

Income Diversification and Intermediation Efficiency: Evidence from Deposit Taking Sacco Societies in Kenya

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Abstract
Research on the relationship between diversification into nontraditional income streams and firm efficiency is scanty. The study seeks to fill the gap by evaluating the relationship between diversification into non interest income and intermediation efficiency of Deposit Taking Sacco Societies (DTSs) in Kenya using a two staged methodology. In the first stage, efficiency scores are generated using Data Envelopment Analysis (DEA), corrected for bias using bootstrapping and used as dependent variable in the fixed effect regression model estimated in the second stage. A balanced panel data of 103 DTSs for a period 2011-2014 was used in the study. The results showed that there exists an inverse relationship between the ratio of noninterest income to total assets and intermediation efficiency. This implied that diversification hurts efficiency.
Keywords: Data Envelopment Analysis, Deposit Taking Sacco, Diversification, Intermediation Efficiency, Noninterest income.

1. Introduction

A cooperative is an autonomous association of persons united voluntarily to meet their common economic, social, and cultural needs and aspirations through a jointly-owned and democratically-controlled enterprise (Birchall, 2004). There are two broad categories of co-operatives; financial co-operatives (Savings & Credit Co-operative Societies- SACCOs) and non-financial cooperatives (includes farm produce and other commodities marketing cooperatives, housing, transport and investment co-operatives). Financial Cooperatives are referred to in different terms in different countries. In countries like UK, USA, Canada and Australia, they are referred to as credit unions.

Traditionally, financial co-operatives only operated Back Office Services Activity (BOSA), collating deposits and extending credit to members. However, in the recent past, to attract a large client base, there has been an aggressive marketing and development of a variety of products and services. This has led to growth of the Front Office Services Activity (FOSA) with the range of products and services ever increasing. In Kenya, financial co-operatives operating FOSA are referred to as Deposit Taking Saccos (DTSs). Besides the basic savings and credit products, they also provide basic 'banking' services such as demand deposits, payments services and channels such ATMs (Sacco Society Regulatory Authority (SASRA), 2013).

Kenya has about 5000 SACCOs out of which 215 are DTSs. However, DTSs accounts for 78% and 77% of the total assets and deposits of the entire Sacco subsector respectively. This underscores the fact that the growth potential for the SACCOs remains in the deposit taking Sacco business (SASRA, 2013). The development of FOSAs to offer banking services, strategic partnerships with other financial and non financial institutions to offer agency banking and increasing the branch networks have all contributed to this growth. The question is whether the growth has been accompanied by improvement in efficiency with which they undertake their intermediation role. The following hypothesis was therefore tested.

H_0: There exists no significant relationship between income diversification and financial intermediation efficiency of Deposit Taking Sacco societies in Kenya.

2. Literature review

According to Mercieca, Schaeck and Wolfe (2007), the diversification in banking sector has three dimensions: (a) financial products and services diversification, (b) geographic diversification, and (c) a combination of geographic and business line diversification. Prior studies on the impact of diversification on bank performance remain inconclusive with divergent views. The conventional view is that product diversification reduces an institution's exposure to any particular activity and thus leads to lower risk. An alternative view is that the expansion of financial institutions activities beyond traditional deposit taking and lending leads to greater risk taking (Acharya, Hasan, & Saunders, 2006; Barry & Laurie, 2010; Esho, Kofman, & Sharpe, 2005; Kiweu, 2012). Fee income is often believed to be more stable than interest revenue, the latter being affected by movements in interest rates and the business cycle (Esho et al., 2005).

Elyasiani and Wang (2012) investigated the effects of diversification on production efficiency of Bank Holding Companies (BHCs) in USA over the period 1997–2007. They used the Data Envelopment Analysis (DEA) to calculate the Malmquist index of productivity and the total factor productivity change. The results showed that activity diversification was negatively associated with technical efficiency. In addition, changes in diversification over time were found not to affect the total factor productivity change but to be negatively associated with technical efficiency change over time. The results thus indicated that diversification harms efficiency.

