction

The empirical relationship between commercialisation and technical efficiency (TE) has been at the heart of policy debate in various farming regimes, including commercial, semi-commercial and subsistence farming (Binswanger & Von Braun 1991; Pingali & Rosegrant 1995; Barrett 2008). Farmers in commercial and semi-commercial regimes tend to supply surplus produce to the market with the objective of maximising profit, subject to input constraints. The additional income earned can have an important welfare effect, particularly when improvements in farmers' productivity levels result in the production of and access to more nutritious, healthier food (Von Braun, 1995). However, this may not be the case with subsistence farming, in which households primarily produce for their own consumption but still supply a certain proportion of their output to the market, even when their own food consumption needs are not fully met (Gebre-ab, 2006). The latter finding contradicts the notion that higher market participation contributes to productivity improvements; instead, it is possible that a higher level of productivity is the main driver of market participation and commercialisation. Hence, it is necessary to consider the potential causality between commercialisation and technical efficiency to improve the understanding of whether increasing commercialisation boosts farmers' productivity levels.

The concept of technical efficiency has been a central part of the theory of production economics. Farmers are supposed to optimise production depending on the resources available, but there are several reasons why a degree of efficiency loss might be experienced (Nishimizu & Page 1982; Byrnes *et al*. 1987; Thiam *et al*. 2001), and this situation is common in sub-Saharan Africa (Cornia 1985; Collier & Dercon 2014). For instance, Ethiopia is one of the economies in sub-Saharan Africa in which average farmers have low technical efficiency scores – as low as 45% compared to the best farms in the corresponding regions (Nisrane *et al*. 2011; World Bank 2015). The implication is that the agricultural sector can grow by improving farmers' productivity levels (Block 1999; Bigsten *et al.* 2003; Diao & Pratt 2007; Tirkaso 2013).

Several socioeconomic factors have been given as the root causes of low agricultural productivity in rural Ethiopia. These include poor linkages between the market and the farming sector, backward technological set-ups coupled with diminishing cultivated land size, poor adoption of technology, and institutional failures (Croppenstedt & Muller 2000; Fafchamps *et al*. 2005). What remains unclear in the literature, however, is the direction of causality between a farmer's technical efficiency score and commercialisation, particularly in relation to the kind of subsistence agriculture found in Ethiopia. Hence, the aim of this paper was to examine the possible interconnection between commercialisation and technical efficiency in Ethiopia, focusing on producers of the country's main crops sampled from seven villages. First, the farmers' technical efficiency score was predicted from the estimates of a stochastic frontier production function. Second, the determinants of technical efficiency were estimated by including the farmers' commercialisation index as an additional explanatory variable. Third, the factors influencing the level of commercialisation for the main crops were identified by including the technical efficiency score as one of the exogenous variables. This result revealed the possible direction of causality between commercialisation and technical efficiency. Finally, the paper draws conclusions about the nexus between technical efficiency and level of commercialisation in predominantly subsistence agriculture.

2. Level of commercialisation and technical efficiency in subsistence agriculture

The commercialisation of agriculture broadly refers to the degree of farmers' participation in output markets (Leavy & Poulton 2008; Jaleta *et al*. 2009). It encompasses farmers' profit-maximising behaviour in relation to decisions about product choice and input use (Pingali 1997). In general, a higher degree of commercialisation is believed to have a significant effect on farmers' welfare. For instance, it could improve farmers' income by creating market linkages for different types of agricultural products (Martey *et al*. 2012; Fischer & Qaim 2012). Furthermore, it is thought to lead farmers towards more specialised production systems based on comparative advantages in resource use, with improved outcomes in employment, health, nutrition, and macroeconomic and environmental performance (Binswanger & Braun 1991; Pingali & Rosegrant 1995; Jaleta *et al*. 2009).

However, it has not been possible to achieve the desired effect of commercialisation in subsistence agriculture because the farmers' market participation is not motivated by profit-maximising behaviour. They are still involved in local and regional markets, but often do not have sufficient surplus production to cover other basic expenditure (Gebre-ab 2006; Barrett 2008). This indicates that an examination of the interconnection between commercialisation and technical efficiency needs to be considered that takes into account the specific nature of commercialisation in predominantly subsistence agriculture.

A framework illustrating why the relationship between commercialisation and technical efficiency requires special analysis is presented in Figure 1. Accordingly, most of the previous thinking about the commercialisation-efficiency nexus commonly supports the notion that being a technically efficient farmer can have a positive effect on the level of commercialisation (Binswanger & Braun

1991; Barrett 2008; Piya *et al*. 2012). This relies on the farmers involved in commercialisation spending the income they generate from their market activity on aspects that are likely to boost productivity, such as health and more nutritious food. This study therefore tested the following hypotheses:

Hypothesis 1: Low technical efficiency is explained by a low degree of commercialisation

According to this hypothesis, a low level of technical efficiency is the result of limited access to input and output markets. For instance, limited market participation means lower income levels, which have direct implications for the farmers' nutritional and health status. Poor diets and poor health subsequently contribute to lower productivity. This argument is based on the empirical work of Pingali and Rosegrant (1995), who suggest that increased household income generated by commercialisation has an implication for the nutritional status of households. Furthermore, farmers who are disconnected from the market may not have access to market information, which is essential for improving farm productivity.

