Do bottom-up and independent agricultural cooperatives really perform better? Insights from a technical efficiency analysis in Ethiopia

Reference:
Gezahegn Tafesse W., Van Passel Steven, Berhanu Tekeste, D'haese Marijke, Maertens Miet.- Do bottom-up and independent agricultural cooperatives really perform better? Insights from a technical efficiency analysis in Ethiopia
Agrekon : quarterly journal on agricultural economics - ISSN 0303-1853 - Matieland, Agricultural econ assoc south africa, 2020, 59:1, p. 93-109
Full text (Publisher's DOI): https://doi.org/10.1080/03031853.2019.1663223
To cite this reference: https://hdl.handle.net/10067/1637720151162165141

Do Bottom-up, Independent, and Participatory Agricultural Cooperatives Really Perform Better?
Insights from a Technical Efficiency Analysis in Ethiopia

Tafesse W. GEZAHEGN[a,b,*], Steven VAN PASSEL[c], Tekeste BERHANU[b], Marijke D'HAESE[d], Miet MAERTENS[a]

[a] Department of Earth and Environmental Sciences, KU Leuven, Celestijnenlaan 200E, 3001-Leuven, Belgium.
[b] College of Business and Economics, Mekelle University, Box 451, Ethiopia.
[c] Department of Engineering Management, University of Antwerp, Belgium.
[d] Department of Agricultural Economics, Ghent University, Coupure Links 653, 9000 Ghent, Belgium.
*Corresponding author; E-mail: tafpeace@gmail.com.

Abstract

The cooperative landscape in Ethiopia is very heterogeneous with a mixture of remains of the pre-1991 government-controlled system and new post-1991 bottom-up collective action initiatives. This heterogeneity, coupled with a large growth in the number of cooperatives in the country, offers an interesting perspective to study the determinants of the (in)efficiency of cooperatives. In this paper, we analyze the performance of Ethiopian agricultural cooperatives, focusing on the degree of technical (in)efficiency and its determinants. We use the stochastic frontier approach in which we account for heteroskedasticity and the monotonicity of production functions, presenting a methodological improvement with respect to previous technical efficiency studies. Results show that community-initiated cooperatives are more efficient than member-initiated ones, and member-initiated cooperatives are more efficient than government-initiated ones. Cooperatives with a higher degree of heterogeneity in members' participation are found to be less efficient, while cooperatives that have paid employees are more efficient. Besides, results show that cooperatives in Ethiopia function more efficiently if they incentivize committee members through monetary compensation.

Keywords: Technical efficiency, Agricultural cooperatives, Stochastic frontier, Cooperative heterogeneity, Tigray, Ethiopia.

JEL classification: J54, O13, Q13

1. Introduction

Cooperatives are prominent institutions in agricultural sectors, especially in developing countries (Deininger, 1995). Given that agricultural systems in Sub-Saharan Africa are typically fragmented into small or micro farms that are spread over vast and remote rural areas, agricultural cooperatives are specifically important in this setting (Wanyama et al., 2009). Governments and NGOs in developing countries often promote cooperatives as organizations to enhance the development of the small-scale farm sector (Chibanda et al., 2009). However, it is unclear from the literature and still contested whether cooperatives can live up to these expectations, and which forms of cooperative organization do so most effectively.

A first stream of literature analyzes the impact of cooperative membership at farm-level on different farm performance and household welfare indicators, including productivity and technical efficiency (e.g. Abate et al., 2014), technology adoption (e.g., Abebaw and Haile, 2013; Fischer and Qaim, 2012; Shiferaw et al., 2009), producer prices and access to markets (e.g., Francesconi and Heerink, 2010; Bernard et al., 2008; Wollni and Zeller, 2007), farm revenue and profits (e.g., Vandeplas et al., 2013; Fischer and Qaim, 2012), and household income and poverty (e.g. Ito et al., 2012), including studies from various countries and settings. Although some studies point out that cooperatives fail to create particular benefits for their members (e.g., Mujawamariya et al., 2013; Bernard and Taffesse, 2012; Poulton et al., 2010; Hellin et al., 2009; Bernard et al., 2008), most studies point to positive effects of cooperative membership. Given this evidence, a more relevant empirical question becomes whether cooperative characteristics matter and whether certain cooperatives are more effective in creating gains for their members. This question is rarely addressed in the empirical literature. Most studies at farm-household level do not distinguish between different cooperatives, or focus only on one cooperative. Only a few papers take into account the heterogeneity among cooperatives and point to important differences in their performance (Fischer and Qaim, 2014; Verhofstadt and Maertens, 2014; Fischer and Qaim, 2012).

A second stream of literature deals with performance at cooperative level and the ability of cooperatives to function efficiently in competitive and global markets (Soboh et al., 2009; Gentzoglanis, 1997; Sexton and Iskow, 1993). Cooperatives are claimed to be technically inefficient because of incentive problems – including agency, horizon, portfolio, and free-rider problems – that increase the costs of monitoring (Royer, 1999; Cook, 1995). Some empirical studies point to large efficiency gaps between cooperatives and private firms in the agricultural sector (e.g., Ahn et al., 2012; Brada and King, 1993; Boyd, 1987; Carter, 1984). Other studies analyze cooperative-level technical efficiency (TE) and its determinants– thereby implicitly accounting for heterogeneity across cooperatives. The efficiency of cooperatives is found to depend on total sales (Hailu et al., 2005; Ariyaratne et al., 2000), the number and the qualification of employees (Gómez, 2006; Hailu et al., 2005), the size of the board and training of members (Huang et al., 2013), financial leverage and asset ownership (Huang et al., 2013; Krasachat and Chimkul, 2009; Ariyaratne et al., 2000), and the specific sector and location in which a cooperative is functioning (Ahn et al., 2012; Krasachat and Chimkul, 2009). These studies focus mainly on high-income countries – exceptions are Ahn et al. (2012) with a focus on coffee, sugar and maize cooperatives in El Salvador; Krasachat and Chimkul (2009) on agricultural cooperatives in Thailand; and Huang et al. (2013) on agricultural marketing cooperatives in China – and on a limited set of determinant factors to explain efficiency differences.

In this paper, we analyze the determinants of TE of diverse agricultural cooperatives in Ethiopia, using a stochastic frontier approach (SFA) and cooperative-level survey data. The focus of this paper is relevant with an innovative contribution in a number of ways. First, the focus on Ethiopia is particularly relevant. While many studies investigate the impact of cooperative membership at farm-household level in Ethiopia (e.g., Abate et al., 2014; Abebaw and Haile, 2013; Francesconi and Heerink, 2010; Bernard et al., 2008), only few studies analyze efficiency at cooperative level in a developing country setting (e.g., Huang et al., 2013; Ahn et al., 2012; Krasachat and Chimkul, 2009), and none in Ethiopia. In addition, there is a very diverse landscape of agricultural cooperatives in Ethiopia with the remains of the pre-1991 government-controlled cooperatives and new post-1991 independent cooperatives. This heterogeneity offers an interesting perspective to study the determinants of the (in)efficiency of cooperatives, which are an integral part of the national strategy for agricultural transformation (MoFED, 2006) and very widespread throughout the country (Getnet and Anullo, 2012). In our study area, the large majority of farmers are members of one or several agricultural cooperatives, making the question of which cooperatives are more efficient, rather than whether or not farmers benefit from cooperative membership, all the more relevant from a policy perspective.

Second, we contribute to the second stream of literature on efficiency at cooperative-level mentioned above. We include a large number of variables related to cooperative size, member characteristics, formation of the cooperative, and management issues as explanatory variables in our model to explain efficiency differences across cooperatives. Existing studies focus on a rather limited set of variables – mainly variables related to cooperative size and financial structure – to explain (in)efficiency, and expanding the set of (in)efficiency determinants will enrich the insights on cooperative performance. Third, we make a methodological contribution to the SFA by accounting for heteroskedasticity associated with cooperative size, and by testing for the theoretical consistency (monotonicity) of the fitted production frontier. Testing for monotonicity allows us to more correctly assess whether a cooperative producing on the production frontier using a higher level of a given input should be considered more efficient than a cooperative producing the same output using a lower level of input below the production frontier. Moreover, since cooperatives are heterogeneous, assuming a non-constant error variance – as we do in this paper – may lead to better estimates of TE.