Kiweu (2012) used a sample consisting of 35 commercial banks in Kenya for the period 2000 – 2012 to examine how income focus verses diversification impacts on bank performance (as measured by ROA and ROE). The study investigated whether diversification of income sources for Kenyan banks leads to better earnings and reduced individual bank and systemic risks. The study found that there are few benefits, if any, to be expected from income diversification from traditional banking. The benefits of the evolution of non-interest income did not seem to fully offset the increase in risk that come with fee based income. A positive correlation between net interest income and non-interest income seemed to exist, a finding that suggests that non-interest income may not be used to stabilize total operating income.

Barry and Laurie (2010) investigated the impact of bank non-interest income on bank risk and return. They found that income derived from traditional sources is less risky than income derived from non interest based revenue. Non-interest income or fee-based income as a source of diversification for bank income was found to be riskier than margin income. It however offers diversification benefits to bank shareholders by reducing bank exposure to interest incomes. While improving bank risk-return tradeoff, these benefits are of second order importance compared to the large negative impact of poor asset quality on shareholder returns.

Goddard, Mckillop and Wilson (2008a) investigated the impact of revenue diversification on financial performance of US credit unions for the period 1993–2004. The impact of a change in strategy that alters the share of noninterest income was decomposed into a direct exposure effect, reflecting the difference between interest and non-interest bearing activities, and an indirect exposure effect which reflects the effect of the institution’s own degree of diversification. The results indicated that; on both risk-adjusted and unadjusted returns measures, a positive direct exposure effect is outweighed by a negative indirect exposure effect for all but the largest credit unions. This implied that similar diversification strategies are not appropriate for large and small credit unions. They concluded that small credit unions should eschew diversification and continue to operate as simple savings and loan institutions, while large credit unions should be encouraged to exploit new product opportunities around their core expertise.

Goddard, Mckillop and Wilson (2008b) used nested analysis of variance to identify the sources of variation in performance, measured by growth of membership and growth of assets, for a large sample of US credit unions. The results suggested that state, common bond and charter effects all make relatively small although statistically significant contributions to the explanation of the variation in growth performance. The findings of the study also indicated that performance is positively related to increase in diversification for large CUs. The relationship was however negative for smaller CUs.

Mercieca et al. (2007) investigated whether the shift into non-interest income activities improves performance of small European credit institutions. Using a sample of 755 small banks for the period 1997 – 2003, they found no direct diversification benefits within and across business lines and an inverse association between non-interest income and bank performance. The results indicated that small banks can improve their performance by expanding their resources within their existing business lines where they possess distinctive comparative advantages.

Huang and Chen (2006) investigated whether the reliance on different sources of non-interest incomes affects bank efficiency. They employed the DEA to calculate the cost efficiency of Taiwan domestic commercial banks from 1992 to 2004. The banks were equally divided into three sub-sample groups based on the percentage of the interest or non-interest incomes to the operating incomes. The Kruskal-Wallis pairwise comparison test was employed to examine whether there were significant differences within the sub-sample groups. The results indicated that bank efficiency tended toward extreme opposite cases. The banks either with the largest or smallest percentages of interest and non-interest incomes to operating incomes outperformed those with middle percentage of those incomes. This implied that the banks with a relative high and low concentration in interest and non-interest incomes operate more cost-efficiently. The banks with more diversified income sources, which are the group of the middle percentage of interest and non-interest incomes to operating incomes, were less cost-efficient.

Esho, Kofman and Sharpe (2005) used a cross-sectional ordinary least squares regression analysis of 198 Australian credit unions and six risk measures to examine the relationship between a credit union’s products mix, pricing policy, risk, and earnings. The results confirmed that increased reliance on fee income generating activities is associated with increased risk. Credit unions with highly concentrated revenues were found to have higher levels of risk and returns. Moreover, credit unions with a higher proportion of total revenue in the form of interest on residential loans and a lower proportion of revenues in interest on personal loans have significantly lower risk and returns, consistent with modern portfolio theory. However, credit unions that diversify by increasing the revenue share of transaction fees on loans and deposits, matched by a reduction in the revenue share of interest on personal loans, will increase their risk while reducing returns. Most importantly the study revealed that diversification may enhance X-efficiencies if larger credit unions are able to employ better managers.