Hypothesis 2: A low degree of commercialisation is the result of poor technical efficiency

A low level of technical efficiency is not the result of limited commercialisation, but rather a cause of it. Farmers with a low level of education or training, limited resources and poor management do not manage to produce marketable output. These farmers are therefore more likely to be dependent on a high proportion of subsistence production and on average show lower levels of commercialisation.

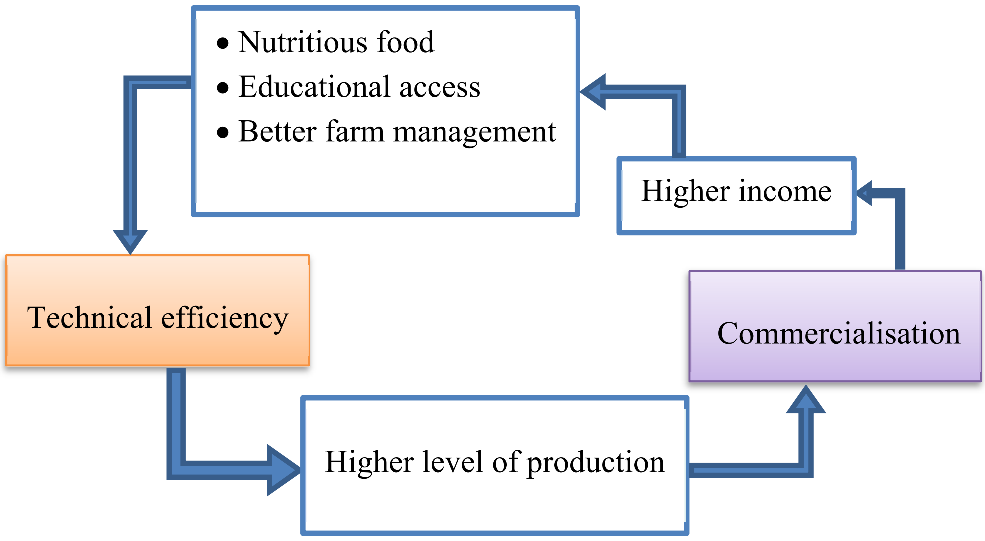

Figure 1: Possible linkage between commercialisation and technical efficiency

3. Data and descriptive statistics

This paper used the 2009 Ethiopian rural household survey data collected by the International Food Policy Research Institute (Hoddinott & Yohannes 2011). This survey compiles household characteristics, agriculture and livestock information, food consumption, health and women's activities, as well as data on community-level electricity and water, sewage and toilet facilities, health services, education, NGO activity, migration, wages, and production and marketing. The analysis in this study was based on a total of 562 households (out of which 540 could be used in the analysis) selected from seven villages in the full survey. These villages are known for the production of major agricultural crops, including wheat, teff, sorghum, khat, coffee, barley, maize and enset. More detailed descriptive statistics for the variables used in estimating the stochastic frontier production function and the determinants of a farmer's level of commercialisation are illustrated in Table 1.

Table 1: Descriptive statistics (N = 540)

Variable	Label	Mean	SD	Min	Max
Production function variables					
Output	Monetary value of total output (birr)	4 785	5 899	0	73 501
Labour	Total number of adults (aged 15-60)	6	3	0	14
Farm size	Total farm size (square metres)	3 470	12 521	0	235 126
Fertiliser	Total fertiliser use (kilograms)	46	83	0	501
Oxen	Total number of oxen (number)	2	1	0	5
Hoe	Total number of hoes (number)	3	2	0	13
Inefficiency determinant variables					
HCI	Household commercialisation index in %	35	85	1	1 811
Off-farm income	Total off-farm income (in birr)	886	4 075	1	60 001
Gender	Dummy for gender (1 = male, 0 = female)	1	0	0	1
Age	Age of the respondent (in years)	52	15	18	100
Education	Total amount of schooling (in years)	4	3	0	16
Radio	Dummy for radio (1 = own, 0 = not)	1	0	0	1
Mobile telephone	Dummy for mobile telephone (1 = own, 0 = not)	0	0	0	1
Credit access	Dummy for credit access (1 = has, 0 = not)	1	0	0	1
Market served	Locations of local markets (market served by household): 1 = for markets in local surroundings 2 = for market in nearest village 3 = for market in other villages 4 = for market in region 5 = for market in Addis Ababa	2	1	1	5

It can be observed that an average household produces 4 785 birr of total output per year, yet with a standard deviation of 5 899 birr and the maximum observed household output in the sample exceeding the mean by a factor of 15. Thus, the sample exhibits a substantial variation in total agricultural output across the sample. The average farm in the sample produced about 800 birr of agricultural output per adult household member, or 13 789 birr per hectare (calculated from sample means in Table 1). Interestingly, the number of hoes was only about half the number of available adults per household. However, average fertiliser use in the sample, at 37 to 40 kilograms per hectare, was close to the figure reported by Rashid *et al*. (2013). Farmers who did not use fertiliser at all would be likely to rely on traditional manure and compost from their farm. The commercialisation index was calculated as the share of agricultural output that has been marketed. The survey indicated that, on average, farmers supply 35% of their agricultural output to the market, while the remaining share is used for home consumption. Meanwhile, the maximum commercialisation index observed was 1 811%, reflecting the existence of farmers in the sample who are involved in non-agricultural (off-farm) income-generating activities. All the households had access to at least one local market in their surrounding area and the average household also served the market in the nearest village, while a smaller number of households sold to other villages, regional markets or even to the capital, Addis Ababa. Heads of households had an average of four years' formal schooling.