2. Background and Data

2.1. Cooperatives in Ethiopia

The government of Ethiopia (GoE) recognizes the importance of cooperatives for improving the socio-economic conditions of the rural poor. Starting from 1994, the GoE has designed various policies to strengthen the development and operation of cooperatives (Bernard et al., 2010). A Federal Cooperative Agency was established in 2002 to promote cooperatives throughout the country. It plays a crucial role in registration, legalization, auditing, certifying, and monitoring cooperatives (MoFED, 2006). The Agricultural Transformation Agency (ATA) is another important government agency that promotes cooperatives at federal level (ATA, 2012). At district level, two agencies are supporting cooperatives: the Woreda Bureau of Agriculture and the Woreda Cooperative Promotion Office (Berhanu and Poulton, 2014). Next to governmental agencies, many NGOs are supporting cooperative unions and primary cooperatives in Ethiopia. Cooperatives are very important in distributing agricultural inputs, especially seeds and fertilizer, to farmers. For the 2010 and 2011 cropping seasons, for example, the share of cooperatives in fertilizer marketing was 93% and 95%, respectively (ATA, 2012).

In the Tigray region – the area this study focuses on – there are 4,265 registered cooperatives. Of these, 2,255 (52.87%) are specialized (single-purpose) agricultural cooperatives; 690 (16.18%) are multipurpose cooperatives engaged in both agricultural input supply and marketing activities; 949 (22.25%) are savings and credit cooperatives; and the remaining 371 (8.70%) are service cooperatives (TCPMDA, 2017). Agricultural cooperatives in the region are visible at all stages of the agricultural value chain (input and credit provisioning, production, processing and marketing) and support farmers to obtain access to improved agricultural technologies, extension advice and training.

2.2. Sampling and data collection

A sample of 511 cooperatives was selected in four zones in the Tigray region in Northern Ethiopia (Figure 1), using a multistage random sampling design. The sample includes seven types of cooperatives (multipurpose, cattle fattening, beekeeping, dairy, sheep & goat fattening, irrigation, and forest and grass cooperatives). In the first stage, we randomly selected 12 districts, three from each of the four zones[1]. In the second stage, 223 *tabias* (*tabia* is the lowest administrative unit) were randomly selected from the selected districts, with the number of tabias selected in each district proportionate to the number of agricultural cooperatives in the district. In the third stage, 511 cooperatives were selected in the 223 *tabias*. Cooperatives in

[1] The selected districts include *Atsbi-Wenberta*, *Ganta-Afeshum*, and *Gulomkeda* from the Eastern zone; *Abergele*, *DeguaTembien*, and *Mereb-Leke* from the Central zone; *Alaje*, *Enderta*, and *Samre* from the South & Southeastern (S&SE) zone; *Asigede-Tsimbela*, *Tsegede*, and *Wolqayt* from the West & Northwestern (N&NW) zone.

the selected *tabias* were stratified according to the type of cooperative (multipurpose cooperatives, beekeeping cooperative, dairy cooperatives, etc.) and selected randomly within these strata and proportionately to the number of cooperatives in the *tabia*. The final sample of 511 cooperatives includes multipurpose cooperatives (about 35%), cattle fattening cooperatives (about 5%), beekeeping cooperatives (about 25%), sheep and goat fattening cooperatives (about 6%), dairy cooperatives (about 4%), irrigation cooperatives (about 21%), and forest and grass cooperatives (4%). Geographically, 26% of the sampled cooperatives are from the Eastern zone, 23% from the Central zone, 26% from the South and Southeast zone, and 25% from the North and Northwest zone, resulting in an almost uniform distribution of sampled cooperatives across geographical zones.

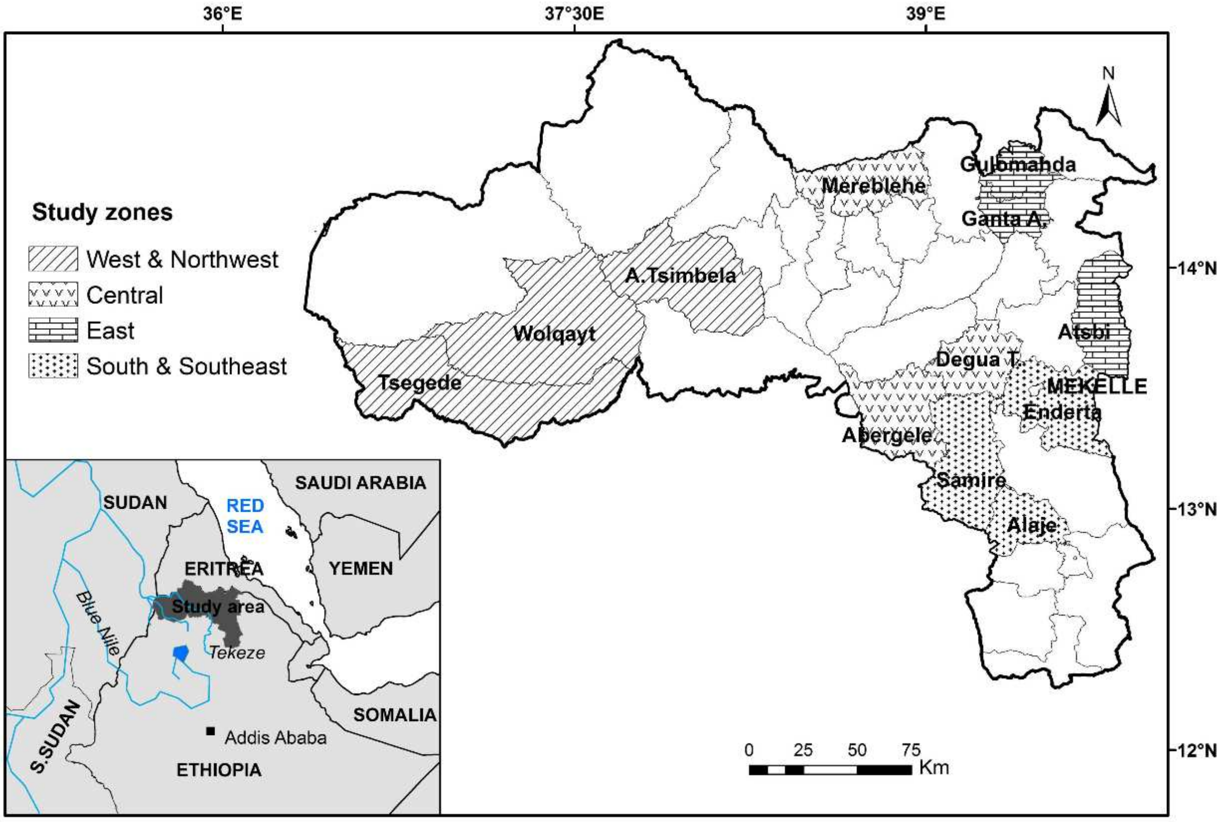

Figure 1: Location of the study area in Tigray region, Ethiopia.

A semi-structured questionnaire was used to survey the 511 selected cooperatives. We conducted the data collection using *Qualtrics* survey software in the period April – August 2017. Prior to conducting the actual survey, the questionnaire was pre-tested. In addition to the survey, we also collected available information from cooperative bylaws, audit reports, and cooperative periodic activity reports, including financial statements and strategic plan documents. For our analysis, we use data on sales, land, labor, capital, membership size, number of employees, and cooperative age from cooperative documents; and data on members' participation heterogeneity, age and education of chairman, members' education, formation initiative, committees and committee meetings, general assembly, audit, training, and compensation from the cooperative survey.

2.3. Overview of surveyed cooperatives

Multipurpose cooperatives purchase farm inputs (such as fertilizers, improved seeds, pesticides), farm tools and equipment (such as sickles, motor pumps, treadle pumps), and consumer goods (such as sugar, oil, coffee) – mainly from a cooperative union – and distribute these to members and non-members at a preset margin. The Regional Bureaus of Agriculture often provide guidance on the price at which cooperatives sell farm inputs to farmers (members and non-members). For example, for fertilizer, the net profit margins that cooperatives are advised to charge range, among regions, from 0.75 to 3.00 ETB[2]/quintal for unions and 5.00 to 7.50 ETB/quintal for primary cooperatives (ATA, 2012). They mainly serve as a distribution channel of items that the government wants the farmers to use. Cattle (sheep and goats) fattening cooperatives purchase oxen and cows (sheep and goats), fatten and resell them. The ownership of the livestock is common in some cases, and individual in other cases; and fattening is done jointly on common land in some cases, and individually on individual land in other cases Beekeeping cooperatives produce honey and sell it to a union, traders, or consumers. Honey production can be done collectively on common land with common beehives; individually on individual land with individual beehives; or on common land but with individual beehives.

