www.jard.edu.pl http://dx.doi.org/10.17306/J.JARD.2024.01810

Journal of Agribusiness and Rural Development

pISSN 1899-5241
eISSN 1899-5772

1(71) 2024, 103–123
Accepted for print: 19.02.2024

DETERMINANTS OF MARKET CHOICE AMONG AGRICULTURAL COOPERATIVES IN SOUTH AFRICA

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Abstract. The potential of agricultural cooperatives to foster socioeconomic development is a critical issue in developing countries. This study examines the factors that influence market choice among South African agricultural cooperatives. Data for 381 agricultural cooperatives were collected from the Cooperative Data Analysis System, drawn from the original database of 3,197 cases from 2017. Cases with missing observations were omitted. A multivariate approach utilising principal component analysis and K-means clustering was employed to identify the typologies of market choices. Multinomial logistic regression was then applied to determine the factors influencing agricultural cooperatives' choice of market typologies. The study reveals that the financial and social efficiency of agricultural cooperatives, the age of the institution, the square of the age of the institution, ownership of livestock, cooperative size, and credit access all influence market typology selection. Training programs such as those in financial management, corporate governance, accounting and bookkeeping, management committees, and the number of managers in cooperatives also impact cooperatives' market choice. The findings of this study should facilitate the design of policies that cater to cooperatives encountering diverse market choices. By influencing the choices of agricultural cooperatives, stakeholders can contribute to more meaningful cooperative involvement in markets.

Keywords: financial efficiency; social efficiency; market choice; agricultural cooperatives; South Africa

INTRODUCTION

Agricultural cooperatives have recently been rediscovered as having the potential to foster socioeconomic development, reduce poverty, and successfully surmount economic and political challenges similar institutions often encounter in developing countries (Borda-Rodriguez and Vicari, 2014). These types of organisations are formed by agricultural producers, farmers, or rural entrepreneurs who come together voluntarily to collectively manage their agricultural activities and pursue common economic, social, and cultural goals. As such, they may produce, process, market, and distribute agricultural products and services. In addition to fostering socioeconomic development and reducing poverty, agricultural cooperatives are recognised as an institution that can enhance the market power of smallholders in developing countries (Neupane et al., 2022). Borda-Rodriguez and Vicari (2014) note that national and international researchers, policymakers, and academics have recently shifted their focus to the success of agricultural cooperatives and the reasons for their resurgence to understand how they have overcome the challenges they face. In other words, these stakeholders want to understand the degree to which such cooperatives have been able to deal with the challenges they confront.

However, previous research on cooperatives has primarily focused on their internal problems and has neglected to examine the factors responsible for their success,

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as highlighted by Iliopoulos and Valentinov (2018), who emphasise that cooperatives present a very successful organisational form worldwide, despite popular misconceptions. Borda-Rodriguez and Vicari (2014) further observe that in recent decades, African agricultural cooperatives have continued to grow despite poor management, government interference, and general institutional failure.

In South Africa, for example, Ortmann and King (2007a), Ortmann and King (2007b), and Nganwa et al. (2010) have shown that several institutional problems hinder cooperatives from becoming business enterprises capable of addressing the agricultural development needs of rural communities. Iliopoulos and Cook (1999), among others, have identified institutional problems, such as transaction costs, horizon costs, and free-rider problems, as plaguing agricultural cooperatives in South Africa. However, the potential for agricultural cooperatives to emerge as genuine member-controlled and business-oriented organisations that improve the well-being of vulnerable people remains a critical developmental issue. Agricultural cooperatives need to become business-oriented organisations to effectively address agricultural development problems in rural communities while also meeting the social needs of their members and communities.

The introduction of the New Cooperatives Act, No. 14 of 2005, in South Africa, along with the provision of grant funding for cooperatives serving large-scale farms, resulted in a proliferation of new agricultural cooperatives catering to smallholders and following traditional cooperative structures. During that period, agricultural economists generally criticised traditional cooperatives due to their inherent susceptibility to free-rider problems (Ortmann and King, 2007a; Ortmann and King, 2007b; Nganwa et al., 2010; Sparks et al., 2011). The focus was on implementing institutional and organisational arrangements to mitigate such problems. Case studies conducted by Nganwa et al. (2010) demonstrated that relatively successful cooperatives in South Africa often adapted their rules to strengthen their institutional and organisational arrangements. More recently, Iliopoulos and Valentinov (2018) have indicated a renewed interest in cooperatives, highlighting that certain cooperatives, including those that are traditionally structured, have succeeded despite their vulnerability to free-rider problems.

One aspect of agricultural cooperatives in South Africa that needs more research is the correlation between their success and access to commodity markets. Economic theory suggests that smallholder farmers can reap benefits from collective action in production and marketing by spreading fixed costs over a larger volume, among other advantages. Understanding the concept of market access in context is essential, as it encompasses multiple dimensions and indicators (Chamberlin and Jayne, 2013). In the context of South African agricultural cooperatives, the Department of Agriculture, Forestry and Fisheries (DAFF) defines market access as technical and non-technical measures for goods to enter a market (DAFF, 2015). Market access is crucial in achieving developmental goals (Bennett and Rich, 2019) and generating income for smallholder farmers (Heijden and Vink, 2013). Kamara (2004) also linked increased agricultural productivity to improved market access in rural communities. According to Bennett and Rich (2019), market access for smallholder farmers remains a challenge in developing countries. They highlight that excluding smallholder farmers from the benefits of market access is a concern for the government, which aims to promote the market choices of smallholder producers through its objectives and policies. In order to foster commercial smallholder production and facilitate the upward movement of smallholder farmers involved in agricultural cooperatives within the value chain, policies and objectives promoting market choice should strive to create accessible markets that enable the sharing of benefits among producers, processors, and traders. Market choice for agricultural cooperatives involves a decision-making process through which specific markets or target segments are selected for particular products or services. This process entails the assessment of various factors, including market demand, competition, pricing, distribution channels, and consumer preferences, to determine the most suitable market opportunities for cooperative members. Therefore, policies and objectives that promote market choice for cooperative members should facilitate commercial smallholder production and enable smallholder farmers involved in agricultural cooperatives to move up the value chain (Bennett and Rich, 2019). However, the potential to reap benefits from collective action is more significant for undifferentiated commodities than for differentiated products, as the latter require more coordination and marketing efforts.

Data envelopment analysis (DEA) is commonly used to measure the relative efficiency of decision-making units (DMUs), producing efficiency scores as fractional data. For instance, Wijesiri et al. (2015), Stewart et al. (2016), and Yobe et al. (2022) have utilised DEA to estimate financial and social efficiency scores for financial and social goals. Financial efficiency refers to the effectiveness and productivity of financial resources and operations within agricultural cooperatives. It encompasses cost management, revenue generation, profitability, and financial sustainability measures. On the other hand, social efficiency refers to the extent to which agricultural cooperatives effectively fulfil their social objectives and contribute to the well-being of their members and the broader community. It includes aspects such as the equitable distribution of benefits, social impact, member participation, and community development. Specifically, Wijesiri et al. (2015), Yobe et al. (2020), and Yobe et al. (2022) have employed input costs such as labour, operating expenses, and financial expenses to estimate social and financial efficiency measures. Norton et al. (2003) and Ai and Norton (2003) have demonstrated that interaction terms are essential in estimating how the effect of one explanatory variable depends on the magnitude of another explanatory variable when determining the outcome variable. Therefore, incorporating interaction terms into efficiency scores, as demonstrated by Norton et al. (2003) and Ai and Norton (2003), can provide insights into agricultural cooperatives' financial and social goals, for which the efficiency scores serve as proxies. The use of interaction terms to explain key relationships has attracted the attention of several researchers, including Sánchez-Navarro et al. (2023), Karaca-Mandic et al. (2012), and Hoefele et al. (2016).