4. The model

The technical efficiency of the farms in the sample was assessed using the method of stochastic frontier analysis, a method initially developed by Aigner *et al*. (1977). The general form of the stochastic frontier production function is given as:

$$Q_i = f\left(X_{ij};\beta\right)\exp\left(v_i - u_i\right), \qquad i = 1,2,\ldots,N,\ v_i - u_i = \varepsilon_i \tag{1}$$

where Q_i is a value of total output for the i^{th} farm household; $f(X_{ij}; \beta)$ is a deterministic part of the production function; X_{ij} is the vector of the i^{th} input used by the j^{th} farm household; β is the vector of technology parameters; (v_i) is a statistical noise component with zero mean and distributed $N(0,\sigma^2)$ and captures the effects of uncontrolled random factors, such as weather or other unexpected events; and (u_i) is a non-negative random variable distributed $N^{+}(\mu,\sigma^2)$ and associated with the measurement of technical inefficiency by the j^{th} farm household.

The technical efficiency level of each farm household was measured by the ratio of observed or actual output to the corresponding "frontier" (or possible maximum output), depending on the level of inputs used by the respective farm households. Hence, it is possible that the actual production level is less than the frontier output or the deterministic part of the model, implying the existence of possible inefficiency. Mathematically, the level of technical inefficiency for the i^{th} farm household is given by:

$$TE_i = \frac{Q_i}{Q_i^*} = \frac{f(x_i;\beta)\exp(v_i - u_i)}{f(x_i;\beta)\exp(v_i)} = \exp(-u_i) \tag{2}$$

where Q_i corresponds to observed agricultural output for the i^{th} farmer, and Q_i^* corresponds to the frontier output level. The potential output level for each farm household can also be predicted after distinguishing the inefficiency (u_i) and noise (v_i) components in Equation (1). The error terms, (u_i) and (v_i) are assumed to be independent of each other, and independently and identically distributed (*i.i.d.)* across observations.

Following Battese and Coelli (1995), (μ) in the distribution $N^{+}(\mu,\sigma^2)$ of the inefficiency term (u_i) can further be modelled such that each farm household exhibits an individual (μ_i) subject to the following functional relationship:

$$\mu_i = z_i\delta \tag{3}$$

Here, z is a vector of the environmental and management-related variables that affect household efficiency (u_i) through a shift in the distributional parameter (μ_i), and δ is the parameter to be estimated. It should be noted that a positive parameter value for δ indicates that the corresponding z variable increases the mean technical inefficiency.

As the main concern of this study was to identify the prevailing causality between technical efficiency and commercialisation, it was necessary to measure the commercialisation index for each individual farm household. This could be calculated by using the ratio of the total value of agricultural sales in the market to the total value of agricultural production, expressed as a percentage (Von Braun & Kennedy 1994). Mathematically, it is given as:

$$HCI_i = \left(\frac{TVS_i}{TVQ_i}\right) \times 100 \tag{4}$$

where HCI_i is the level of commercialisation of the i^{th} household, TVS_i is the total value of agricultural sales by the i^{th} household, and TVQ_i is the total value of the agricultural product produced by the i^{th} household.

5. Estimation strategy

When econometrically estimating a production frontier according to the general model in Equation (1), the functional relation has to be specified. Typically, a Cobb-Douglas or translog functional form is considered. In addition, assumptions have to be made about the distribution $N^+(\mu, \sigma^2)$ of the inefficiency term (u_i). Three additional distributional assumptions, such as truncated normal, exponential and gamma distribution, are common in the literature in this respect (Stevenson 1980; William 1990; Battese & Coelli 1995; Wang & Schmidt 2009).

After testing for the most appropriate functional form, this study adopted the Cobb-Douglas form of stochastic frontier production function. It was then tested further for the most appropriate distributional assumption for the inefficiency term (u_i), allowing either a half-normal, truncated half-normal, exponential or gamma distribution. The estimates from the truncated model proved to be insignificant and contradicted the core theoretical justification of the prevalence of technical inefficiency (Aigner *et al*. 1977; Greene 1990; Coelli *et al*. 2005). Consequently, Akaike's information criterion (AIC) was used to select the most robust estimate, which finally led to the selection of the exponential model, since it had the lowest AIC value compared to the other models. In the subsequent discussion, the study relied on the estimates made by the exponential model.

The Cobb-Douglas specification of the general stochastic frontier production function outlined in Equation (1) is given in Equation (5). Parameter estimates were obtained for the $k = 7$ input variables of labour, amount of land, amount of fertiliser used, number of oxen available, number of hoes on the farm, plough availability or not, and access to extension services or not.

$$\ln(Q_i) = \beta_0 + \sum_{k=1}^{7} \beta_k \ln(x_{ik}) + (v_i - u_i) \tag{5}$$

Furthermore, this estimation of the Cobb-Douglas production function using the stochastic frontier approach differentiated the inefficiency (u_i) and idiosyncratic error (v_i) components of the error term. As part of this model, determinants of a farmer's technical inefficiency level z were specified according to Equation (3). This inefficiency model provided parameter estimates for the determinants of technical inefficiency scores considering a vector of variables capturing the household's socioeconomic covariates, namely age, gender, level of education, access to various information devices, credit access, access to various regional markets and the household's commercialisation index (Helfand & Levine 2004; Jaleta *et al*. 2009; Tirkaso 2013).

$$\mu_i = \delta_0 + \sum_{k=1}^{10} \delta_k \ln(z_{ik}) + \delta_i \ln(HCI_i) \tag{6}$$

Equation (6) allows the testing of the statistical effect of the household's commercialisation index on the mean technical inefficiency within the stochastic frontier production function. It should be noted that the parameters in Equation (6) are estimated jointly with the parameters β of the production frontier (Equation (5)) using maximum likelihood. The z variables do not affect output or technical efficiency directly, since they enter the estimation equation (Equation (5)) through the distribution of (u_i).