3. Methodology

3.1 Data envelopment analysis (DEA)

The study adopted a two staged methodology. In the first stage, Data envelopment analysis (DEA) was used to generate efficiency scores. DEA is a multi-factor productivity analysis model for measuring the relative efficiencies of a homogenous set of decision making units (DMUs). It uses the principles of linear programming theory to examine how a particular DMU such as a DTS operates relative to other DMUs in the sample. The method constructs a frontier based on actual data. Firms on the frontier are efficient, while firms off the efficiency frontier are inefficient (Nasieku, Kosimbei, & Obwogi, 2013). Because efficiency is measured as the distance to this frontier, without considering statistical noise, DEA is a deterministic model (Andor & Hesse, 2011).

Two different DEA models have been put forward; Charnes, Cooper and Rhodes (1978) proposed a model with an input orientation and assumed constant return to scale (CRS). Banker, Charnes and Cooper (1984) proposed a variable return to scale (VRS) model which was a variation of the CRS model. The easiest way to present the DEA model is in a ratio form. For each DMU a ratio of all outputs over all inputs is given as $u'y_i/v'x_i$ where u is a $M \times 1$ vector of output weights and v is a $K \times 1$ vector of input weight. To select optimal weight the problem is specified as a mathematical programming problem thus;

$$\begin{aligned} & max_{u,v}(u'y_i/v'x_i), \\ st \quad & u'y_j/v'x_j \le 1, j = 1,2, \dots, N \\ & u, v \ge 0 \end{aligned} \qquad 1$$

To ensure that the problem does not have infinite number of solutions, a constraint $v'x_i = 1$ is imposed which provides;

$$\begin{aligned} & max_{\mu,v}(\mu' y_i) \\ & st \\ & v'x_i = 1 \\ & \mu' y_j - v' x_j \le 0, \quad j = 1,2, \dots, N \\ & u, v \ge 0 \end{aligned} \qquad 2$$

where the change from u and v to μ and v depicts transformation. This form is known as the *multiplier* form of linear programming problem (Tim Coelli, 1996).
The problem can be converted into a dual as follows;

$$\begin{aligned} & Min_{\lambda,\theta}\theta \\ st \quad & -y_i + Y\lambda \ge 0 \\ & \theta x_i - X\lambda \ge 0 \\ & \lambda \ge 0 \end{aligned} \qquad \mathbf{3}$$

where θ is a scalar and λ is $N \times 1$ Vector of constants. This envelopment form involves fewer constraints than the multiplier form$(K + m < N + 1)$ and hence generally preferred form to solve. The value of θ obtained were the efficiency score for the i^{th} DMU and shall satisfy $\theta \le 1$. The LP must be solved N times once for each DMU.

CRS DEA is only appropriate when all DMU are operating at an optimal scale however if some DMU are not operating at optimal scale, it is appropriate to use Variable Return to Scale (VRS) DEA. The CRS Linear programming is modified to account for VRS by adding a convexity constraint, $N1'\lambda = 1$. Thus the problem becomes;

$$
\begin{aligned}
& Min_{\lambda,\theta}\theta \\
& st \quad -y_i + Y\lambda \geq 0 \\
& \quad \theta x_i - X\lambda \geq 0 \\
& \quad N1'\lambda = 1 \\
& \quad \lambda \geq 0
\end{aligned}
\qquad (4)
$$

where $N1$ is an $N \times 1$ vector of ones. This approach forms a convex hull of intersecting planes which envelope the data points more tightly than the CRS conical hull and thus provides technical efficiency scores which are greater than or equal to those obtained using the CRS model**.** Equation 4 was adopted and solved using the DEA Computer Program Version 2.1.

3.2 Regression analysis

In the second stage of analysis, the efficiency scores are regressed against income diversification. Other independent variables incorporated in the study include; asset quality, profitability and size to act as control variables. The following panel model was estimated;

$$TEFF_{it} = \alpha_0 + \beta_1 DIV_{it} + \beta_2 ASQ_{it} + \beta_3 PROF_{it} + \beta_4 SIZE_{it} + \varepsilon_{it}$$

Where i = 1,2, …,103, and t = 1,2,3,4

In the model, i stand for the i^{th} cross-sectional unit and t for the t^{th} time period. The dependent variable is the intermediation efficiency (TEFF) which is hypothesized to depend on income diversification (DIV), Asset Quality (ASQ), Profitability (PROF) and size (SIZE) for each DTS i on the sample over the 2011-2014 period of analysis.