Furthermore, to comprehensively analyse the various market access attributes highlighted by DAFF (2015), this study employs a categorisation approach for different market typologies. This approach has previously been utilised in research, as demonstrated by Yobe et al. (2019), Nainggolan et al. (2013), and Diniz et al. (2013), who employed a multivariate technique comprising principal component analysis (PCA) and K-means cluster analysis to construct typologies. These studies showcase how clustering the market access attributes enables differentiation between different markets accessed by agricultural cooperatives and provides a deeper understanding of the typologies. Lastly, the study employs the multinomial logit model to estimate the effects of social and financial efficiency on access to various market typologies.

This study investigates the role of social and financial goals in agricultural cooperatives and their impact on market access. The article proposes an approach to examine how agricultural cooperatives' financial and social efficiency influence their access to different market typologies. In other words, the research question addressed in this paper is: What is the relationship between financial and social efficiency and the market access of agricultural cooperatives in South Africa? Previous studies have shown that institutions often pursue social and financial goals (Wijesiri et al., 2015; Stewart et al., 2016; Yobe et al., 2020, 2022). While the importance of these goals in microfinance institutions has been well-established (Bibi et al., 2018; Wijesiri et al., 2015), there needs to be corresponding research that delves into the understanding of similar goals in agricultural cooperatives. Therefore, this article aims to provide empirical evidence on the interplay between agricultural cooperatives' financial and social efficiency and their market access. The results of this study will contribute to the understanding of the factors that influence the relative success of certain cooperatives. Additionally, these findings will inform government programs to establish new cooperatives and revitalise existing ones that have mainly become inactive in South Africa and other regions. Researching cooperatives is crucial, as these organisations have the potential to promote sustainable development in agricultural sectors and improve the living standards of rural households in many countries.

This paper examines the relationship between agricultural cooperatives and market access. The paper is structured as follows: Section 2 provides an overview of agricultural cooperatives and their role in facilitating market access for small-scale farmers. Section 3 outlines the methodology used to analyse the data, including the sample selection and data collection procedures. Section 4 presents the results of the analysis. Section 5 discusses the implications of the findings for policy and practice, highlighting the opportunities and challenges associated with agricultural cooperatives in the context of the enhancement of small-scale farmers' market access. Finally, Section 6 presents the conclusion and recommendations for future research and policy initiatives.

Agricultural cooperatives and market access

Market imperfections, high transaction costs, and information asymmetries constrain market access and market choice for smallholder farmers in many developing countries (Alene et al., 2008). Agricultural cooperatives and similar farmer organisations that foster collective action offer an alternative to individual marketing, helping farmers overcome these challenges and constraints (Markelova et al., 2009).

From a new institutional economics perspective, Nganwa et al. (2010) and Verhofstadt and Maertens (2014) emphasise the importance of exploring the performance of agricultural cooperatives. They argue that reducing transaction costs is crucial for establishing and operating smallholder cooperatives. Farmer organisations provide critical services for their members' market access, such as knowledge dissemination, training, extension services, and financial support, ultimately increasing farm profits (Hellin et al., 2009).

Through collective action, members of agricultural cooperatives gain better bargaining power with large buyers and input suppliers, resulting in reduced input and transaction costs and improved market access (Verhofstadt and Maertens, 2014). However, establishing a viable organisation is a complex process with several challenges, including agreeing on rules, securing member buy-in, ensuring participation and contribution, and enforcing compliance with regulations (Gadzikwa et al., 2006). Under specific conditions, high transaction costs may discourage farmers from organising (Hellin et al., 2009). Market access for differentiated commodities also poses transaction cost challenges for small producers seeking to take advantage of collective action. Additionally, members with limited resources, such as education, financial capacity, and management skills, may need help to participate successfully (Hellin et al., 2009).

The performance of cooperatives depends on the type of products they produce and the market they serve (Ito et al., 2012; Verhofstadt and Maertens, 2014). Cooperatives typically focus on specific enterprises, and the type of enterprise and the target market are crucial for their success. Access to markets directly impacts cooperatives' farm performance, but the results vary depending on the crops or livestock produced. Some studies suggest that cooperatives are better suited to the cultivation of higher-value crops like horticultural products, while transaction costs may be higher for perishable goods than for non-perishable staple foods (Bernard and Spielman, 2009; Markelova et al., 2009; Verhofstadt and Maertens, 2014; Alene et al., 2008; Barham and Chitemi, 2009).

Improving smallholder farmers' access to input and output markets is crucial for the enhancement of farm productivity and raising living standards, as Chamberlin and Jayne (2013) have emphasised. They point out two main features of the current discourse on market access policy in sub-Saharan Africa. Firstly, the challenging environment for smallholder farmers is characterised by remote locations, far from input and produce markets, resulting in increased costs and limited access to support services. Secondly, the need for more clarity in defining market access and the ad hoc selection of indicators pose challenges in understanding and addressing market access issues (Chamberlin and Jayne, 2013).

METHODOLOGY

Data

The present study utilises data from the Cooperative Data Analysis System (CODAS) database to analyse agricultural cooperatives in South Africa. Three hundred and eighty-one agricultural cooperatives with complete data were selected from a database of 3,197 cases from 2017. Cases with missing observations were excluded from the analysis. The Directorate of Cooperatives and Enterprise Development obtained permission to access the online data, which were then retrieved using Microsoft Excel and subsequently imported into Statistical Package for the Social Sciences (SPSS) and Stata software for analysis.

Analytical techniques

Multivariate approach for classification

The Cooperative Data Analysis System (CODAS) is an Information Management System developed explicitly for agricultural, forestry, and fisheries cooperatives. Its primary objectives include facilitating data storage, collation, and analysis in an accessible format to ensure data accuracy, reliability, and currency. Additionally, CODAS aims to assess the current status, performance, and scope of existing cooperatives in South Africa's agriculture, forestry, and fisheries sectors. To achieve these goals, a questionnaire was administered to agricultural cooperatives to gather data on their market access attributes. The questionnaire comprised a series of targeted questions designed to elicit information on various aspects of market access, such as the types of markets accessed by the cooperatives and the nature of the products they sell. This study obtained the relevant information from CODAS and analysed it to identify the key factors influencing agricultural cooperatives' market access and propose strategies to enhance their market access. By utilising the questionnaire responses, the researchers could identify the cooperatives' strengths and weaknesses with respect to market access and provide recommendations for improvement.

The study employed a multivariate approach to establish market access typologies by combining principal component analysis (PCA) and K-means cluster analysis. According to Jolliffe (2002), PCA is a technique used to reduce data dimensionality while retaining most of the original information. By generating orthogonal linear combinations of the variables, PCA identifies the principal components (PCs) that account for the largest variance in the data. The first PC captures the highest variance and is orthogonal to subsequent PCs. Similarly, the second PC accounts for the second largest variance and is orthogonal to both the first PC and any subsequent PCs, and so on. To facilitate interpretation and simplify the factor structure of the data, varimax rotation is often applied (Costello and Osborne, 2005). However, it is important to note that varimax rotation does not enhance the variance extracted from the items (Costello and Osborne, 2005). In some cases, the PCA scores obtained from the initial estimation can be utilised as inputs in a subsequent PCA estimation.