However, in order to assess the role of the household's predicted technical efficiency score for the observed commercialisation index, a slightly different empirical model had to be formulated (Equation (7)):

$$\ln(HCI_i) = \beta_0 + \sum_{k=1}^{12} \beta_k \ln(z_{ik}) + \phi_i \ln(TE_i) + \upsilon_i \tag{7}$$

In this regression, HCI_i is the i^{th} farmer commercialisation index, Z_i are the instrumental variables representing (fully exogenous) continuous and dummy variables respectively, and v_i is the stochastic error term. Furthermore, the predicted technical efficiency score from the stochastic frontier model was included as an explanatory variable. However, this could result in endogeneity bias affecting the estimated parameter, ϕ_i, because of a potential reverse causality between the level of commercialisation and a household's estimated technical inefficiency score.

Such an endogeneity bias may result in a non-zero covariance between Z_i and v_i, which leaves the OLS estimator biased and inconsistent (Wooldridge 2010). Hence, applying the OLS estimator to the model in Equation (7) would not be informative about the actual causal relationship between a household's commercialisation and technical inefficiency score, because the estimated coefficient ϕ_i of the effect of technical efficiency on commercialisation cannot be trusted.

A two-stage least squares (2SLS) estimator was therefore employed. This estimator uses the instrumental variable (IV) technique to correct for the bias of the estimated coefficient from the endogenous regressor ϕ_i. The IV approach uses a first-stage regression in order to predict the $\ln(TE_i)$, using instrumental variables that have to be different from the set of explanatory variables already included in Equation (7).

Generally, such instruments are required to meet the exogeneity and rank condition, implying that they should be uncorrelated with the error term v_i and correlated with the endogenous variable in the structural model. The explanatory variables from the inefficiency model in Equation (6) would be natural candidates, since they could potentially explain $\ln(TE_i)$. However, a valid instrumental variable has to fulfil additional statistical conditions, which requires checking the exogeneity and validity of the instruments in a first-stage auxiliary regression model (Sargan 1958; Hausman 1978; Wooldridge 1995; Kleibergen 2007; Wooldridge 2010).

It was possible to test the exogeneity of the regressors in question in Equation (7) using the Hausman test. Furthermore, the validity of the instruments could be assessed through the Kleibergen-Paap LM test for under-identifying restrictions. In addition, based on the F-statistics in the first-stage regression model, an assessment was undertaken of whether the selected instruments were potentially only weakly correlated with the endogenous variable. In the case of such a weak instrument, the 2SLS estimator could be even more inconsistent than the original OLS estimator (Bound *et al*. 1995; Angrist & Pischke 2009; Sanderson & Windmeijer 2016).

As a result of this testing procedure, the educational level of the household head was selected as an instrument. The intuition behind using this instrument is related to the evidence that a higher educational level may improve a farm's technical efficiency score, since it is expected to increase human capital and may contribute to changes in farmers' attitudes towards modern technology (Tchale 2009; Nisrane *et al*. 2011; Dhehibi *et al*. 2012).

6. Results and discussion

The calculation of consistent and unbiased maximum likelihood estimates of a stochastic frontier production function begins with verification of the skewedness of ordinary least squares (OLS) residuals (Olson *et al*. 1980; Waldman 1982). If the third moment of a residual is positive, then it will always be the case that all the least squares estimates represent a local maximum of the likelihood function. The estimated kernel density plot for the predicted OLS residuals showed a positive skewedness, confirming the uniqueness and consistency of the maximum likelihood estimator.

Table 2 presents the maximum likelihood estimates of a stochastic frontier production function considering the exponential distribution of the error terms. First, a one-step estimation of the stochastic frontier production function was performed, which showed that farm size, fertiliser use, oxen and hoe were statistically significant. Importantly, σ_u became statistically significant at the 1% level, confirming the existence of technical inefficiency in the sample. A two-step model was therefore estimated that considered the covariates expected to affect the technical inefficiency level in the frontier model. The result indicated that the educational level of the household's head, mobile telephone access and level of commercialisation were statistically significant. Meanwhile, the two models were compared using the likelihood ratio test. This favoured the two-step estimate (as indicated by the likelihood rate and AIC statistics). Overall, the findings were robust with respect to the assumed distribution of the error term. All statistically significant factors of production had theoretically consistent signs, implying the positive effect of regressors on output level. However, labour was statistically not significant. The estimated result representing the variance components of the two error terms, σ_u and σ_v, was also statistically significant.