Non-interest income to total assets was used as a proxy for DTSs' diversification strategy into non-traditional activities (Maghyereh & Awartani, 2014; Sufian, 2009). It was expected that the variable would have a positive coefficient indicating that diversification enhances efficiency. The ratio of non-performing loans provisions to total loans was used as a proxy of the Asset Quality (Kiyota, 2011; Sufian, 2009) or credit risk. The ratio of liquid asset to total assets was used as an indicator of liquidity position (Moore, 2010; Pacelli & Mazzarelli, 2015). The variable was expected to enter the regression model positively (Sufian, 2009).

ROA (Return on assets) as a measure of profitability was expected to have a positive relationship with efficiency since highly profitable banks are more efficient (Alrafadi, Kamaruddin, & Yusuf, 2014; Arora, 2014; Maghyereh & Awartani, 2014; Othman, Mansor, & Kari, 2014; Srairi, 2010; Sufian, 2009). LNTA (Natural logarithm of total assets) was used as a proxy of bank size to captures the possible cost advantages associated with size (economies of scale). The variable was expected to take a positive sign.

3.3 Data

The study used a balanced panel data of 103 licensed DTSs for the period 2011-2014. Though the study envisaged a census of all 135 DTSs licensed by the regulator at the close of 2013, complete data was available for 103 DTSs. The data was collected from DTSs' financial statements filed with the regulator, SASRA.

4. Results and findings

4.1 Descriptive Statistics of DEA Inputs and Outputs

The study adopted the intermediation approach of DEA since the focus was the intermediation efficiency. It sought to evaluate the efficiency with which DTSs collate member's deposit, capital and employ labour to advance loans to the members and also acquire investments for their benefits. Effectively, total deposits, labour cost and core capital were selected as inputs whereas gross loans and investments as outputs. Table 1 presents the descriptive statistics of these input and output. It can be observed that the mean deposits amounted to Ksh. 1.31billion with a standard deviation of Ksh. 2.46 billion. Labour cost had a mean of Ksh. 38 million with a standard deviation of Ksh. 63 million. The trend is the same for all other variables where the standard deviation is significantly higher than the mean which shows that the data is highly spread. This can also be seen from the difference between the maximum and minimum values. This indicates that DTSs included in the study differ significantly in their scale of operation.

Table 1: Descriptive Statistics of inputs and outputs

	Total deposits	Labour cost	Core capital	Gross loans	Investments
Mean (Ksh. Millions)	1,310	38	211	1,550	69
Median (Ksh. Millions)	492	16	77	547	19
Maximum (Ksh. Millions)	18,300	566	5,000	19,800	1,350
Minimum (Ksh. Millions)	0	1	-60	20	0
Std. Dev. (Ksh. Millions)	2,460	63	446	3,030	162
Skewness	4	4	6	4	5
Kurtosis	20	23	49	18	32
Observations	412	412	412	412	412

Bias corrected efficiency scores

The results of a regression model are only valid if basic assumptions of the regression analysis are satisfied. One such assumption is the assumption of independence within the sample. Simar and Wilson (1998) pointed out that efficiency scores generated by DEA models are clearly dependent on each other in statistical sense. The reason for dependency is the well-known fact that the DEA efficiency score is a relative efficiency index, not an absolute efficiency index. The calculation of the DEA efficiency of one DMU involves all other DMUs in the observation set (Xue & Harker, 1999).

The presence of the inherent dependency among efficiency scores implies that the assumption of independence within the sample is violated. As a result, the conventional regression procedure is invalid. To address this issue, Simar and Wilson (1998) proposed a double bootstrap procedure, which enables consistent inference in the second-stage regression models. Casu and Molyneux (2003) concur that to overcome the problem of inherent dependency of DEA efficiency scores used in regression analysis, the bootstrapping technique should be applied. The bootstrap is a computer-based method for assigning measures of accuracy to statistical estimates. It is based on the idea of re-sampling from the original data to assign statistical properties for the quantities of interest (Sufian & Habibullah, 2014). In this study, the bootstrapping was implemented using rDEA package embedded in statistical package R.