Similarly, Alinovi et al. (2009, 2010) and Ciani and Romano (2014) employed a two-stage factor analysis technique to calculate an index measurement. Initially, the observed variables obtained from the data collection instrument were used to estimate the first set of latent variables, and subsequently these latent variables were used to compute a multidimensional latent variable. Estimating PCA dimensions for the second time enhances the accuracy of the results and facilitates interpretation.

One of the advantages of K-means cluster analysis is its ability to address potential misclassification of observations at the boundaries between clusters (Hair et al., 2006), thereby further improving the dimensionality reduction achieved through PCA. Kaur and Kaur (2013) highlight that PCA scores are appropriate inputs for K-means cluster analysis, unlike dummy variables, as the K-means algorithm requires continuous and numeric variables. Hence, directly applying K-means cluster analysis to dummy variables (i.e., qualitative data) would be inappropriate. In this study, K-means cluster analysis utilises the market access typology dimensions obtained from PCA, as explained earlier. This multivariate approach has recently been employed by Yobe et al. (2019), Diniz et al. (2013), Nainggolan et al. (2013), and Dossa et al. (2011).

Additionally, K-means cluster analysis aims to group the dimensions into homogeneous clusters. For this study, after performing K-means clustering on the PCA dimensions, the desired outcome would be reasonably homogeneous groupings of market access typologies. Moreover, the cluster solutions should align with relevant background knowledge. If very few observations are assigned to these clusters, they are deemed unsuitable, should not be further used in the analysis, and should be discarded (Hair et al., 2006). The validity of the clustering process and the reliability of the created clusters can be assessed by the statistical significance of the cluster groupings in a one-way ANOVA, as demonstrated by Yobe et al. (2019).

Market access typologies based on indicators such as subsector, commodities produced, type of business (main or secondary activity), and market type were employed by DAFF (2015). However, due to the issue of dimensionality, such data are limited in their ability to provide meaningful market access indicators since there is no clear group structure. In such cases, clustering the data allows for the emergence of a distinct group structure (Jolliffe, 2002). By employing PCA on the binary variables, the dimensionality of the data is reduced, enabling the categorisation of market access into distinct typologies (Jolliffe, 2002), as applied in previous studies by Yobe et al. (2019), Nainggolan et al. (2013), and Diniz et al. (2013). The PCA scores extracted and retained for the market access typologies were subjected to varimax rotation. This study utilised two rounds of PCA. Hair et al. (2006) suggest that PCA is appropriate for variables when the Kaiser-Maier-Olkin (KMO) values exceed 0.5 and when Bartlett's sphericity test yields a statistically significant result ($p < 0.05$).

The choice of a suitable clustering algorithm depends mainly on the size of the dataset. Hierarchical clustering is preferable for datasets with a relatively small sample size, typically less than 250 (Garson, 2009 cited in Chibanda et al., 2009). Conversely, larger datasets require algorithms such as K-means clustering. Kaur and Kaur (2013) note that the K-means algorithm is better equipped to handle larger datasets, typically containing more than 250 observations.

Multinomial logistic regression

The multinomial logistic (MNL) regression model estimates the effects of the variables that influence the agricultural cooperatives' choices of market access typologies. Financial and social efficiency and several other independent variables are included in the model. The MNL model predicts the likelihood of an agricultural cooperative of given characteristics selecting an identifiable market access typology.

The probability associated with a cooperative selecting a particular market access typology is represented by P_{nj} (j = 1, 2, 4 and 5), where n represents the agricultural cooperative; j = 1 represents the cooperative selecting the market typology in Cluster 1; j = 2 represents the cooperative choosing the typology in Cluster 2; and so on. According to Train (2009), if the unobserved utility portion (ε_n) is identically and independently distributed (iid) across alternatives, then the specification of the MNL model is as follows:

$$P_{nj} = \frac{e^{(\beta' X_{nj} + \gamma' H_{nj})}}{\sum_{j=1}^{4} e^{(\beta' X_{nj} + \gamma' H_{nj})}} \tag{1}$$

If the βs and the γs are set to zero for one of the activities (for instance, cluster 1), the MNL model for each activity ($j \neq 1$) can be expressed as:

$$P_{nj,j\neq 1} = \frac{e^{(\beta' X_{nj} + \gamma' H_{nj})}}{1 + \sum_{j=2}^{4} e^{(\beta' X_{nj} + \gamma' H_{nj})}} \; (j = 2, 4 \text{ and } 5) \text{ and}$$

$$P_{n1} = \frac{1}{1 + \sum_{j=2}^{4} e^{(\beta' X_{nj} + \gamma' H_{nj})}} \tag{2}$$

Where: H_n – is a random disturbance, and X_{nj} – is the explanatory variable.

Selection of Input and output variables

When using DEA to assess the relative efficiency of DMUs (Decision-Making Units), fractional data scores are generated, representing financial and social efficiency scores. Several important input variables should be considered when estimating financial efficiency through DEA, including labour (Stewart et al., 2016; Wijesiri and Meoli, 2015; Wijesiri et al., 2015; Bibi et al., 2018; Yobe et al., 2020, 2022) and operating expenses (Bibi et al., 2018; Wijesiri and Meoli, 2015; Fernandes Filipa Da et al., 2018). Financial efficiency was estimated in the first stage of DEA by Bibi et al. (2018), Wijesiri et al. (2015) and Yobe et al. (2020). Regarding the selection of the output variable for social efficiency in DEA, insights from previous studies on agricultural cooperatives were considered (Yobe et al., 2020, 2022). The number of active borrowers was used as a proxy for the output variable for social efficiency by Wijesiri and Meoli (2015) and Bibi et al. (2018). Additionally, Bibi et al. (2018) utilised input variables such as operating and financial expenses to estimate social efficiency. Overall, indicators such as the number of registered members in agricultural cooperatives and associated labour and operating expenses serve as measures for assessing social efficiency using DEA. This study employed the CCR (Charnes, Cooper, and Rhodes) model, a DEA model which is a widely used non-parametric linear programming approach for estimating the relative efficiencies of DMUs with multiple inputs and outputs. Table 1 presents the indicators for these input and output variables and their definitions.

RESULTS

The findings of the multivariate analysis are presented in Table 2. The application of PCA to the market access

Table 1. Input and output variables used in the DEA model to assess financial and social efficiency in the current year (in Rands)

Specification	Indicators	Definition
Input variables	labour expenses[a,b]	annual wage expenses (Rand)
	operating and financial expenses[a,b]	annual operating expenditure (Rand)
Output variables	turnover[a]	annual turnover (Rand)
	membership[b]	number of registered members

[a]Denotes variables used for the financial efficiency indicator.
[b]Denotes variables used for the social efficiency indicator.
Source: own elaboration.