Dairy cooperatives collect milk from members and sell it at a small margin; in some cases the cooperative processes milk into cheese, butter, and yoghurt. Some cooperatives buy milk from nonmembers as well while others do not. Irrigation cooperatives produce and sell fruits and vegetables, on irrigated land. In some cases production and marketing are done collectively (on common land under irrigation); in other cases only marketing is done collectively and production is done on individual land served by a common irrigation system; and in still other cases only the irrigation system is collective. Cooperatives usually finance motor pumps and canal maintenance, and members use irrigation water on a rotating basis, covering fuel expenses individually. In the case of river diversion (where no pump is needed), the only cooperatively-funded expense is canal construction and/or maintenance costs. Forest and grass cooperatives produce seedlings, grass, and other natural resource-related products on common land and sell these collectively.

To facilitate the analysis, we reclassify the seven types of cooperatives into three broader categories: multipurpose cooperatives (MPCs); livestock cooperatives (LBCs), including cattle and goat fattening cooperatives, dairy cooperatives, and beekeeping

[2]ETB (Ethiopian Birr) ≈ 0.04 USD at the time of the study.

cooperatives; and natural resource cooperatives (NRCs), including irrigation cooperatives and forest cooperatives. There is considerable heterogeneity among the cooperatives with differences in age, size, some initiated by government, NGO or members, some with hired employees, some jointly owning land, etc.

3. Method

We use the Battese and Coelli (1995) SFA to estimate and explain the technical inefficiency of cooperatives. Most studies (e.g., Huang et al., 2013; Soboh et al., 2012; Candemir et al., 2011; Krasachat and Chimkul, 2009; Ariyaratne et al., 2000; Ariyaratne et al., 1997) use the nonparametric data envelopment analysis to examine the efficiency of agricultural cooperatives, and only a few (e.g. Hailu et al., 2005) use the SFA. The simultaneous estimation of TE scores and the effect of various covariates on the TE of cooperative organizations is a major contribution of this paper. We use the SFA to be able to distinguish the effects of noise from the effects of inefficiency[3], and to examine the determinants of cooperative (in)efficiency. Since agricultural output or revenue is a stochastic variable because of weather conditions and other exogenous random forces (Reinhard et al., 2002), deviations from the frontier might not be entirely under control of the cooperatives, making the SFA a more appropriate tool for this study.

3.1. Production function

Building upon the technical efficiency literature, we specify the stochastic production frontier (SPF) as:

$$q_i = f(x_i;\beta)\exp(v_i - u_i) \qquad (1)$$

where q_i is the output of cooperative *i*; x_i is a vector of inputs (land, labor, and capital) used by cooperative *i*; β is a vector of technology parameters to be estimated; v_i is a two-sided random error term that is $iid\ N(0,\sigma_v^2)$ distributed; and u_i is a non-negative error term that captures the technical inefficiency of cooperative *i*. To characterize u, we use the half-normal distribution, which is proposed by Kumbhakar et al. (2015) to be most appropriate for firms operating in a competitive market[4], since the cooperatives in our research area do face

[3] However, the SF approach confounds the effects of misspecification of functional form with inefficiency. On the other hand, since DEA is non-parametric, it is less prone to specification error, but lumps noise and inefficiency together, calling the combination inefficiency.

[4] With low variance values, the probability that *u*=0 is high, implying high probability that firms will be fully efficient. If the market is competitive, inefficient firms will be forced out of the market in the long run (i.e., it is very likely that the surviving firms will cluster around the fully efficient level). By contrast, if firms are from a regulated industry, one would expect convergence in efficiency to have occurred (efficiency levels would be similar though not necessarily close to 100%). If regulatory incentives are strong, including those for the more efficient firms, convergence should tend toward the frontier, again suggesting that the half-normal model would be appropriate (Kumbhakar et al., 2015).

competition from private traders and businesses. We estimate technical inefficiency and simultaneously explain it by a set of variables in one step. The approach parameterizes the distribution of u as a function of exogenous variables that are likely to affect efficiency (Kumbhakar et al., 2015). Following the existing literature (e.g., Huang et al., 2013; Chen et al., 2009; Liu and Zhuang, 2000), we proxy *output* by the sum of the *sales* of agricultural products (both inputs and outputs) each cooperative earned in 2016.

Measuring TE generally assumes output (and not profit) maximization, given input quantities (Henningsen and Henning, 2009). Since the cooperatives in this study, except for MPCs, are more of marketing-oriented in nature[5], it seems justified to assume that they can theoretically work for sales (a proxy for output) maximization. Even for MPCs, since the input prices they charge are rather exogenously determined (determined either by a cooperative union or by the government – as explained in section 2.3.), sales maximization can be pursued via, for example, input diversification, and not via price maximization. To estimate the stochastic production frontier, a choice between the translog and Cobb-Douglas (C-D) specifications is made by testing the adequacy of each relative to the other using likelihood ratio (LR) tests. Since different cooperatives may employ different production technologies, the parameters of the SPF may vary across cooperative types. To test for this, we introduce *input-cooperative-type* interaction terms into the model. The more general translog form that nests the C-D is given as:

$$
\begin{aligned}
\ln q = {} & \beta_0 + \beta_L \ln L + \beta_B \ln B + \beta_K \ln K \\
& + \{0.5\beta_{LL} \ln L(\ln L) + 0.5\beta_{BB} \ln B(\ln B) + 0.5\beta_{KK} \ln K(\ln K) \\
& + \beta_{LB} \ln L(\ln B) + \beta_{LK} \ln L(\ln K) + \beta_{BK} \ln B(\ln K)\} \\
& + \beta_{mL} m(\ln L) + \beta_{mB} m(\ln B) + \beta_{mK} m(\ln K) \\
& + \beta_{rL} r(\ln L) + \beta_{rB} r(\ln B) + \beta_{rK} r(\ln K) + \beta_m m + \beta_r r + z'\beta_z + v - u
\end{aligned}
\tag{2}
$$

where $\ln$ stands for natural logarithm; L is size of land used; B is labor used; K is capital used; m and r are dummies for multipurpose and resource cooperatives, respectively; z is a vector of zone dummies allowing for neutral output shift among different zones, as in Akridge and Hertel (1992). *Labor* refers to the number of hired employees and committee and/or ordinary members who are actively engaged in the day-to-day activities of a cooperative. In the case of cooperatives other than MPCs, labor is proxied by total membership. Since the nature of these cooperatives does not tolerate idle members, everyone is expected to supply labor: labor supply is a membership requirement. In MPCs, labor comprises hired employees

[5] That is, they collect members' products for sale, and therefore, their customers (buyers) are not their own members to whom they may not charge the highest possible price.

and members of management committee, who are active in the day-to-day activities. Eq.(2) represents a flexible production technology that allows the production parameters (of the first order terms) to vary among the three cooperative types. This model can be rewritten for multipurpose (Eq.3), resource (Eq.4), and livestock (Eq.5) cooperatives as follows, where $\{\cdot\}$ represents the common expression in the curly brackets in Eq.(2).

$$\ln q = (\beta_0 + \beta_m) + (\beta_L + \beta_{mL})\ln L + (\beta_B + \beta_{mB})\ln B + (\beta_K + \beta_{mK})\ln K + \{\cdot\} + z'\beta_z + v - u \qquad (3)$$

$$\ln q = (\beta_0 + \beta_r) + (\beta_L + \beta_{rL})\ln L + (\beta_B + \beta_{rB})\ln B + (\beta_K + \beta_{rK})\ln K + \{\cdot\} + z'\beta_z + v - u \qquad (4)$$

$$\ln q = (\beta_0 + 0) + (\beta_L + 0)\ln L + (\beta_B + 0)\ln B + (\beta_K + 0)\ln K + \{\cdot\} + z'\beta_z + v - u \qquad (5)$$

Our approach allows for testing the assumption of common technology (all cooperative types have the same technology) by imposing the parameter restrictions given in Eq.(6).

$$\begin{aligned} H_0 : \beta_m &= \beta_r = 0 \\ \beta_{mL} &= \beta_{rL} = 0 \\ \beta_{mB} &= \beta_{rB} = 0 \\ \beta_{mK} &= \beta_{rK} = 0 \end{aligned} \qquad (6)$$

If the parameters vary across cooperative types (H_0 is rejected), one can estimate Eqs.(3), (4), and (5) separately. However, more precise estimates are obtained by estimating all the parameters jointly using a system approach (Triebs et al., 2016). Following this line of argument, we estimate the production technologies of the different cooperative types jointly.