Table 2: Estimates of the parameters in the Cobb-Douglas frontier production function

Dependent variable: ln(Output) parameters	One-step estimate		Two-step estimate	
	Coefficient	**SE**	**Coefficient**	**SE**
Production function variables				
ln(Labour)	0.166	0.109	0.129	0.108
ln(Farm size)	0.046**	0.022	0.038*	0.021
ln(Fertiliser)	0.113***	0.028	0.104***	0.028
ln(Oxen)	0.441***	0.130	0.391***	0.127
ln(Hoe)	0.135*	0.074	0.108	0.072
Plough (dummy)	0.006	0.061	-0.002	0.058
Extension access (dummy)	0.089	0.092	0.076	0.089
Inefficiency determinant variables				
ln(Age)			-0.386	0.378
ln(Education)			-0.352**	0.145
Gender (dummy)			0.280	0.248
Radio access (dummy)			-0.375	0.231
Mobile phone access (dummy)			-0.533*	0.300
HCI (%)			-0.243***	0.072
Market_2 (nearby village)			-0.230	0.680
Market_3 (distant village)			-0.391	0.297
Market_4 (regional centres)			-0.499	0.606
Market_5 (Addis Ababa)			-2.928	1.867
Credit access (dummy)			-0.196	0.223
σ_u	0.982***	0.068		
σ_v	0.603***	0.041		
λ	1.628***	0.094		
γ	0.726			
Log likelihood	-794		-770	
AIC	1 620		1593	
Mean efficiency	0.48		0.51	
Observations	540		540	

*** $p < 0.01$, ** $p < 0.05$ and * $p < 0.1$; SE represents standard error

Note: $\lambda = \sigma_u / \sigma_v$ shows whether there is technical inefficiency by comparing the ratio of two sigmas concerning the extent to which total output varies due to the degree of noise or inefficiency.

$\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$ is the share of inefficiency in the total variation of the error term.

Figure 2 illustrates the kernel density estimate plot for the predicted technical inefficiency score. The plot shows a smoothly fitted normal probability distribution, supporting the robustness of the estimate.

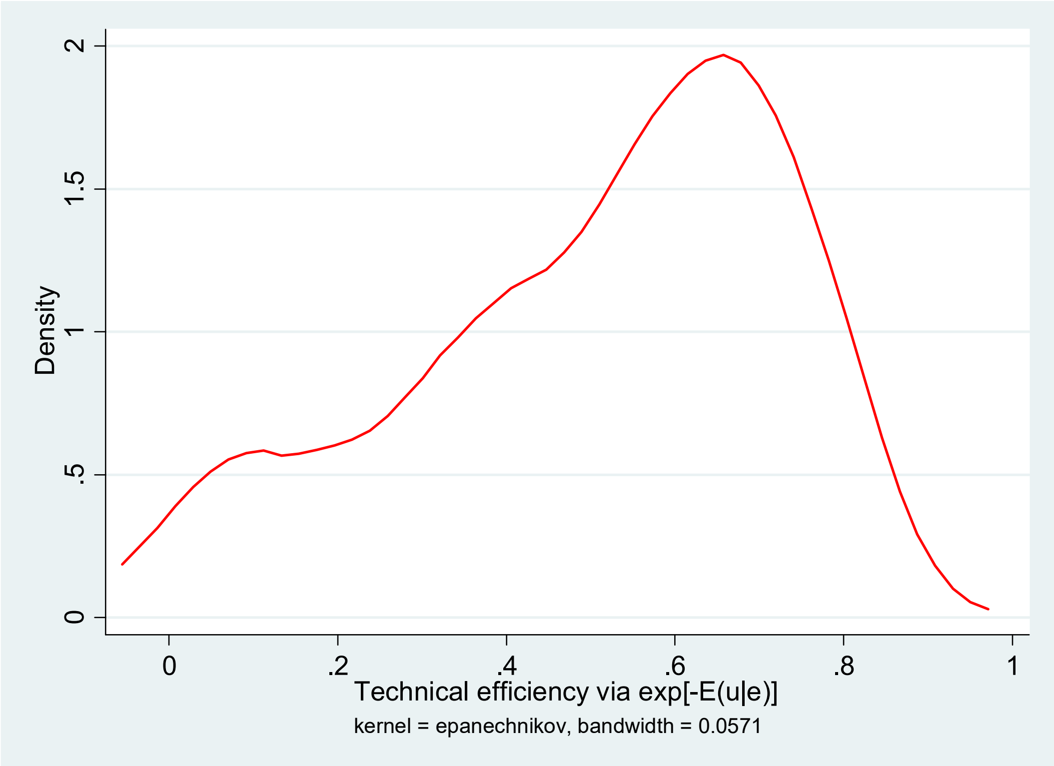

Figure 2: Kernel density estimate plot of the predicted technical inefficiency score

6.1 Estimates of the technical efficiency score

The examination of the parameters of the error components, such as σ_u, σ_v, λ and γ is a crucial step in measuring the efficiency level. In this respect, the variance parameter of the inefficiency component σ_u for the exponential distribution had statistically significant variance parameters. Furthermore, it was vital to examine the statistical properties of lambda (λ), which confirms the existence of efficiency loss, and gamma (γ), showing the percentage of total variation in output that was lost due to the existence of technical inefficiency or other, uncontrolled factors in these models (see Aigner *et al*. 1976). Accordingly, the estimated λ confirmed the presence of efficiency loss in the exponential model at a 99% confidence interval. Moreover, the estimate of γ indicated that the 73% variation in total output was due to the presence of technical inefficiency among the farmers. Accordingly, the farmers had a mean efficiency score of 51% under the selected model. The predicted mean efficiency score is summarised in Table 3.