Table 2. Principal component loading estimated scores for market access indicators – first round

Component	PC-1	PC-2	PC-3	PC-4	PC-5	PC-6	PC-7	PC-8
Eigenvalues	1.92	1.62	1.52	1.38	1.33	1.14	1.11	1.00
% of variance	12.80	10.80	10.12	9.17	8.88	7.63	7.42	6.69
Cumulative %	12.80	23.60	33.72	42.89	51.77	59.40	66.82	73.51
Market access indicators								
Fruit and vegetables[1]	**0.8013**			–0.3867				
Livestock[1]	–0.7503			–0.3957				
Fruit and vegetables[2]	–0.5907		0.4608				–0.3115	
Livestock[2]	0.4991		0.4852					–0.3120
Forestry[2]		**0.8610**						
Forestry[1]		0.8568						
None specified[2]			–0.9358					
Fisheries[1]			–0.3553					
Crops[1]				0.9637				
Other[1]					0.8249			
Processing[1]						0.8272		
Processing[2]					0.5066	0.6051		
Crops[2]							0.9571	
Formal market access								0.6850
Other[2]					0.3892	–0.3220		0.5688

Extraction method: Principal component analysis (PCA).
Rotation method: Varimax with Kaiser normalisation.
Principal component scores less than 0.3 were suppressed.
Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy = 0.116.
Bartlett's test of sphericity: *df* = 105; approx. chi-square = 2012.623; Sig. = 0.000.
[1]Denotes the main type of business. [2]Denotes the secondary type of business.
Source: own elaboration.

typologies resulted in eight principal components (PCs) that accounted for 73.51% of the variance in the data, with an eigenvalue of one (Table 2). The KMO measure and Bartlett's sphericity test yielded values of 0.716 and a p-value less than 0.001, respectively, indicating that the dataset of agricultural cooperative households could be appropriately factored in. A varimax rotation with Kaiser normalisation was performed on the PCs to enhance interpretation. Additionally, PC coefficients below 0.3 were suppressed to facilitate ease of interpretation.

PC-1 explains the most considerable variation (12.80%) in agricultural cooperatives' market access typology scores. This PC represents primary and secondary fruit and vegetable and livestock production activities. Livestock farming as the main activity and fruit and vegetable production as the secondary activity have negative loadings on this PC. Due to the dominant contribution of fruit and vegetable production as the main activity, PC-1 is labelled "Fruit, Vegetable, and Livestock Production".

PC-2 accounts for 10.80% of agricultural cooperatives' market access and participation variance. It is predominantly influenced by forestry as both a main and secondary activity. Therefore, PC-2 is named "Forestry".

PC-3 explains 10.12% of the variance and represents agricultural cooperatives in fruit and vegetable production and forestry as secondary activities. Thus, it is labelled "Fruit, Vegetable, and Livestock Production – Secondary".

Table 3. Principal component loading estimated scores for market access indicators – second round

Component	PPC-1	PPC-2	PPC-3	PPC-4	PPC-5	PPC-6
Eigenvalues	1.00	1.00	1.00	1.00	1.00	1.00
% of variance	12.50	12.50	12.50	12.50	12.50	12.50
Cumulative %	12.50	25.00	37.50	50.00	62.50	75.00
Market access indicators						
PC-2: Forestry[1,2]	0.7355					
PC-4: Cropping[1]	0.6273					
PC-5: Other activities[1,2]		0.8645				
PC-3: Fruit, vegetable[2] and livestock production[2]		–0.4554	–0.3903	–0.3065		
PC-7: Cropping[2]			0.9002			
PC-1: Fruit, vegetable[1] and livestock production[2]				0.9341		
PC-8: Formal market access					0.9523	
PC-6: Processing[1,2]						0.9331

Extraction method: Principal component analysis (PCA).
Rotation method: Varimax with Kaiser normalisation.
Principal component scores less than 0.3 were suppressed.
[1]Denotes the main type of business. [2]Denotes the secondary type of business.
Source: own elaboration.

PC-4, contributing 9.17% of the variance, captures agricultural cooperatives primarily engaged in cropping, with reduced participation in fruit and vegetable production and livestock farming. It is identified as "Cropping – Main".

PC-5 reflects significant participation in other main and secondary activities, including processing. Hence, it is named "Other Activities". It explains 8.88% of agricultural cooperatives' market access variance.

PC-6 explains 7.63% of the variance and represents agricultural cooperatives heavily involved in processing as both main and secondary activities. It is labelled "Processing", with other secondary activities having negative loadings on this PC.

PC-7 accounts for 7.42% of the variation and represents the dimension of agricultural cooperatives participating in cropping as a secondary activity. It is referred to as "Cropping – Secondary".

Finally, PC-8 contributes 6.69% of the variation in the data. It is characterised by positive loadings of variables related to formal market access and other activities, leading to its designation as "Formal Market Access."

The estimated PC scores for the market access dimensions obtained in the first round of PCA were inputs in the second PCA estimation. The results of this procedure on the eight market access dimensions demonstrated that agricultural cooperatives could be further classified. Six PC dimensions were obtained, as reported in Table 3. PPC-1 shows that forestry and cropping – main could be grouped. In this regard, PPC-1 was named "Forestry and Cropping – main". In the PPC-2 dimension, other activities dominated and was therefore given the name "Other activities". PPC-3 was dominated by PC-7, Cropping – secondary, and loaded negatively by PC-1, Fruit, vegetable and livestock production – secondary. Therefore, PPC-3 was named "Cropping". The dimension PC-1, Fruit, vegetable and livestock production – main, dominated PPC-4, and thus PPC-4 was named "Fruit, vegetable and livestock production – main". The last two PCs, PPC-5 and PPC-6, represented Formal market access and Processing, respectively; hence, PPC-5 was called "Formal market access" and PPC-6 "Processing".

K-means clustering was subsequently used on the six market access dimensions of the second stage of PCA to group variables into distinct clusters. Table 4 shows these PC dimensions across the five clusters. The results of the K-means clustering show that the PCA dimensions could be grouped into reasonably homogeneous groupings. The respective clusters were named

Table 4. Agricultural cooperatives' market access dimensions across clusters

PC dimensions of market access	1 Forestry[1,2] and Cropping[1], Other activities[1,2]	2 Processing[1,2], Fruit & vegetable[1] and livestock production[2]	4 Formal market access	5 Cropping[2]
Forestry[1,2] and cropping[1]	**1.2202**	–0.1546	–0.5034	0.6133
Other activities[1,2]	**0.7725**	0.0053	–0.1241	–0.4495
Cropping[2]	–0.5449	–0.1110	–0.1356	**2.8866**
Fruit and vegetable[1] and livestock[2]	0.0230	**0.0528**	0.0373	–0.0600
Formal market access	–0.5004	–0.1140	**0.1741**	0.0904
Processing[1,2]	–0.4660	**1.5491**	–0.61603	0.2036
Observations	69	92	189	31

[1]Denotes the main type of business.
[2]Denotes the secondary type of business.
Cluster 3 was omitted in further analyses.
Source: own elaboration.

based on their relationship with the PC market access dimensions.

The K-means five-cluster solution also made sense based on background knowledge of the agricultural cooperatives and the markets. However, one of the clusters in the solution, i.e. Cluster 3 – Outlier, had at least five observations. In such instances, Hair et al. (2006) state that these observations are outliers, and the cluster should be discarded and not used in further analyses. Cluster 1 represents the agricultural cooperatives whose dominant PC dimensions of market access were forestry (main and secondary activity), cropping (main activity), and other activities (main and secondary activity). This cluster was named "Forestry, cropping, and other activities". The agricultural cooperatives in Cluster 2 represent those institutions participating mainly in processing (main and secondary activity), fruit and vegetable (main activity) and livestock production (secondary activity) and, as a result, this cluster was called "Fruit, vegetables, livestock, and processing". Naming Clusters 4 and 5 was relatively straightforward. The PC dimensions representing formal market access and cropping as a secondary activity loaded strongly on Clusters 4 and 5, respectively, and the clusters were thus named "Formal market access" and "Cropping – secondary", respectively.