3.2. Inefficiency and heteroskedasticity

As technological and market conditions may vary over cooperative types, we include cooperative type dummies in the production function in order to control for unobserved heterogeneity. However, dummy variable models should only be used when the different categories have the same error variance (Schepers, 2016; Holgersson et al., 2014; Gujarati, 2003) or standard deviation (S.D), which is not likely to be the case in our sample. Due to differences in the *membership-size* of individual cooperatives of different types, the problem of heteroskedasticity could arise. Size differentials may also lead to heteroskedasticity of errors. Ignoring the heteroskedasticity of v (u) biases the estimates of TE (both TE and frontier function) parameters (Kumbhakar et al., 2015; Wang and Schmidt, 2002)[6]. To account for variance heterogeneity, we follow Kumbhakar et al. (2015) to model the heteroskedasticity of v as a function of *membership-size*, and that of u as a function of a vector of observable variables, which can also be used as inefficiency determinants. Thus, following frontier

[6] Unlike a classical linear model in which heteroscedasticity affects only the efficiency of the estimators and not their consistency, ignoring heteroscedasticity in the SFA framework leads to inconsistent estimates (Wang and Schmidt, 2002).

efficiency studies (e.g., Hadri, 1999; Caudill et al., 1995; Caudill and Ford, 1993), we employ a model that allows for heteroskedasticity in u_i and v_i, and parameterize the variances as:

$$u_i \sim N^+(0,\sigma_{ui}^2) \quad \text{with} \quad \sigma_{ui}^2 = \exp(w'\pi) \tag{3}$$

and

$$v_i \sim N(0,\sigma_{vi}^2) \quad \text{with} \quad \sigma_{vi}^2 = \exp(h'\kappa) \tag{4}$$

where w is a vector of *cooperative* and *member characteristics*, *formation initiative*, and *management* and *audit variables*; h is *membership-size*. Note that h and w may overlap with each other and with the vector x, but must not be functions of q (Wang and Schmidt 2002); π, κ are vectors of parameters to be estimated. The production function coefficients β and the inefficiency model parameters π are estimated by maximum likelihood together with the variance parameters σ_u (S.D of u), σ_v(S.D of v), $\sigma^2 = \sigma_u^2 + \sigma_v^2$ (=total variance), and $\gamma = \sigma_u^2 / \sigma^2$ = the proportion of inefficiency variance in total variance.

Similar to previous studies, the vector of inefficiency determinants w includes *number of employees*, *cooperative age*, *age of chairman*, and *training*. Since cooperatives are *democratically*-controlled, *voluntary*, and *autonomous* associations of persons with *common* economic and social needs (ICA, 1995) that depend on their members' patronage, their *formation initiative* and *members' participation heterogeneity* may impact their efficiency. *Formation initiative* refers to whether the formation of a cooperative was initiated by members themselves, community, or by an external agent, such as government or an NGO. *Participation heterogeneity* is a dummy variable capturing the degree of heterogeneity in members' participation (1=high; 0=low) in meetings, policy crafting, labor supply, financial contribution, patronage (buying from and selling to their cooperative), and other cooperative affairs. Moreover, *presence of education committee* and *committee members' level of education* are likely to affect the performance of a cooperative, as they are reflective of human capital. Timely *audit* might also affect efficiency by checking fraud and injecting vigilance into the actions of the persons in charge. As well, since no rational person wants to show unreserved commitment to an unpaid activity the result of which is a public good (a good or benefit enjoyed by all members regardless of their contribution towards it), we hypothesize that monetary *compensation* to committee members will have a positive effect on the efficiency of a cooperative. The effects of *membership size*, *number of general meetings*, and *number of management committee meetings* on cooperative efficiency are also scant in the literature. Therefore, we include these factors in the vector w as inefficiency determinants. We fit a translog mode based on hypothesis tests for model adequacy (translog vs. C-D), relevance of the inefficiency effect, and common technology assumption (Table 2). We need to note that potential endogeneity bias cannot be completely ruled out. Certain variables, like *membership* *size*, *compensation*, *number of employees*, and *audit* might be endogenous in the model, and determined jointly with technical efficiency by underlying unobserved factors. Hence, we need to interpret our results with care and refrain from making too strong causal claims.

4. Results and discussion

4.1. Descriptive statistics

In Table 1, we report the mean and S.D of the variables used in the SFA model. In about 75% of the cooperatives, heterogeneity in members' participation (financial contribution, participation in meetings, labor supply, etc.) was found to be high, implying a potential free-rider problem. The average cooperative was found to have been audited for about 1.5 times in a decade. This is at a stark contrast with the mandatory frequency of audit stipulated in the bylaws of almost all cooperatives, namely once a year. Committee members are almost never compensated in most of the cooperatives. At best, only 13% of the MPCs pay compensation. Overall, only close to 8% of the cooperatives were found to compensate committee members for the time and effort they invest in the organization. The compensation, which is not a regular payment, is paid in the form of per diem and/or travel expenses. Regarding formation initiative, 54.7%, 34.7%, 7.3%, and 3.3% of the cooperatives were initiated by members, government, NGOs, and community, respectively. Community-initiated cooperatives are those whose establishment was motivated and endorsed by the community at large, rather than a few members, the government, or an NGO. They are mainly transformed from informal and traditional associations, such as *idir* (traditional burial association) and *iqub* (traditional financial association).

Table 1: Descriptive statistics for different types of cooperatives

Variable name	Variable description	All cooperatives		Multipurpose cooperatives		Livestock cooperatives		Natural resource cooperatives	
Inputs and output:									
Output (q)	Total sales revenue (1,000 ETB)	77.092	(2.284)	612.164	(1.656)	20.697	(1.541)	26.709	(1.768)
Land (L)	Total area of land used (hectare)	0.647	(2.672)	0.080	(2.242)	1.820	(2.084)	3.133	(2.018)
Labor (B)	Total labor used (number)	14.910	(0.867)	7.973	(0.249)	18.357	(0.798)	28.474	(0.974)
Capital (K)	Total capital (fixed asset) (ETB)	87553	(1.621)	208981	(1.518)	54176.4	(1.175)	48533.0	(1.834)
Cooperative and member characteristics									
Size	Natural log of number of members	4.447	(1.967)	6.781	(0.639)	2.910	(0.798)	3.349	(0.974)
Employees	Number of non-member employees[a]	0.520	(1.631)	0.738	(2.373)	0.420	(0.764)	0.342	(1.184)
Age-coop	Years since establishment of the cooperative	9.082	(7.680)	16.59	(6.956)	4.214	(3.419)	5.421	(3.594)
Heterogeneity	Heterogeneity in member participation (high=1)	0.745	(0.437)	0.787	(0.411)	0.733	(0.444)	0.697	(0.462)
Educ-chairman	Years of education of chairman	5.824	(2.889)	5.533	(2.513)	6.328	(2.970)	5.421	(3.205)
Age-chairman	Age of the chairman	41.49	(10.96)	47.09	(9.929)	37.96	(10.38)	38.56	(9.912)
Educ-members	Average year of education of management committee	5.811	(2.537)	6.100	(1.808)	5.656	(2.925)	5.612	(2.799)
Formation initiative									
Member-initiated	Member-initiated cooperative (yes=1)	0.547	(0.499)	0.623	(0.487)	0.473	(0.501)	0.553	(0.501)
Government-initiated	Government-initiated cooperative (yes=1)	0.347	(0.477)	0.279	(0.450)	0.374	(0.486)	0.408	(0.495)
NGO-initiated	NGO-initiated cooperative (yes=1)	0.073	(0.260)	0.008	(0.091)	0.153	(0.361)	0.039	(0.196)
Community-initiated	Community-initiated cooperative (yes=1)	0.033	(0.180)	0.090	(0.288)	0.000	(0.000)	0.000	(0.000)
Management and audits									
Educ-committee	Presence of an education committee (yes=1)	0.429	(0.496)	0.533	(0.501)	0.382	(0.488)	0.342	(0.478)
General-assembly	Average number of general meetings per year	3.598	(6.391)	1.140	(1.087)	5.738	(7.833)	3.853	(7.243)
Committee-meetings	Number of management committee meetings	24.92	(17.94)	26.47	(17.91)	22.58	(15.06)	26.47	(21.91)
Audits	Average number of audits per year	0.183	(0.363)	0.248	(0.478)	0.146	(0.300)	0.144	(0.201)
Training	Average number of management trainings per year	0.631	(0.659)	0.375	(0.630)	0.775	(0.539)	0.796	(0.767)
Compensation	Monetary compensation for committee members (yes=1)	0.073	(0.260)	0.131	(0.339)	0.038	(0.192)	0.039	(0.196)

Standard deviations are reported in parentheses. [a]The phrase "non-member employees" is used to indicate the exclusion of member employees (in some cases, cooperatives hire their own members as cashiers, guards, or accountants).