Table 3: Summary of technical efficiency score

	Technical efficiency (N = 540)
Mean	0.507
Standard deviation	0.223
Minimum	0.002
Maximum	0.914

6.2 Implications of factor elasticity estimates

The factor input elasticity estimates, representing a proportionate change in total output induced by a given proportionate change in input level, are given in Table 2. Accordingly, all variable inputs in the production function had theoretically consistent signs: farm size, fertiliser use and number of oxen were significant at a confidence interval of 90%, 99% and 99% respectively. This indicated that, allowing farmers to have 10% more agricultural land in hectares would lead about to a 0.4% increase in total output, all other factors being constant. Similarly, a 10% greater use of fertiliser in kilograms would result in an increase of about 1.1% in total output, assuming other factors are constant. Importantly, the effect of oxen was considerable in comparison: if an individual farmer owned 10% more oxen, this would result in an increase of about 4% in total output, holding other factors constant. The overall implications behind the elasticity values were that total output was highly responsive to a small change in the percentage of farm size, fertiliser use and number of oxen, which is in line with a study by Nisrane *et al*. (2011). In particular, fertiliser utilisation at the sample mean amounted to 132 kilograms per hectare,[1] which demonstrates that, in principle, fertiliser is available in the survey region, but still used by many households at a relatively low intensity. It is therefore crucial to improve farmers' input mixes, given the individual effects of greater farm size, greater fertiliser use and more oxen. The estimated coefficient on labour was not significant, possibly due to the fact that this variable could only be approximated by the number of adults in the household.

Regarding the determinants of technical inefficiency, previous studies on the sources of farmers' technical efficiency indicate that socioeconomic, demographic and institutional characteristics are the main determinants of the technical inefficiency score (Kebede 2001; Nisrane *et al*. 2011; Tirkaso 2013). These include the farmer's age, educational level, gender, access to ICT services, level of commercialisation and distance to markets. Considering these findings from the literature, the maximum likelihood estimate for the determinants of technical inefficiency indicated that all the explanatory variables had the expected sign. The lower part of the two-step estimate in Table 2 illustrates the maximum likelihood estimates for the determinants of the technical inefficiency score.

The estimated result essentially indicates that a farmer's level of education, access to mobile telephones and level of commercialisation are statistically significant at the 95%, 90% and 99% level respectively. This denotes the importance of improving a farmer's educational level in order to achieve a higher level of technical efficiency. The effect of mobile telephone access was also important in reducing technical inefficiency in the household. Similarly, an increase in the level of household commercialisation led to a reduction in technical inefficiency, other factors remaining constant. The implication is that a higher degree of market participation has a significant effect in reducing technical inefficiency among farmers. However, this requires scrutiny of the potential causality between technical efficiency and the level of commercialisation, which will be discussed below. The variables representing the types of market served by the household were not statistically significant.

6.3 Causality between technical efficiency and level of commercialisation

This section provides estimates of the identification of the causal relationship between a farmer's level of commercialisation and technical efficiency, taking the simultaneity bias problem explained in Section 5 into consideration. The specification given in Equation (7) suggests the existence of a potential endogeneity problem due to simultaneity bias between commercialisation and technical efficiency, which the Hausman test failed to reject.

Table 4 presents estimates from the first-stage auxiliary model in which technical efficiency estimates were regressed upon the instrumental variable; these estimates were useful in determining the applicability of the 2SLS estimation technique. In particular, they showed the relevance and validity of the household head's level of education. The corresponding result in Table 4 indicates that educational level of the household head was positive and statistically significant. In this case, an

[1] This figure is calculated by dividing total fertiliser use in all villages by total farm size in square kilometres.

increase in educational level of the household head by 10% could increase the technical efficiency level by about 1.2%, assuming that other factors are fixed. The Kleibergen-Paap LM (KPLM) statistic rejected the null hypothesis of the under-identification test at 10%, implying that the instrument's rank condition was satisfied.

Two additional and important robustness tests were conducted in order to validate the relevance and exogeneity of the instruments used in the model (Stock & Watson 2003). Accordingly, the joint significance test for instruments rejected the null hypothesis at the 1% significance level ($F(7, 553) = 99.85$, with a $probability > F = 0.000$), implying that the estimated coefficients were both different from zero (also called the "weak instruments" test). Moreover, the Hausman F-statistics-based test for endogeneity rejected the null hypothesis at the 5% level.

Table 4: First-stage regression on a household's technical efficiency level (TE)

	Dependent variable is lnTE
Educational level of household head (years of schooling)	0.119*** (0.046)
Constant	-1.303*** (0.167)
F-statistics	6.84***
KPLM statistics	6.89***
Observations	538

Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1

Hence, the 2SLS estimator was implemented based on the variable 'education' as a valid instrument. The potential relationship between the level of the farmers' commercialisation and their corresponding technical efficiency score thus can be identified by the corresponding 2SLS estimation technique.