Table 5 presents the results of the one-way ANOVA of the K-means cluster analysis. The results confirm that

Table 5. ANOVA results for the K-means cluster analysis

PC dimensions of market access	Cluster		Error		F	Sig.
	Mean square	df	Mean square	df		
Forestry[1,2] and Cropping[1]	16.3371	5	0.8102	404	20.1647	*
Other activities[1,2]	57.7742	5	0.2973	404	194.2980	*
Cropping[2]	68.5028	5	0.1646	404	416.2533	*
Fruit and vegetable[1] and livestock[2]	45.7345	5	0.4464	404	102.4622	*
Formal market access	69.1460	5	0.1566	404	441.5217	*
Processing[1,2]	3.4265	5	0.9700	404	3.5326	*

*$p < 0.01$.
[1]Denotes the main type of business.
[2]Denotes the secondary type of business.
Source: own elaboration.

Table 6. Definitions and summary statistics of the variables used in the analysis

Variable definition	Mean	Std. Dev.	Min	Max
DEA input variables				
Annual expenditure (in '000 rands)	171.00	654.00	35.00	7546
Annual wages (in '000 rands)	87.00	619.00	11.00	1.16e+4
DEA output variables				
Annual turnover (in '000 rands)	332.00	2 052.00	10.00	3.80e+04
Number of registered members	30	158	1	2 565
Second-stage explanatory variables				
Financial efficiency (FIN_EFF)[a]	0.1682	0.1521	0.0029	1
Social efficiency (Registered members) (SOC_EFF)[a]	0.0136	0.0755	0.0000	1
Years since registration (AGE)	9.2598	14.6029	1	118
Animals (ANIMALS)[b]	0.22047	0.4151	0	1
Cooperative size (COOPSIZEOP_1)[c]	0.0051	1.0320	–1.0747	14.099
Cooperative borrowings (COOPBORROW_2)[c]	0.0103	1.0340	–1.5502	14.4676
Active members (NUM_ACT)	25.6089	144.6761	0	2 565
AGM attendees (NUM_AGM)	23.3700	142.2927	0	2 565
Management committee (NUM_MGTCOM)	5.5302	2.7639	0	20
Managers (NUM_MGR)	0.75066	0.4332	0	1
Full-time employees (EMP_FT)	5.7192	27.5902	0	500
Part-time employees (EMP_PT)	2.8084	9.7903	0	150
Financial management training (FIN_MGT)[b]	0.2572	0.4377	0	1
Corporate governance training (CORP_GOV)[b]	0.1207	0.3263	0	1
Marketing training (MRKTING)[b]	0.1575	0.3647	0	1
Accounting and bookkeeping (ACC_BKPNG)[b]	0.5958	0.4914	0	1

Number of observations = 381.
[a]DEA score.
[b]Dummy variables where 1 = yes, 0 = no.
[c]See below for the estimation of these PCA variables.
Source: own elaboration.

the method was suitable for classifying the retained PC clusters. The PC dimensions in the study were statistically significant ($p < 0.01$), suggesting that the predetermined number of clusters was suitable for clustering.

The descriptive statistics presented in Table 6 characterise the sample agricultural cooperatives in South Africa. Low financial and social efficiency scores indicate relatively inefficient agricultural cooperatives. The cooperatives' age averaged nearly ten years. On average the cooperatives had 26 active members and 24 members who attended AGMs. The cooperatives had six individuals on their management committees, on average.

Furthermore, the results show that some cooperatives did not have managers. Institutions that reported having managers had a maximum of one individual with this designation. The number of full-time employees of cooperatives in the sample ranged from 6 to 500 (mean = 6), and the number of part-time employees ranged from 3 to 150 (mean = 3).

Principal component analysis: Kaiser-Meyer-Olkin, total variance explained, Bartlett's Test and scree plot for membership dimensions

The PCs for cooperative size were also extracted from the correlation matrix of variables presented in Table 9. The KMO measure was 0.532, and Bartlett's test was statistically significant at $p < 0.001$. Two dimensions of

Table 7a. Principal component analysis: Kaiser-Meyer-Olkin for membership dimensions

Measure of sampling adequacy.		0.762
Bartlett's test of sphericity	Approx. Chi-square	26512.374
	df	435
	Sig.	0.000

Table 7b. Principal component analysis: Total variance explained for membership dimensions

Component		1	2	3	4	5	6	7	8
Initial eigenvalues	total	11.052	3.644	2.627	1.874	1.773	1.416	1.181	1.002
	% of variance	36.840	12.147	8.756	6.248	5.910	4.722	3.936	3.341
	cumulative %	36.840	48.987	57.742	63.990	69.900	74.622	78.558	81.898
Extraction sums of squared loadings	total	11.052	3.644	2.627	1.874	1.773	1.416	1.181	1.002
	% of variance	36.840	12.147	8.756	6.248	5.910	4.722	3.936	3.341
	cumulative %	36.840	48.987	57.742	63.990	69.900	74.622	78.558	81.898
Rotation sums of squared loadings	total	10.551	3.807	2.574	1.969	1.859	1.380	1.230	1.199
	% of variance	35.170	12.690	8.581	6.562	6.196	4.601	4.100	3.998
	cumulative %	35.170	47.860	56.441	63.003	69.199	73.800	77.900	81.898
Female AGM		0.988							
Female last AGM		0.984							
Female active		0.980							
Youth active		0.980							
Youth registered		0.978							
Youth AGM		0.977							
Male AGM		0.961							
Male last AGM		0.960							
Male active		0.958							
Female registered		0.931							
Male registered		0.916							
Number of employees (FT.)			0.982						
Female employees (FT)			0.968						
Male Employees (FT)			0.953						
Youth employees (FT)			0.904						
Female comm# chair				–0.877					
Male comm# chair				0.834					
Male manager				0.653					
Female manager				–0.652					
Disabled AGM					0.946				

Table 7b – cont.

Component	1	2	3	4	5	6	7	8
Disabled registered				0.938				
Male employees (PT)					0.836			
Female employees (PT)					0.757			
Male mgmt comm#					0.510			
Youth mgmt comm#						0.739		
Youth comm# chair						0.620	0.486	
Youth employees (PT)					0.414	0.451		
Youth manager							0.887	
Disabled employees (FT)								0.696
Female mgmt comm#								0.570

Extraction method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 6 iterations.
Source: own elaboration.

Table 8. Linear regression for social and financial efficiency models

Independent variables	Social efficiency		Financial efficiency	
	Coef.	Rob. SE.	Coef.	Rob. SE.
Years since registration (AGE)	–0.0001	0.0008	**0.0046****	**0.0023**
Squared Years registered (AGE_SQ)	5.719e-07	6.69e-06	**–4.129 e-05****	**1.89e-05**
Piggery farming (PIGGERY)[a]	–6.586e-7	4.74e-07	**–4.145e-06*****	**7.08e-07**
Poultry farming (POULTRY)[a]	–1.829e-7	1.24e-07	–1.525e-7	4.60e-07
Cooperative size (COOPSIZEOP_1)[b]	**–0.0033***	**0.0017**	**–0.0101****	**0.0046**
Cooperative borrowings (COOPBORROW_2)[b]	–0.00156	0.0009	0.0014	0.0137
Accounting and bookkeeping compliance (ACCBK_COMPL)[a]	0.0047	0.0099	–0.0109	0.0164
Annual financial audit compliance (FINAUD_COMPL)[a]	–0.00136	0.0086	0.0352	0.0249
VAT compliance (VAT_COMPL)[a]	0.0053	0.0063	**–0.0508****	**0.0201**
Profit tax compliance (PROFIT_COMPL)[b]	–0.0038	0.0074	**0.0430****	**0.0203**
Cooperative principles compliance (COOPPRINC_COMPL)[a]	–0.0021	0.0056	–0.0039	0.0169
_cons	**0.0137*****	**0.0047**	**0.1316*****	**0.0184**
Prob > F		0.0012		0.0000
R-squared		0.0041		0.0469
Observations[b]	385		387	

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.
Rob. SE = Robust standard errors.
[a]Dummy variables where 1 = yes, 0 = no.
[b]See above for the estimation of these PCA variables.
Source: own elaboration.