4.2. Model adequacy tests

Table 2 reports the results of the LR tests for model adequacy, relevance of the inefficiency component, and existence of common technology. The null hypothesis of zero second-order coefficients of *land*, *labor*, and *capital* is rejected. Accordingly, we use the translog specification to estimate the SPF in Eq.(2). The null hypothesis of no one-sided error (there is no technical inefficiency component) is rejected as well, implying that the SFA with inefficiency model is a more appropriate representation than the standard OLS estimation (Diaz and Sánchez, 2008). The third test in Table 2 rejects the null hypothesis of common technology across cooperative types, suggesting that a pooled model (without interaction terms) is not appropriate for the data. Based on these tests, we use the translog specification with inefficiency model and *input-cooperative-type* interaction variables.

Table 2: LR tests for functional form, relevance of the inefficiency component, and common technology.

Null hypothesis (H_0)	**Test statistic**
$H_0 : \beta_{ij} = 0 \ \forall i, j = L, B, K$	29.16***
$H_0 : \sigma_u = 0$	22.06***
$H_0 : \beta_m = \beta_r = 0; \beta_{mL} = \beta_{rL} = 0; \beta_{mB} = \beta_{rB} = 0; \beta_{mK} = \beta_{rK} = 0$	378.9***

Significance levels are reported as ***1%.

4.3. Stochastic frontier analysis

Table 3 reports the econometric results of the production and inefficiency models. The diagnostic statistics at the bottom of the table report estimates of the two error components and their shares in the total error variance. The value of gamma ($\gamma = \sigma_u^2 / \sigma^2$) is reasonably high at 0.886, implying that the share of the variance of the inefficiency component is considerable. This is consistent with the rejection of the null hypothesis of no technical inefficiency component.

Table 3: Stochastic frontier half-normal model

PRODUCTION MODEL	**Coefficient**	**S.E**
Constant	-2.184***	0.344
lnL	0.153*	0.082
lnB	0.938***	0.240
lnK	0.548***	0.126
lnL(lnL)	0.005	0.010
lnB(lnB)	0.065	0.063
lnK(lnK)	0.050**	0.020
lnL(lnB)	0.100***	0.036
lnL(lnK)	-0.065***	0.018
lnB(lnK)	0.039	0.094
mlnL	0.374***	0.093
mlnB	0.907	0.553
mlnK	-0.586***	0.180
rlnL	0.178	0.108
rlnB	0.358	0.262
rlnK	-0.211	0.145
m	6.270***	0.709
r	0.599	0.504
Central zone	0.045	0.187

S&SE zone	0.101	0.203
W&NW zone	-0.020	0.178
HETEROSKEDASTICITY MODEL		
ln(Size)	-0.286***	0.067
Constant	1.147***	0.263
INEFFICIENCY MODEL		
Cooperative and member characteristics		
ln(Size)	0.385	0.242
Employees	-0.517**	0.201
Age-coop	0.105***	0.033
Heterogeneity	1.531***	0.508
Educ-chairman	0.237***	0.090
Age-chairman	0.408**	0.171
Age-squared	-0.005**	0.002
Educ-members	-0.073	0.096
m	2.433**	1.041
r	3.843***	1.171
Formation initiative (*Member-initiated*=base category)		
Government-initiated	0.666*	0.376
NGO-initiated	1.103	1.006
Community-initiated	-2.780**	1.149
Management and audits		
Educ-committee	1.024***	0.380
General-assembly	-0.003	0.057
Committee-meetings	-0.015	0.010
Audits	0.339	0.430
Training	0.515**	0.252
Compensation	-1.774**	0.693
Constant	-16.388***	4.656
Diagnostic statistics:		
σ_v	0.716	0.010
σ_u	1.992	0.156
σ^2	4.480	0.532
γ	0.886	
Wald chi2	955.55	
Prob.> chi2	0.000	
Log likelihood	-524.56	
N	329	

Significance levels are reported as ***1%, ** 5%, * 10%. ln stands for natural logarithm.

4.3.1. Output elasticities and returns to scale (RTS)

The statistically significant and positive (negative) parameters of the squared-terms in the production model imply an increasing (decreasing) marginal product of the input concerned, with the statistically significant and positive ones implying a possible underutilization of a resource. Statistically significant and positive (negative) coefficients of cross-products are indicative of complementarity (substitutability) between inputs. The results of the heteroskedasticity model indicate the lack of homoskedasticity in the data. *Size* is found to be relevant for modeling heteroskedasticity in the idiosyncratic (random shock) component v of the error term. This shows that the variance of the random error (equivalently, that of *output*) is a function of *membership-size*. On average, the *output* of cooperatives with more members is found to be more volatile. This claim is supported by the data: the S.D of the output of cooperatives with above-average membership size (S.D=2285) is much higher than the S.D of cooperatives with below-average membership size (S.D=345).

Table 4: Elasticities and RTS scores

	Output elasticities with respect to:			
Coop type	**Land**	**Labor**	**Capital**	**RTS**
Multipurpose cooperatives	0.105 (0.090)	1.164 (0.256)	0.218 (0.138)	1.487 (0.136)
Livestock cooperatives	0.083 (0.099)	0.569 (0.224)	0.568 (0.152)	1.054 (0.196)
Natural resource cooperatives	0.148 (0.125)	1.006 (0.275)	0.334 (0.131)	1.488 (0.274)

Standard deviations are reported in parentheses.

Table 4 presents estimates of elasticities and RTS. Elasticities are computed at the mean input levels. RTS are the sum of elasticities with respect to each input. Generally, the results are consistent with economic theory: the marginal products of all the inputs are positive for all cooperative types, as implied by the positive elasticities. Microeconomic theory requires 'well-behaved' production functions monotonically increase in all inputs. The violation of monotonicity inhibits not only a reasonable interpretation of efficiency estimates, but also the analysis of factors that might affect TE (Henningsen and Henning, 2009). Besides monotonicity, microeconomic theory often assumes that production functions are quasi-concave in all inputs, as this implies convex input sets, and hence, decreasing marginal rates of technical substitution. However, since cooperatives are, at least in principle, not profit maximizing firms, quasi-concavity may not hold for them. Thus, there is not necessarily a technical rationale for our production function to be quasi-concave (Henningsen and Henning, 2009), and we do not test our model for this requirement.

Average values of RTS seem to suggest increasing returns to scale (IRS) in MPCs and NRCs (RTS>1), and constant returns to scale in LBCs (RTS close to 1). The findings of IRS for MPCs and NRCs imply that these cooperative types are not operating at optimal scale, probably due to imperfect competition, constraints on finance (Coelli et al., 2005), and government intervention. As a result, their level of overall technical inefficiency is likely to be the combination of scale inefficiency and pure technical inefficiency. The close-to-unity value of RTS in LBCs, on the other hand, are suggestive of operation at optimal scale. This implies that pure technical, and not scale, inefficiency is the main cause of overall technical inefficiency in these cooperative categories.