The summary of the results are shown in table 2. The results indicate that, in the year 2011, the Variable Return to Scale Technical efficiency (VRSTE) score was 0.646 where as the bias corrected VRSTE was 0.306. The trend where the VRSTE score are higher than the bias corrected score is replicated in all the years. This is expected since the DEA efficiency scores tend to be overstated due to sampling bias. According to Tziogkidis (2012), the DEA sampling bias is associated with the fact that the observed sample is (randomly) drawn from an underlying, unobserved population and the efficiency scores of the DMUs in the sample depend on the DMUs that define the frontier. This causes DEA efficiency scores to be overestimated compared to the “true” frontier, with the only highly unlikely exception that the DMUs which define the population frontier are all included in the sample. The bias corrected efficiency scores replaced the VRSTE for purposes of regression analysis.

Table 2: Summary of Bias Corrected Efficiency Scores

YEAR	VRSTE	Bias Corrected VRSTE
2011	0.646	0.306
2012	0.648	0.311
2013	0.706	0.403
2014	0.707	0.381
Average	**0.677**	**0.350**

4.2 Diagnostic tests

The panel data collected has both cross sectional and time series characteristics. Panel data pose several estimation and inference problems that plague cross-sectional and time series data. To overcome the problems, there are various estimation techniques that can be applied to panel data. This includes; pooled OLS, Fixed Effects Model (FEM) and Random Effect Model (REM). Diagnostic tests are used to identify the best model for the study. This section the study reports panel data diagnostics tests which were carried out.

Random Effect or Pooled OLS Model

According to Torres (2007), the Breusch-Pagan Lagrange multiplier (LM) test helps in deciding between a random effects regression and a simple OLS (pooled effects) regression. The null hypothesis in the LM test is that variances across entities are zero i.e. there are no significant difference across units (no panel effect). The Breusch Pagan LM test gave a χ^2 value of 43.27 (p=0.0000). This led to the rejection of the null hypothesis and a conclusion that the pooled effects (OLS) regression model was not appropriate for the study.

Random Effects or Fixed Effects Model

Breusch Pagan LM test showed that pooled effects model was not appropriate for the study. The appropriate model for the study was panel regression model which could either be random effects model (REM) or fixed effects model (FEM). Fixed effect regression modeling is more appropriate when the study seeks to examine the effect of independent variables over time. More so, the independent entity should be having a relationship with the independent variables. In contrast random effect model assumes that independent variables have no collinearity with independent entities. In addition, it assumes that there are random variations across the error terms and both independent variables and specific's entities are too treated as independent variables. To make a choice between random and fixed effects panel regression model, Hausman test was applied.

Hausman test basically tests whether the unique errors (u_i) are correlated with the regressors and the null hypothesis is that they are not (Greene, 2012). The test's null hypothesis is that the preferred model is random effects vs. the alternative fixed effects (Torres, 2007). The results gave a χ^2 value of 33.61 with a p value of 0.0000 which is less than 0.05. This resulted to the rejection of null hypothesis and acceptance of the alternative hypothesis. This implied that the most appropriate model for the analysis is the fixed effects regression model.

Time Fixed Effects

To determine if time fixed effects are needed when running a fixed effect model, a joint test is carried out to determine if the dummies for all years are equal to 0, if they are, then no time fixed effects are needed (Torres, 2007). The results for time fixed effects gave an F value of 3.01 with a p value of 0.0000 which is less that 0.05 indicating that there are no significant time affects and therefore no need to introduce dummy variables.

Heteroskedasticity

An important assumption is that the residuals have a constant variance or are homoskedastic across time and individuals. When heteroskedasticity is present the standard errors of the estimates are biased. The presence of heteroskedasticity was tested using modified Wald test. For modified Wald test the null hypothesis is that there exists homoskedasticity (or constant variance) (Drukker, 2003). The test results gave a χ^2 value of 2.3e+05with a p value less than 0.05 (p=0.0000). This resulted to rejection of the null hypothesis and acceptance of the alternative hypothesis. This leads to the conclusion that there exists heteroskedasticity.