Table 9. Variables used to compute cooperative size dimensions (n = 381)

Variable	Mean	Std. Dev.	Min	Max
Expenditure (EXPENYR)	176.00	611.00	0.06	6,875.00
Turnover (TURNYR)	379.00	185.00	0.05	2,710,000.00
Annual wages (WAGEYR)	59.00	186.00	0.03	2,645.00
Total owed to creditors (OWEDYR)	6.00	458.00	0	650.00
Outstanding Loans (banks) (LOANYR)	8.00	587.00	0	650.00

Values in thousands of rands per annum for the previous year 2016/2017.
Source: own elaboration.

cooperative size were extracted, and together they accounted for 71.80% of the variation in the cooperative size indices. These indices had an eigenvalue greater than one. The first PC described the relationship between the turnover, expenditure and annual wages of the agricultural cooperative in the previous year, and it was therefore named 'Size of operations' (COOPSIZEOP_1). This component explained 40.77% of the variation in cooperative size indices.

$$\text{COOPSIZEOP\_1} = 0.877(\text{TURNYR}) + 0.855(\text{EXPENYR}) + 0.721(\text{WAGEYR}) \quad (3)$$

The second component points to a linear relationship between the total money owed to creditors and the outstanding loans to financial institutions, and it indicates the size of borrowing of the agricultural cooperative. Therefore, the PC was named 'Size of borrowings' (COOPBORROW_2).

$$\text{COOPBORROW\_2} = 0.889(\text{OWEDYR}) + 0.804(\text{LOANYR}) \quad (4)$$

Residuals prediction

Ordinary Least Squares (OLS) regression estimated the social and financial efficiency models. Afterwards, the predicted residuals from these OLS regressions were included in the second-stage regressions to test for endogeneity. The estimated social and financial efficiency models are presented in Table 8.

The results presented in Table 8 indicate a decrease in financial efficiency associated with participation in piggery farming. Furthermore, for every one-year increase in the age of agricultural cooperatives, the financial efficiency score is expected to rise by 0.005. However, this positive effect on financial efficiency eventually diminishes as the institutional age increases, leading to decreased financial efficiency.

Additionally, the findings reveal that compliance with Value Added Tax (VAT) regulations is associated with a lower financial efficiency score. On the other hand, adherence to profit tax requirements is linked to an increase in the financial efficiency score.

Variables for cooperative size dimensions

The PCs for cooperative size were extracted from the correlation matrix of variables presented in Table 9. As described earlier, the KMO measure and Bartlett's sphericity test were also used. The use of varimax with the Kaiser normalisation rotation was also included. The KMO measure was 0.532, and Bartlett's test was statistically significant at $p < 0.001$. The two extracted dimensions measuring overall cooperative size accounted for 71.80% of the variation in the cooperative size indices. Indices which had eigenvalues greater than one were Cooperative size (COOPSIZEOP_1) and Cooperative borrowings (COOPBORROW_2).

The first PC describes the relationship between turnover, expenditure, and annual wages in the previous year. This component explains 40.77% of the variation in cooperative size indices. The second component points to a linear relationship between total money owed to creditors and outstanding loans to financial institutions.

Multinomial logistic (MNL) regression models for market access typologies

Table 10 presents the three regression models employed to identify the factors influencing the market access typology. In the first model, the potential impacts of endogeneity were not considered during the estimation. However, the other two models addressed endogeneity

Table 10. Multinomial logistic (MNL) regression estimates (coefficients only)

	Cluster 1 (Forestry and Cropping, Other activities)			Cluster 2 (Processing, Fruit & vegetable and livestock production)			Cluster 5 (Cropping)		
Independent variables	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Financial efficiency (FIN_EFF)	–1.055	**25.23****	**25.06****	0.151	–3.688	–3.747	0.259	6.775	7.725
Social efficiency (SOC_EFF)	15.95	**310.1*****	**328.1*****	16.65	33.32	25.85	**17.50***	263.1	268.1
Years since registration (AGE)	0.0645	**–0.156****	**–0.152****	0.0558	0.0371	0.0370	0.00230	0.0136	0.0139
Squared years registered (AGE_SQ)	5.23e-4	**1.47e-3****	**1.44e-3****	9.35e-5	6.02e-5	5.93e-5	3.31e-4	8.01e-5	7.61e-5
Animals (ANIMALS)[a]	**–1.055*****	**–1.187*****	**–1.185*****	**–1.349*****	**–1.365*****	**–1.368*****	**–1.153***	**–1.199***	**–1.215***
Cooperative size (COOPSIZEOP_1)[b]	**0.447***	**1.703*****	**1.707*****	0.310	0.338	0.318	0.415	**1.297***	**1.320***
Cooperative borrowings (COOPBORROW_2)[b]	**0.306****	**0.694*****	**0.690*****	0.212	0.240	0.243	0.279	0.0600	0.0589
Active members (NUM_ACT)	0.0136	0.0138	0.00671	0.0353	0.0349	0.0368	0.0304	0.0300	0.0323
AGM attendees (NUM_AGM)	0.0112	0.0120	0.00838	0.0304	0.0300	0.0302	0.0237	0.0233	0.0245
Management committee (NUM_MGTCOM)	0.106	**–0.127***	**–0.128***	**–0.0974***	**–0.101***	**–0.103***	0.0513	0.0247	0.0206
Managers (NUM_MGR)	0.386	0.355	0.345	**0.877****	**0.911****	**0.934****	0.168	0.257	0.231
Full-time employees (EMP_FT)	0.0100	0.0101	0.0107	**–0.0166***	0.0157	0.0146	0.0196	0.0198	0.0186
Part-time employees (EMP_PT)	0.0168	0.0233	0.0227	0.00619	0.00821	0.00877	0.0786	0.0960	0.100
Financial management training (FIN_MGT)[a]	**–0.852***	**–0.867***	**–0.954***	0.0183	0.0152	0.0298	0.723	0.700	0.700
Corporate governance training (CORP_GOV)[a]	0.546	0.563	0.545	**–0.949***	**–0.918***	**–0.933***	0.581	0.580	0.605
Marketing training (MRKTING)[a]	0.530	0.670	0.620	0.352	0.326	0.330	0.708	0.611	0.634
Accounting and bookkeeping (ACC_BKPNG)[a]	0.299	**–1.447****	**–1.313****	0.237	0.200	0.145	0.187	0.694	0.790
Social efficiency residual (SOC_RES)		**–294.7****	**–287.1****		–17.81	–18.35		–246.6	–256.6
Financial efficiency residual (FIN_RES)		**–26.43****	**–25.54****		3.701	3.765		–6.756	–7.542
Financial x social efficiency (FIN_SOC)			**–82.10***			0.910			–5.561
_cons	0.523	**–6.420****	**–6.396****	0.276	0.0245	0.0282	**–2.197*****	–6.044	–6.217