4.3.2. Technical (in)efficiency

The TE of MPCs, LBCs, and NRCs are about 49, 88, and 55%, respectively, indicating significant possibilities to increase efficiency levels. On average, technical inefficiency could be reduced by about 36% by operating at optimal scales and/or eliminating pure technical inefficiencies in production and/or marketing[7] via the adoption of the best practices of efficient agricultural cooperatives (Krasachat and Chimkul, 2009). The scale-inefficient cooperatives

[7] Since our *output* variable is proxied by *sales*, the marketing performance of a cooperative has implications for its level as well.

could be made more efficient by adjusting their size, at least, in the long-run so they can operate at the point where average cost (product) is minimized (maximized). LBCs appear to be the most efficient cooperative type. Considering the most diversified business they are doing, one would expect MPCs to have the highest TE as a result of a better spread of labor and capital over broader sales. Yet, high scale inefficiency may be counteracting the efficiency gain from diversification. Given the ownership of the inputs used by LBCs, the issue of common pool resources might underlie the highest TE they have. The major sources of revenue for LBCs are sheep, goats, oxen, cows (meat, milk), and bees (honey). These animals, in the study area, normally live not only on purchased feed, but also on free feed from open-access land with a negative externality. As long as these external (social) costs are not accounted for in the efficiency analysis, the level of land used (for land is the source of feed) by these cooperatives is likely to be underestimated. Similarly in the case of beekeeping, even though the cooperatives have an officially fixed area of land to operate on, this does not apply to the bees, which can go anywhere to collect nectars, implying that the major source of sales is not land-constrained. Therefore, if the externalities are internalized, i.e., land utilization is seen from social point of view, the high level of efficiency would likely drop.

In the inefficiency model, a statistically significant and negative (positive) coefficient of a variable indicates that cooperatives with a larger value of that particular variable tend to have a higher (lower) level of TE. Given that we cannot rule out the possibility of endogeneity bias, we interpret significant coefficients as correlations rather than causations. A unit increase in the *number of employees* is associated with a reduction in inefficiency of about 33, 4, and 26% in MPCs, LBCs, and NRCs, respectively. This looks a quite plausible finding assuming that paid employees have expertise in the area of their employment, and are expected to have a better incentive to focus on their job than unpaid volunteers. This finding is consistent with the result of Hailu et al. (2005). On the other hand, a unit increase in *cooperative age* is found to be associated with a decrease in efficiency of about 7, 1, and 5 % in MPCs, LBCs, and NRCs, respectively. Contrary to our findings, Krasachat and Chimkul (2009) report a positive effect of cooperative age on scale efficiency. *Members' participation heterogeneity* is found to be associated with reduced efficiency, for about 98, 11, and 76% in MPCs, LBCs, and NRCs, respectively. This may be attributed to a free-rider problem implied in the participation differentials among members. Especially in MPCs, the correlation is very high, implying that multipurpose cooperatives are more prone to the consequences of free-riding problem, probably on account of their large membership size. The negative correlation between participation heterogeneity and efficiency substantiates prior expectations. Since cooperatives are founded on the member-owner, member-user, and member-beneficiary principle, members' participation is very crucial. Members of a well-functioning co-operative exhibit a high degree of homogeneity in many respects (Höhler and Kuhl, 2017) and democratic decision making processes profit from the homogeneity of interests (Bijman, 2005). MPCs, LBCs, and NRCs chaired by a person with one more year of formal schooling are, respectively found to perform about 15, 2, and 12% less efficiently. This negative correlation between chairman's level of education and efficiency defies expectation. A potential reason could be that more educated chairmen are less committed to their position for some reason. For example, the perceived opportunity-cost of time spent chairing a cooperative might be higher for persons with higher level of education. As such, level of education may be serving as an inverse proxy for the level of satisfaction of the chairman with his/her current position. This finding may also be supported by the claim of Liang et al. (2015) that professional management widens the gap between members and management, assuming that a higher level of education creates a feeling of professionalism on the chairman's part.

A unit increase in chairman's age is found to be associated with a decrease in efficiency of about 26, 3, and 20% in MPCs, LBCs, and NRCs, respectively up to a point beyond which the relationship becomes positive. This u-shaped relation implies that cooperatives led by youngest and oldest chairmen operate more efficiently compared to those led by middle-aged chairmen. Probably, this is due to the possibility that young chairmen are more eager and cautious, and old chairmen are more experienced, and hence more knowledgeable in management practices as compared to the middle-aged ones. Findings regarding *formation initiative* are consistent with expectation. A voluntary and *self-initiated*[8] effort is more likely to be successful than an externally-initiated (top-down) one. In the study area, typically, the idea to form a cooperative comes from a donor, or the government in an attempt to address youth unemployment. In so doing, little attention is paid to the commonality – in terms of interest, needs, goals, etc. – among the founding members. Externally-induced cooperatives are less likely to have members with common needs and aspirations. The top-down nature of cooperatives is often claimed to discourage member involvement (Dunn, 1988) though it can potentially be a solution in settings where social capital is too low to allow for the grassroots emergence of cooperatives, as has been documented for Russia (Kurakin and Visser, 2017).

Results show that community-initiated cooperatives are more efficient than member-initiated ones, and member-initiated cooperatives are more efficient than government-initiated ones. The marginal effects are large enough to count against too much involvement of governments in the initiation of cooperatives. On the other hand, no significant difference was found in the efficiency of member-initiated (reference category) and NGO-initiated (insignificant coefficient) cooperatives.

[8] Self-initiated refers to member- and community-initiated cooperatives.

Table 5: TE and marginal effects of inefficiency determinants

	Cooperative category		
	Multipurpose cooperatives	Livestock cooperatives	Natural resource cooperatives
TE scores	0.493 (0.275)	0.879 (0.108)	0.546 (0.225)
Marginal effects			
Employees	-0.330 (0.290)	-0.036 (0.047)	-0.258 (0.226)
Age-coop	0.067 (0.059)	0.007 (0.010)	0.052 (0.046)
Heterogeneity	0.976 (0.857)	0.107 (0.139)	0.764 (0.668)
Educ-chairman	0.151 (0.133)	0.017 (0.022)	0.118 (0.103)
Age-chairman	0.260 (0.229)	0.029 (0.037)	0.204 (0.178)
Age-squared	-0.003 (0.003)	0.000 (0.000)	-0.002 (0.002)
Government-initiated	0.425 (0.373)	0.047 (0.061)	0.332 (0.290)
Community-initiated	-1.774 (1.557)	-0.195 (0.253)	-1.388 (1.213)
Educ-committee	0.653 (0.573)	0.072 (0.093)	0.511 (0.447)
Training	0.329 (0.288)	0.036 (0.047)	0.257 (0.225)
Compensation	-1.132 (0.994)	-0.124 (0.162)	-0.886 (0.774)

Standard deviations (SD) are reported in parentheses. Only the marginal effects of variables with significant coefficients in Table 3 are reported.

We also find that MPCs, LBCs, and NRCs with an education committee perform about 65, 7, and 51% less efficiently than those without, respectively. A possible explanation for this counterintuitive result is that the members of the committee may be getting idle under the disguise of that position. Their contribution as committee members might be too low to make up for the forgone labor hours they would supply as ordinary members. Contrary to normal expectations and the finding of Huang et al. (2013), a unit increase in the number of trainings is found to reduce efficiency by about 33, 4, and 26% in MPCs, LBCs, and NRCs, respectively. This finding suggests that the finance, time, and other human and material resources the government commits to trainings deserve serious scrutiny. For example, it should be made certain that: (1) trainings are compatible with the practical problems cooperatives face; (2) the trainers have the appropriate expertise; and (3) the trainees are the right persons the training should be targeted to.