Table 5: 2SLS estimate for the determinants of household commercialisation, HCI

Variables	Estimate	SE	P > t
ln(Technical efficiency)	-1.485	1.495	0.321
ln(Labour)	0.462	0.359	0.199
ln(Farm size)	0.008	0.067	0.910
ln(Fertiliser)	0.051	0.067	0.444
ln(Oxen)	0.447	0.266	0.093
ln(Hoe)	0.233	0.271	0.391
ln(Plough)	-0.085	0.118	0.470
Credit access (dummy)	0.288	0.254	0.256
Association membership (dummy)	-0.158	0.218	0.469
Market_2 (Nearby village)	1.792	0.547	0.001
Market_3 (Distant village)	2.638	0.538	0.000
Market_4 (Regional centres)	2.575	0.634	0.000
Market_5 (Addis Ababa)	3.347	1.033	0.001
Constant	-2.442	2.533	0.335
F-statistics	19		0.000
Hausman test statistics	50.71		0.000
Observations	538		

Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1

The estimation results in Table 5 show that farmers can participate in up to five different types of markets (Table 1) categorised as local, nearby village, distant village, regional centres and Addis Ababa. The effects of these markets were controlled given that they reflect the market size from village level to large cities. It was expected that those farmers involved in trading activities in large cities such as Addis Ababa would also be more likely to exhibit a higher level of commercialisation compared to those framers participating in local markets. According to the estimation results, all types of markets were positive and statistically significant at the 1% level of significance. The magnitude of the estimated coefficients suggested that, on average, those farmers participating only in local village markets had a lower commercialisation level than those farmers also participating in markets beyond their nearest village.

However, the 2SLS estimates reported in Table 5 show that the technical efficiency score became statistically insignificant. Moreover, with the exception of variables representing market size, the main explanatory variables were not statistically significant in determining a farm household's level of commercialisation. The estimates support the claim that technical efficiency is endogenous and does not cause commercialisation. This coincides with the argument by Gebre-ab (2006) that surplus production, or being productive, is not a main driver of market participation in largely subsistence agriculture, since smallholder farmers can still supply a certain proportion of their produce to the market with the objective of covering other household requirements (or basic needs, such as medicine). Thus, for the households in the dataset, this study identified low technical efficiency to be the result of a low level of commercialisation, rather than its cause.

7. Conclusions

This study analysed the prevalence of the potential link between smallholder commercialisation and technical efficiency and found that the former played a significant role in improving the latter. Specifically, the stochastic frontier estimates indicated that increasing the level of market participation could enhance a farmer's level of technical efficiency, supporting the argument that commercialisation improves smallholders' productivity by increasing their income and thereby improving access to healthy and nutritious food (Pingali & Rosegrant 1995). This implies that any policy effort aimed at creating an efficient tie between the farm sector and the market will improve the performance of agricultural production. Thus policy measures directed at increasing the market participation rate of farmers by providing an improved level of education, sufficient access to ICT tools such as radios and mobile telephones, an improved transport infrastructure and access to transportation services will significantly contribute to improvements in agricultural productivity.

References

Aigner D, Lovell C & Schmidt P, 1977. Formulation and estimation of stochastic frontier production function models. Journal of Econometrics 6: 21–37.

Angrist JD & Pischke JS, 2009. Mostly harmless econometrics: An empiricist's companion. Princeton NJ: Princeton University Press.

Barrett CB, 2008. Smallholder market participation: Concepts and evidence from eastern and southern Africa. Food Policy 33: 299–317.

Battese GE & Coelli TJ, 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empirical Economics 20: 325–32.

Bigsten A, Kebede B, Shimeles A & Taddesse M, 2003. Growth and poverty reduction in Ethiopia: Evidence from household panel surveys. World Development 31: 87–106.

Binswanger HP & Von Braun J, 1991. Technological change and commercialization in agriculture: The effect on the poor. The World Bank Research Observer 6: 57–80.

Block SA, 1999. Agriculture and economic growth in Ethiopia: Growth multipliers from a four-sector simulation model. Agricultural Economics 20: 241–52.

Bound J, Jaeger DA & Baker RM, 1995. Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak. Journal of the American Statistical Association 90: 443–50.

Byrnes P, Färe R, Grosskopf S & Kraft S, 1987. Technical efficiency and size: The case of Illinois grain farms. European Review of Agricultural Economics 14: 367–81.