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$.
Number of observations = 381.
Model 1: Parsimonious model; LR Chi-square (51) = 96.68; Prob > Chi-square = 0.0001; Log likelihood = -410.56437; Pseudo R-square = 0.1053.
Model 2: Includes residuals of financial and social efficiency; LR Chi-square (57) = 109.48; Prob > Chi-square = 0.0000; Log likelihood = –404.16512; Pseudo R-square = 0.1193
Model 3: Includes residuals of financial and social efficiency and financial and social efficiency interaction term; LR Chi-Square (60) = 113.33; Prob > Chi-square = 0.0000; Log likelihood = -402.23999; Pseudo R-square = 0. 0.1235
Cluster 3 is an omitted outlier, and cluster 4 is the base category.
[a]Dummy variable.
[b]PCA score.
Source: own elaboration.

concerns by including residuals obtained from the estimation in Table 8. The results of these two models are reported here, as they provide more reliable coefficient estimates. All three models demonstrated an excellent fit to the data, as indicated by the strong rejection of the likelihood ratio Chi-Square test for the hypothesis that all regression coefficients are jointly equal to zero ($p < 0.001$). The presence of statistically significant residuals (FIN_RES and SOC_RES), which controlled for endogeneity in the models, further confirmed the existence of endogeneity. After controlling for endogeneity, the reported coefficients in Table 9 showed similarities between Model 2 and Model 3 but some differences compared to Model 1. The final model included an interaction term for social and financial efficiency. The reference category, Cluster 4 (Formal market access typology), accounted for approximately 49.6% of the agricultural cooperatives in the sample.

The estimated coefficients of the independent variables provide insights into the impact of these variables on the likelihood of agricultural cooperatives engaging in specific market access typologies compared to the base category. The estimated model reveals that an increase in financial efficiency (FIN_EFF) and social efficiency (SOC_EFF) scores enhances the likelihood of agricultural cooperatives participating in market access typologies such as the Forestry, cropping, and other activity cluster, as opposed to the base category. However, a different effect is observed for cooperatives that combine financial and social efficiency (FIN_SOC). In this case, the likelihood of participating in the "Formal market access" typology increases, as indicated by the statistically significant coefficient of the interaction term FIN_SOC in Model 3.

As the age of agricultural cooperatives (AGE) increases, the likelihood of accessing and participating in the "Formal market access" typology increases relative to that of engaging in activities represented in the "Forestry, cropping and other activities" cluster. However, at a certain point the reverse is observed; this effect is captured by the variable called Squared years registered (AGE_SQ).

The estimated negative coefficients of the variable for livestock (ANIMALS) in all the clusters demonstrate that agricultural cooperatives that keep livestock are more likely to access and participate in markets represented by the base category ("Formal market access" cluster) than any other market access typology.

Agricultural cooperatives with a positive score for cooperative size (COOPSIZEOP_1) and borrowings (COOPBORROW_2) generally have a higher likelihood of participating in the market access typology represented by the Forestry cropping and other activities cluster instead of the activities in the base category. In addition, the likelihood of accessing and participating in the type of markets represented in the "Cropping – secondary" cluster increases for agricultural cooperatives with cooperative borrowings (COOPBORROW_2).

As the number of individuals on agricultural cooperatives' management committees (NUM_MGTCOM) increases, they are more likely to engage in the market access typology represented by the base category than they are to access and participate in activities represented by Clusters 1 and 2. The estimated model also shows that cooperatives with managers (NUM_MGR) are more likely to select activities in the base category than those of the "Fruit, vegetables, livestock and processing" cluster.

Agricultural cooperatives that reported having had training in financial management (FIN_MGT) and accounting and bookkeeping (ACC_BKPNG) had a higher likelihood of participating in the market access typologies in the base category rather than those in the"Forestry, cropping and other activities" cluster. The same was also observed for cooperatives that reported having had corporate governance training (CORP_GOV), in that they had a higher likelihood of participating in the base category than in activities in the "Fruit, vegetables, livestock and processing" cluster.

In summary, this study reveals that the participation of agricultural cooperatives in specific markets is influenced by factors such as financial and social efficiency, the age of the institutions, and livestock activities. Additionally, indicators related to the cooperatives' size and borrowing, the presence of individuals on management committees, and the competence of cooperative managers strongly influence market access and participation. Furthermore, it is found that training in financial management, corporate governance, accounting and bookkeeping plays a significant role in facilitating the access of agricultural cooperatives to markets.

DISCUSSION

The regression analyses reveal significant variations in the factors influencing the market choices of agricultural cooperatives. The results highlight the importance of financial and social efficiency, institutional age, cooperative size and borrowing, training in financial management, corporate governance, accounting and bookkeeping, the individuals on management committees, the managers of cooperatives, and livestock activities as crucial factors shaping the market access decisions of agricultural cooperatives.

The study results also show that agricultural cooperatives that are socially and financially efficient are more likely to engage in the market typology represented by the "Forestry, cropping and other activities" cluster than in the formal markets category. The diversification of both wood and non-wood products, as exemplified in this cluster, is a crucial aspect for cooperatives, as emphasised by Hintz and Pretzsch (2023). Inputs for the DEA efficiency scores were labour and operating expenses; the financial efficiency indicator was turnover, while that for social efficiency was the number of registered members. The "Forestry, cropping, and other activities" cluster represents markets that include forestry (as the main and secondary type of business), cropping (as the main type of business), and other activities (as a main and secondary type of business); this cluster is a reasonably diversified market access typology. As for the base category, formal market access activities dominate this typology. Therefore, the higher efficiency scores of cooperatives that optimised the DEA inputs and outputs imply that they could engage in market types identified in the "Forestry, cropping, and other activities" cluster, moving away from activities related to formal market access in the base category. Cooperatives producing for such markets may be better suited to the use and allocation of resources to achieve efficiency. According to Markelova et al. (2009), producer organisations generally require various forms of assistance, such as social and financial assistance, to operate successfully. Often, this help is from outside sources. Markelova et al. (2009) add that while some degree of external assistance is often necessary for these institutions to establish themselves and operate successfully, it can introduce problems related to an organisation's sustainability and dependency.

The studies conducted by Okoye et al. (2016), Mango et al. (2018), and Randela et al. (2008) have all highlighted the significant influence of the household head's age on the decision to participate in or refrain from participating in the marketing of agricultural produce. Although the unit of analysis in these studies differs from that used in the present study, they underscore the importance of age in determining market typologies. The observed shift in market typologies with increasing age has several implications for agricultural cooperatives. The results of this study suggest that older agricultural cooperatives exhibit a certain level of risk aversion when selecting their market typologies. Furthermore, since age is often associated with managerial capacity and experience within institutions (Wijesiri et al., 2015), the choice of specific market typologies may be influenced by age-related attributes. The market typologies preferred by older cooperatives imply a higher likelihood of success, as they represent an optimal combination of enterprises contributing to well-established institutions' success. Other factors contributing to this shift include a reluctance to adopt certain technologies and a drive to minimise transaction costs. Alene et al. (2008) have also identified similar factors affecting market participation among household farmers. According to Wijesiri et al. (2015), age serves as a proxy for managerial ability, indicating that older institutions have acquired the necessary managerial experience to participate in formal markets. This finding helps to explain why older agricultural cooperatives demonstrate a higher likelihood of participation compared to the base category. Age, and the managerial ability it represents, play a crucial role in reducing transaction costs, as increased age facilitates access to market information (Alene et al., 2008).