Cooperatives that compensate their committee members are found to be more efficient than their "non-compensating" counterparts. Given the very low number of cooperatives with a compensation scheme (only about 8%) in the sample, the fact that this variable turns out with a significant effect is impressive. More surprisingly, during the interview, many respondents said that compensation would not make a difference. Some likened the cooperative and the committee members with husband and wife, and said: "Using cooperative resources to compensate committee members for what they do for their own cooperative will be like taking money from a husband and giving it to his wife, which makes no difference." Others would say: "What difference do I make if I take money from my left pocket and put it in my right pocket?". Still others said that they are already exerting the maximum possible effort to run their cooperative so that compensation would have no effect at all: "Whether I get compensation or not, I cannot be more committed to the cooperative than I already am," they would say. One particular respondent reacted to the same question this way: "Listen brother, let alone a cooperative, we are leading a district for free. It is not a big deal." There was another respondent whose attitude seems to lend a fresh perspective to the issue: "No, taking compensation, big or small it doesn't matter, would make ordinary members think that committee members should shoulder every responsibility in the cooperative. This will erode the commitment of ordinary members," said he. Despite all this, however, compensation appears to promote TE. One might suspect that there is something different about these 8% cooperatives. That is, their better TE and the fact that they compensate committee members may be driven by a better endowment (money) as compared to the other cooperatives. However, a *t-test* on the equality of average capital – a proxy for endowment – of the 8% and the rest 92% revealed no significant mean difference ($t = 0.237; p = 0.813$). Thus, there seems to be a disagreement between the respondents' opinion about the effect of compensation on their commitment – and hence performance – and its practical effect.

Though the direction of relationship of most of the variables with TE looks plausible, the magnitudes of some of the marginal effects seem to be rather high and should be interpreted very carefully, and not at face value. For example, the average difference of efficiency (about 71%) between cooperatives with and without compensation scheme is apparently very high. However, by design of our model, the value represents the *conditional expectation* rather than the *causal effect* of compensation: it shows the difference in the level of TE between two separate cooperatives, one with and the other without compensation scheme, rather than the extent by which the inefficiency of a given non-compensating cooperative would reduce had it opted for compensating its committee members. In the first interpretation, the unobservable factors affecting TE are not assumed to be constant across the two cooperatives, while in the second interpretation, not only the included variables but also the unobservables in the error term are kept constant (Verbeek, 2012). Therefore, the estimated marginal effects are likely to have captured, at least partly, the effect of differences in unobserved cooperative characteristics as well.

5. Conclusion

In this article, we investigate the performance of agricultural cooperatives in Ethiopia by analyzing the determinants of their technical efficiency using a stochastic frontier approach. We find an average technical efficiency of 64% with differences in efficiency scores for different types of cooperatives with different activities. The results point out that more recent cooperatives are more efficient; and that cooperatives initiated in a bottom-up way by the community are more efficient than top-down cooperatives formed through government- and NGO-initiatives – with particularly the former being most inefficient. We find that heterogeneity in the level of member participation in the cooperative is detrimental to its efficiency, while monetary compensation for committee members improves efficiency. Some clear-cut policy and research recommendations follow from our results. First, governments and NGOs should refrain from interfering too much with the formation of cooperatives in Ethiopia. Already for decades, there is considerable donor and policy attention for cooperation and horizontal coordination among farmers in order to reduce transaction costs and overcome market imperfections and constraints in agricultural production and improve the performance of the smallholder farm sector in developing countries. Yet, interfering too strongly in stimulating this cooperation through top-down initiation of cooperatives is counterproductive for the efficiency of the cooperative institutions created.

Second, cooperatives can optimize their rules and management practices to operate more efficiently. Our results imply that cooperatives with paid employees and those that incentivize committee members for their leadership role through monetary compensation would be more technically efficient. Third, our analysis points to several cooperative characteristics that determine the efficiency of cooperatives. These variables may also be relevant in studies estimating the effects of cooperative membership at farm-household level in order to analyze heterogeneous effects of cooperative membership. Especially variables related to the formation and heterogeneity among members might be specifically relevant in such studies.

Acknowledgement

The authors acknowledge funding from the VLIR-UOS-ZEIN2015PR406 (13V95615T) PROGRAMME(TEAM), Belgium. We also thank participants at the 20th PhD Symposium of the Belgian Association of Agricultural Economists held in Brussels, Belgium for their useful comments on an earlier version of the article.

Data availability statement

Data supporting the results in this paper are available from the corresponding author upon reasonable request.

Word count:7486

References

ABATE, G. T., FRANCESCONI, G. N. & GETNET, K. (2014). Impact of agricultural cooperatives on smallholders' technical efficiency: Empirical evidence from Ethiopia. *Annals of Public and Cooperative Economics,* 85**,** 257-286.

ABEBAW, D. & HAILE, M. G. (2013). The impact of cooperatives on agricultural technology adoption: Empirical evidence from Ethiopia. *Food Policy,* 38**,** 82-91.

AHN, S. C., BRADA, J. C. & MÉNDEZ, J. A. (2012). Effort, technology and the efficiency of agricultural cooperatives. *The Journal of Development Studies,* 48**,** 1601-1616.

AKRIDGE, J. T. & HERTEL, T. W. (1992). Cooperative and investor-oriented firm efficiency: A multiproduct analysis. *Journal of Agricultural Cooperation,* 7**,** 1-14.

ARIYARATNE, C. B., FEATHERSTONE, A. M., LANGEMEIER, M. R. & BARTON, D. G. (1997). An analysis of efficiency of midwestern agricultural cooperatives. *Western Agricultural Economics Association, Selected Papers of the 1997 Annual Meeting.*

ARIYARATNE, C. B., FEATHERSTONE, A. M., LANGEMEIER, M. R. & BARTON, D. G. (2000). Measuring X-efficiency and scale efficiency for a sample of agricultural cooperatives. *Agricultural and Resource Economics Review,* 29**,** 198-207.

ATA (2012). (Agricultural Transformation Agency). Agricultural Cooperatives Sector Development Strategy 2012–2106. Unpublished Report. Addis Ababa, Ethiopia. .

BATTESE, G. E. & COELLI, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics,* 20**,** 325-332.

BERHANU, K. & POULTON, C. (2014). The political economy of agricultural extension policy in Ethiopia: economic growth and political control. *Development Policy Review,* 32**,** s197-s213.

BERNARD, T., SPIELMAN, D. J., SEYOUM TAFFESSE, A. & GABRE-MADHIN, E. Z. (2010). *Cooperatives for staple crop marketing: evidence from Ethiopia, research monograph 164,* Washington, D.C. 20006-1002, U.S.A., Intl Food Policy Res Inst.

BERNARD, T. & TAFFESSE, A. S. (2012). Returns to scope? Smallholders' commercialisation through multipurpose cooperatives in Ethiopia. *Journal of African Economies,* 21**,** 440-464.

BERNARD, T., TAFFESSE, A. S. & GABRE-MADHIN, E. (2008). Impact of cooperatives on smallholders' commercialization behavior: evidence from Ethiopia. *Agricultural Economics,* 39**,** 147-161.

BIJMAN, J. (2005). Cooperatives and heterogeneous membership: eight propositions for improving organizational efficiency.

BOYD, M. L. (1987). The performance of private and cooperative socialist organization: postwar Yugoslav agriculture. *The Review of Economics and Statistics***,** 205-214.

BRADA, J. C. & KING, A. E. (1993). Is private farming more efficient than socialized agriculture? *Economica***,** 41-56.

CANDEMIR, M., ÖZCAN, M., GÜNEŞ, M. & DELIKTAŞ, E. (2011). Technical efficiency and total factor productivity growth in the hazelnut agricultural sales cooperatives unions in Turkey. *Mathematical and Computational Applications,* 16**,** 66-76.

CARTER, M. R. (1984). Resource allocation and use under collective rights and labour management in Peruvian coastal agriculture. *The Economic Journal,* 94**,** 826-846.

CAUDILL, S. B. & FORD, J. M. (1993). Biases in frontier estimation due to heteroscedasticity. *Economics Letters,* 41**,** 17–20.

CAUDILL, S. B., FORD, J. M. & GROPPER, D. M. (1995). Frontier estimation and firm-specific inefficiency measures in the presence of heteroscedasticity. *Journal of Business and Economic Statistics* 13**,** 105–111.

CHEN, Z., HUFFMAN, W. E. & ROZELLE, S. (2009). Farm technology and technical efficiency: Evidence from four regions in China. *China Economic Review,* 20**,** 153-161.

CHIBANDA, M., ORTMANN, G. F. & LYNE, M. C. (2009). Institutional and governance factors influencing the performance of selected smallholder agricultural cooperatives in KwaZulu-Natal. *Agrekon,* 48**,** 293-306.

COELLI, T. J., RAO, D. S. P., O'DONNELL, C. J. & BATTESE, G. E. (2005). *An introduction to efficiency and productivity analysis*, Springer Science & Business Media.