Coelli TJ, Rao DSP, O'Donnell CJ & Battese GE, 2005. An introduction to efficiency and productivity analysis. New York: Springer.
Collier P & Dercon S, 2014. African agriculture in 50 years: Smallholders in a rapidly changing world? World Development 63: 92–101.
Cornia GA, 1985. Farm size, land yields and the agricultural production function: An analysis for fifteen developing countries. World Development 13: 513–34.
Croppenstedt A & Muller C, 2000. The impact of farmers' health and nutritional status on their productivity and efficiency: Evidence from Ethiopia. Economic Development and Cultural Change 48: 475–502.
Dhehibi B, Bahri H & Annabi M, 2012. Input and output technical efficiency and total factor productivity of wheat production in Tunisia. African Journal of Agricultural and Resource Economics 7: 70–87.
Diao X & Pratt AN, 2007. Growth options and poverty reduction in Ethiopia – An economy-wide model analysis. Food Policy 32: 205–28.
Fafchamps M, Gabre-Madhin E & Minten B, 2005. Increasing returns and market efficiency in agricultural trade. Journal of Development Economics 78: 406–42.
Fischer E & Qaim M, 2012. Linking smallholders to markets: Determinants and impacts of farmer collective action in Kenya. World Development 40: 1255–68.
Gebre-Ab N, 2006. Commercialization of smallholder agriculture in Ethiopia. EDRI Notes and Paper Series No. 3, Ethiopian Development Research Institute, Addis Ababa, Ethiopia.
Greene WH, 1990. A gamma-distributed stochastic frontier model. Journal of Econometrics 46: 141–63.
Hausman JA, 1978. Specification tests in econometrics. Econometrica 46: 1251–71.
Helfand SM & Levine ES, 2004. Farm size and the determinants of productive efficiency in the Brazilian center-west. Agricultural Economics 31: 241–9.
Hoddinott J & Yohannes Y, 2011. Ethiopian Rural Household Surveys (ERHS), 1989-2009. http://www.ifpri.org/publication/ethiopian-rural-household-surveys-erhs-1989-2009 (Accessed 5 June 2017).
Jaleta M, Berhanu G & Hoekstra DA, 2009. Smallholder commercialization: Processes, determinants and impact. ILRI Discussion Paper No. 13, International Livestock Research Institute, Nairobi.
Kebede TA, 2001. Farm household technical efficiency: A stochastic frontier analysis. A study of rice producers in Mardi watershed in the Western Development Region of Nepal. Master's thesis, Department of Economics and Social Sciences, Agricultural University of Norway, Ås, Norway.
Kleibergen F, 2007. Generalizing weak instrument robust IV statistics towards multiple parameters, unrestricted covariance matrices and identification statistics. Journal of Econometrics 139: 181–216.
Leavy J & Poulton C, 2008. Commercialisations in agriculture. Ethiopian Journal of Economics 16: 1–37.
Martey E, Al-Hassan RM & Kuwornu JKM, 2012. Commercialization of smallholder agriculture in Ghana: A Tobit regression analysis. African Journal of Agricultural Research 7(14): 2131–41.
Nishimizu M & Page JM Jr, 1982. Total factor productivity growth, technological progress and technical efficiency change: Dimensions of productivity change in Yugoslavia, 1965-78. The Economic Journal 92: 920–36.
Nisrane F, Berhane G, Asrat S, Getachew G, Taffesse AS & Hoddinott J, 2011. Sources of inefficiency and growth in agricultural output in subsistence agriculture: A stochastic frontier analysis. ESSP II Working Paper 019 IFPRI, Addis Ababa. Available athttp://www.ifpri.org/sites/default/files/publications/esspwp19.pdf (Accessed 10 December 2016).
Olson JA, Schmidt P & Waldman DM, 1980. A Monte Carlo study of estimators of stochastic frontier production functions. Journal of Econometrics 13: 67–82.
Pingali PL, 1997. From subsistence to commercial production systems: The transformation of Asian agriculture. American Journal of Agricultural Economics 79(2); 628–34.

Pingali LP & Rosegrant WM, 1995. Agricultural commercialization and diversification: Processes and policies. Food Policy 20: 171–85.

Piya S, Kiminami A & Yagi H, 2012. Comparing the technical efficiency of rice farms in urban and rural areas: A case study from Nepal. Trends in Agricultural Economics 5(2): 48–60.

Rashid S, Tefera N, Minot N & Ayele G, 2013. Can modern input use be promoted without subsidies? An analysis of fertilizer in Ethiopia. Agricultural Economics 44: 595–611.

Sanderson E & Windmeijer F, 2016. A weak instrument F-test in linear IV models with multiple endogenous variables. Journal of Econometrics 190: 212–21.

Sargan JD, 1958. The estimation of economic relationships using instrumental variables. Econometrica 26: 393–415.

Stevenson RE, 1980. Likelihood functions for generalized stochastic frontier estimation. Journal of Econometrics 13: 57–66.

Stock JH & Watson MW, 2003. Introduction to econometrics. Boston: Addison Wesley.

Tchale H, 2009. The efficiency of smallholder agriculture in Malawi. African Journal of Agriculture and Resource Economics 3: 101–21.

Thiam A, Bravo□Ureta BE & Rivas TE, 2001. Technical efficiency in developing country agriculture: A meta□analysis. Agricultural Economics 25: 235–43.

Tirkaso TW, 2013. The role of agricultural commercialization for smallholders productivity and food security: An empirical study in rural Ethiopia. Master's thesis, Agricultural Economics and Management, Swedish University of Agricultural Sciences, Uppsala, Sweden.

Von Braun J, 1995. Agricultural commercialization: Impacts on income and nutrition and implications for policy. Food Policy 20: 187–202.

Von Braun J & Kennedy E, 1994. Agricultural commercialization, economic development, and nutrition. Baltimore MD: Johns Hopkins University Press.

Waldman DM, 1982. A stationary point for the stochastic frontier likelihood. Journal of Econometrics 18: 275–9.

Wang WS & Schmidt P, 2009. On the distribution of estimated technical efficiency in stochastic frontier models. Journal of Econometrics 148: 36–45.

William HG, 1990. A gamma-distributed stochastic frontier model. Journal of Econometrics 46: 141–63.

Wooldridge JM, 1995. Score diagnostics for linear models estimated by two stage least squares. Advances in Econometrics and Quantitative Economics: 66–87.

Wooldridge JM, 2010. Econometric analysis of cross section and panel data. Cambridge MA & London: MIT Press.

World Bank, 2015. World development indicators. Available at http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators (Accessed 3 October 2016).