However, as agricultural cooperatives age, their preference for market typologies tends to change, likely reflecting the experience gained by these institutions over time. With advanced age, agricultural cooperatives acquire a wealth of experience and capabilities (Wijesiri et al., 2015), which provides them with opportunities for diversification. As a result, they may shift from participating in formalised market typologies to those encompassing forestry, cropping, and other types. Furthermore, establishing cooperatives involves formulating rules that govern various aspects, such as membership, employment, meetings, production, and marketing activities. Changing these issues and potentially modifying the rules takes time, which explains the gradual transition in market typology. However, this inflexibility can give rise to a central collective action problem within agricultural cooperatives, known as the free-rider problem (Benos et al., 2023). For instance, when cooperatives fail to adapt quickly to changing market conditions, members may engage in systematic side-selling to competing chain actors. Markelova et al. (2009) emphasise the need for collective action groups to develop the capacity to establish their own rules rather than relying on externally imposed ones, and this process often requires time.

Agricultural cooperatives that owned livestock showed a higher likelihood of selecting the formal market access typology over all the other market typologies. The study of Randela et al. (2008) indicates that livestock ownership is a vital determinant of market choice. However, the effect of livestock ownership in this study is striking. Agricultural cooperatives would be expected to prefer the "Fruit, vegetables, livestock and processing" cluster market typology, including livestock. In rural communities, livestock ownership is associated with various factors, e.g. draught power, risk-aversion (Yobe et al., 2019; Twine, 2013), and wealth accumulation (Mutenje et al., 2010). Therefore, the ownership of assets such as livestock may influence market participation and choice, especially for Clusters 1 (Forestry and Cropping, Other activities) and 5 (Processing, Fruit & vegetable and livestock production). The interesting case of the "Fruit, vegetables, livestock and processing" cluster, which accommodates livestock production, is not easily explained by the factors just mentioned. The choice of market typology could reflect the different marketing arrangements of the two market typologies. Formal markets are far more likely to have favourable marketing arrangements than other typologies, which could be the underlying reason for this market preference.

The participation of agricultural cooperatives in the formal markets represented by the "Forestry, cropping and other activities" cluster increases with the positive score for borrowings (the borrowing dimension was constructed by loans and the amount that a cooperative owes). Credit information is thus crucial, as the results show that it determines the enterprise market choice. Mango et al. (2018) and Randela et al. (2008) demonstrate that access to information about transport and markets is vital for market participation. Therefore, cooperatives with access to credit information – implied by the variable for borrowings – find formal markets ("Forestry, cropping and other activities" cluster) less accessible. Access to loans and the amount that a cooperative owes, i.e. credit or borrowings, demonstrates the influence of credit on the selection of markets by agricultural cooperatives. Besides, access to credit ensures that a certain amount of resources are available for the enterprise to function. Inaccessible and unsuitable credit could adversely influence cooperatives' market typology selection. Therefore, credit access can screen or enable agricultural cooperatives' market type selection.

Similarly, an increase in the profitability score is associated with greater participation in and access to formal markets for agricultural cooperatives. The variables used to construct the profitability score, such as turnover, expenses, and wages, are commonly utilised in computing other profitability measures. Profitability plays a crucial role in the market typology selection of agricultural cooperatives, as evidenced in this study. Profitable institutions are more inclined to opt for typologies that represent formal markets. This finding is not surprising, as profitability indicates the availability of financial resources that can be utilised to influence production and ensure favourable returns in market transactions.

Consequently, various mechanisms can be implemented within these institutions to ensure that profitability influences the choice of market typology. However, it is important to acknowledge that any threats to profitability arising from factors such as increasing labour costs due to activism or legislation can undermine the observed relationship. Likewise, inflation can erode profitability, leading to potential shifts in market typology selection.

The results indicate that an increase in the size of the management committee enhances the likelihood of agricultural cooperatives selecting the base category as their market typology rather than opting for typologies represented by Clusters 2 and 3. The influence of size measures on market participation for enterprises or individuals has been extensively studied in previous research. For instance, Randela et al. (2008) demonstrate the impact of the dependency ratio on market participation. While some cooperatives in this study reported that they did not have management committees, such committees can play an influential role in selecting market access typologies for cooperatives.

A management committee within an organisation typically holds delegated authority from its members to accomplish specific goals. One crucial role of a management committee is to ensure the effective management of the organisation and the achievement of its objectives.

Additionally, the committee oversees the organisation's activities to ensure alignment with its founding principles, objectives, and values.

Furthermore, managers in agricultural cooperatives increase the likelihood of the institution's participation in the base category market typology. In units of analysis such as households, the household head usually serves as the key decision-maker. In these cases, the age and education level of the household head are critical factors in determining market participation (Okoye et al., 2016; Mango et al., 2018; Randela et al., 2008). Similarly, this study recognises managers as individuals with roles similar to household heads. Managers are employed and entrusted with overseeing an organisation's business operations or a group of employees. The contributions of managers to an organisation are observed in various ways, including company profits, organisational structure, and overall employee morale. The selection of the market typology is another aspect in which managers contribute to organisations, specifically agricultural cooperatives.

All the training types with statistically significant coefficient estimates indicate that agricultural cooperatives are more likely to participate in formal markets than other market access typologies. Agricultural cooperatives that received financial management training, as well as training in accounting and bookkeeping, decreased their likelihood of selecting the "the Forestry, cropping, and other activities" cluster, whereas cooperative governance training reduced the likelihood of cooperatives selecting the "Fruit, vegetables, livestock and processing" cluster. In this study, the data does not indicate the specific capacity and characteristics of the person receiving the training, e.g., an employee, manager, or member. It suffices to mention that a person with skills like those provided by these types of training can influence a cooperative's market typology selection.

CONCLUSION AND RECOMMENDATIONS

The study reveals that financial and social efficiency impact agricultural cooperatives' selection of market typologies. Additionally, the age of the institution and the square of the age of the institution were identified as key factors influencing market choice. Other important determinants of market typology choice include livestock ownership, cooperative size, access to credit, and participation in specific training programs such as those in financial management, corporate governance, and accounting and bookkeeping. The presence of management committees and the influence of managers also play a role in the market choices made by agricultural cooperatives.

The study does not establish one market typology as superior to others but highlights the various factors influencing the decision to participate in different typologies. These findings will be of interest to policymakers and development practitioners who can leverage them to promote cooperative market engagement.

To enhance the involvement of agricultural cooperatives in the market, policymakers and development practitioners can focus on promoting factors such as financial and social efficiency, livestock ownership, profitability, access to credit, and targeted training programs. These factors have been found to influence the choice of market typology, leading to more meaningful participation in the market by cooperatives. Policymakers can also support cooperative development by providing entrepreneurship and cooperative development training, particularly by developing short, modular, competency-based programs that reduce training time and opportunity costs, benefiting young entrepreneurs. Skills levy institutions can actively address the skills development needs of entrepreneurs and cooperatives, specifically focusing on unemployed individuals, young people, women, and people with disabilities. Furthermore, policymakers can highlight the economic benefits of cooperation and economies of scale that cooperatives offer by reducing input, operational, and distribution costs, thereby promoting the success of cooperative models.

While the present study provides valuable insights into the factors influencing agricultural cooperatives' financial and social efficiency in South Africa, its generalizability to other regions or countries may be limited due to the small sample size. Nevertheless, the findings contribute to the existing literature in this field and should promote further research on the market typologies that lead to improved cooperative performance.

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