COOK, M. L. (1995). The future of US agricultural cooperatives: A neo-institutional approach. *American Journal of Agricultural Economics,* 77**,** 1153-1159.

DEININGER, K. (1995). Collective agricultural production: A solution for transition economies? *World Development,* 23**,** 1317-1334.

DIAZ, M. A. & SÁNCHEZ, R. (2008). Firm size and productivity in Spain: a stochastic frontier analysis. *Small Business Economics,* 30**,** 315-323.

DUNN, J. R. (1988). Basic cooperative principles and their relationship to selected practices. *Journal of Agricultural Cooperation,* 3**,** 83.

FISCHER, E. & QAIM, M. (2012). Linking smallholders to markets: determinants and impacts of farmer collective action in Kenya. *World Development,* 40**,** 1255-1268.

FISCHER, E. & QAIM, M. (2014). Smallholder farmers and collective action: what determines the intensity of participation? *Journal of Agricultural Economics,* 65**,** 683-702.

FRANCESCONI, G. N. & HEERINK, N. (2010). Ethiopian agricultural cooperatives in an era of global commodity exchange: does organisational form matter? *Journal of African Economies,* 20**,** 153-177.

GENTZOGLANIS, A. (1997). Economic and financial performance of cooperatives and investor-owned firms: An empirical study. *Strategies and Structures in the Agro-food Industries***,** 171-182.

GETNET, K. & ANULLO, T. (2012). Agricultural cooperatives and rural livelihoods: Evidence from Ethiopia. *Annals of Public and Cooperative Economics,* 83**,** 181-198.

GÓMEZ, E. G. (2006). Productivity and efficiency analysis of horticultural co-operatives. *Spanish Journal of Agricultural Research,* 4**,** 191-201.

GUJARATI, D. (2003). *Basic Econometrics Fourth Edition McGraw Hill Gujarati, DN. Basic Econometrics*, McGraw Hill. International Edition.

HADRI, K. (1999). Estimation of a doubly heteroscedastic stochastic frontier cost function. *Journal of Business and Economic Statistics* 17**,** 359–363.

HAILU, G., GODDARD, E. W. & JEFFREY, S. R. (Year). Measuring efficiency in fruit and vegetable marketing co-operatives with heterogeneous technologies in Canada. *In:* American Agricultural Economics Association Annual Meeting, Providence, Rhode Island, 2005.

HELLIN, J., LUNDY, M. & MEIJER, M. (2009). Farmer organization, collective action and market access in Meso-America. *Food Policy,* 34**,** 16-22.

HENNINGSEN, A. & HENNING, C. H. (2009). Imposing regional monotonicity on translog stochastic production frontiers with a simple three-step procedure. *Journal of Productivity Analysis,* 32**,** 217.

HÖHLER, J. & KUHL, R. (2017). Dimensions of member heterogeneity in cooperatives and their impact on organization–a literature review. *Annals of Public and Cooperative Economics*.

HOLGERSSON, H., NORDSTRÖM, L. & ÖNER, Ö. (2014). Dummy variables vs. category-wise models. *Journal of Applied Statistics,* 41**,** 233-241.

HUANG, Z., FU, Y., LIANG, Q., SONG, Y. & XU, X. (2013). The efficiency of agricultural marketing cooperatives in China's Zhejiang province. *Managerial and Decision Economics,* 34**,** 272-282.

ICA (1995). (International Cooperative Alliance). Statement on the Co-Operative Identity, available at: http://www.ica.coop/coop/principles.html, as of June 20, 2006, last modified on 2/9/2006.

ITO, J., BAO, Z. & SU, Q. (2012). Distributional effects of agricultural cooperatives in China: Exclusion of smallholders and potential gains on participation. *Food Policy,* 37**,** 700-709.

KRASACHAT, W. & CHIMKUL, K. (2009). Performance measurement of agricultural cooperatives in Thailand: An accounting-based data envelopment analysis. *Productivity, Efficiency, and Economic Growth in the Asia-Pacific Region.* Springer.

KUMBHAKAR, S. C., WANG, H. & HORNCASTLE, A. P. (2015). *A practitioner's guide to stochastic frontier analysis using Stata*, Cambridge University Press.

KURAKIN, A. & VISSER, O. (2017). Post-socialist agricultural cooperatives in Russia: a case study of top-down cooperatives in the Belgorod region. *Post-Communist Economies,* 29**,** 158-181.

LIANG, Q., HUANG, Z., LU, H. & WANG, X. (2015). Social capital, member participation, and cooperative performance: Evidence from China's Zhejiang. *International Food and Agribusiness Management Review,* 18**,** 49.

LIU, Z. & ZHUANG, J. (2000). Determinants of technical efficiency in post-collective Chinese agriculture: Evidence from farm-level data. *Journal of Comparative Economics,* 28**,** 545-564.

MOFED (2006). (Ministry of Finance and Economic Development). Building on progress – A Plan for Accelerated and Sustained Development to End Poverty (PASDEP) (2005/06–2009/10), Volume I (Main Text), Addis Ababa, Ethiopia.

MUJAWAMARIYA, G., D'HAESE, M. & SPEELMAN, S. (2013). Exploring double side-selling in cooperatives, case study of four coffee cooperatives in Rwanda. *Food Policy,* 39**,** 72-83.

POULTON, C., DORWARD, A. & KYDD, J. (2010). The future of small farms: New directions for services, institutions, and intermediation. *World Development,* 38**,** 1413-1428.

REINHARD, S., LOVELL, C. K. & THIJSSEN, G. (2002). Analysis of environmental efficiency variation. *American Journal of Agricultural Economics,* 84**,** 1054-1065.

ROYER, J. S. (1999). Cooperative organizational strategies: A neo-institutional digest. *Journal of Cooperatives,* 14**,** 44-67.

SCHEPERS, J. (2016). On regression modelling with dummy variables versus separate regressions per group: Comment on Holgersson et al. *Journal of Applied Statistics,* 43**,** 674-681.

SEXTON, R. J. & ISKOW, J. (1993). What do we know about the economic efficiency of cooperatives: an evaluative survey. *Journal of Agricultural Cooperation,* 8.

SHIFERAW, B., OBARE, G., MURICHO, G. & SILIM, S. (2009). Leveraging institutions for collective action to improve markets for smallholder producers in less-favored areas. *African Journal of Agricultural and Resource Economics,* 3**,** 1-18.

SOBOH, R., OUDE LANSINK, A. & VAN DIJK, G. (2012). Efficiency of cooperatives and investor owned firms revisited. *Journal of Agricultural Economics,* 63**,** 142-157.

SOBOH, R. A., LANSINK, A. O., GIESEN, G. & VAN DIJK, G. (2009). Performance measurement of the agricultural marketing cooperatives: the gap between theory and practice. *Review of Agricultural Economics,* 31**,** 446-469.

TCPMDA (2017). Tigray Co-operative Promotion and Market Development Agency (TCPMDA): unpublished report. Mekelle, Ethiopia.

TRIEBS, T. P., SAAL, D. S., AROCENA, P. & KUMBHAKAR, S. C. (2016). Estimating economies of scale and scope with flexible technology. *Journal of Productivity Analysis,* 45**,** 173-186.

VANDEPLAS, A., MINTEN, B. & SWINNEN, J. (2013). Multinationals vs. cooperatives: The income and efficiency effects of supply chain governance in India. *Journal of Agricultural Economics,* 64**,** 217-244.

VERBEEK, M. (2012). A guide to modern econometrics. 4th ed. Rotterdam: John Wiley and Sons.

VERHOFSTADT, E. & MAERTENS, M. (2014). Smallholder cooperatives and agricultural performance in Rwanda: do organizational differences matter? *Agricultural Economics,* 45**,** 39-52.

WANG, H.-J. & SCHMIDT, P. (2002). One-step and two-step estimation of the effects of exogenous variables on technical efficiency levels. *Journal of Productivity Analysis,* 18**,** 129-144.

WANYAMA, F. O., DEVELTERE, P. & POLLET, I. (2009). Reinventing the wheel? African cooperatives in a liberalized economic environment. *Annals of Public and Cooperative Economics,* 80**,** 361-392.

WOLLNI, M. & ZELLER, M. (2007). Do farmers benefit from participating in specialty markets and cooperatives? The case of coffee marketing in Costa Rica1. *Agricultural Economics,* 37**,** 243-248.