Serial correlation

According to Gujarati (2012), serial correlation may be defined as correlation between members of series of observations ordered in time or space. Drukker (2003) argues that, because serial correlation in linear panel-data models biases the standard errors and causes the results to be less efficient, researchers need to identify serial correlation in the idiosyncratic error term in a panel-data model. The study used the Wooldridge Drukker test to test for presence of serial correlation. In this test the null hypothesis that there is no serial correlation. The result gave an F value of 2.945 with a p value of more than 0.05 (p=0.0892). This resulted to acceptance of the null hypothesis indicating that there existed no serial correlation.

Diagnostic results showed that the appropriate model for the study was fixed effect model without dummies. However, there existed heteroscedasticity but no serial correlation. When heteroscedasticity is present, the standard errors of the estimates are biased. The remedy is to compute robust standard errors correcting for the possible presence of heteroscedasticity (Antonie, Cristescu, & Cataniciu, 2010; Hoechle, 2007). The study therefore used White heteroscedasticity consistent standard errors.

Descriptive statistics for the study variables

The descriptive statistic for the study variables are presented in table 3. The bias corrected technical efficiency had a mean of 0.350 with an overall standard deviation of 0.192. The standard deviation between the DTSs is higher (0.141) as compared to within the same DTSs over the years (0.131). This depicts that efficiency varies more from one DTS to the next DTS rather from year to year for each DTS.

Diversification as measured by the ratio of non interest income to total assets had an average of 0.032. The minimum recorded value was zero implying than some DTSs had no noninterest income. This indicates that the extent of income diversification is still limited in some DTSs. It can also be seen that the variations between the DTSs (standard deviation=0.002) is significantly lower compared with variations within the same DTS over the years (standard deviation=0.037). This depicts the concerted efforts by DTSs to diversify over the years.

Asset quality as measured by the ratio of nonperforming loans to gross loans gave a mean of 0.038 with an overall standard deviation of 0.076. This indicates that only 3.8% of all loans granted by DTSs are likely to default. The result mirror those of the regulator who reported an average 0.053 and 0.0472 in the year 2013 and 2014 respectively (SASRA, 2014). It is also important to note that there exists no significant differences between the DTSs (standard deviation=0.054) and within the same DTSs over the years (standard deviation=0.053). This implies that there exist some elements of stability in the asset quality by DTSs.

Profitability (return on assets) had an average of 0.022 with overall standard deviations of 0.024. The minimum ROA was -0.116 indicating those some DTSs reported losses over the period 2011-2014. The cross sectional variations were found to be higher than temporal variation within the same DTS. Size as measured by logarithm of total asset had an average of 8.880 with overall standard deviations of 0.586. The smallest DTS had a log of total asset of 7.729 whereas the biggest had 10.456 depicting a significant disparity in the size of the licensed DTSs.

Table 3: Descriptive statistics for study variables

Variable		Mean	Std. Dev.	Min	Max
Bias Corr. T. Eff.	overall	0.350	0.192	-0.016	1.082
	between		0.050	0.306	0.403
	within		0.187	0.028	1.126
Diversification	overall	0.032	0.037	0.000	0.295
	between		0.002	0.030	0.034
	within		0.037	-0.001	0.295
Asset Quality	overall	0.038	0.076	0.000	0.544
	between		0.008	0.029	0.049
	within		0.075	-0.011	0.553
Profitability	overall	0.022	0.024	-0.116	0.151
	between		0.003	0.019	0.024
	within		0.024	-0.113	0.154
Size	overall	8.880	0.586	7.729	10.456
	between		0.089	8.781	8.983
	within		0.581	7.778	10.383

Correlation Analysis of the regression variables

The study evaluated the correlation among the study variables aimed at establishing the nature and strength of the relationship between variables under examination. Table 4 shows that there exists significant correlations between bias corrected efficiency scores and all independent variables at 0.01 level of significance except profitability (p=0.434) and size (p=0.299). The correlation between efficiency scores and asset quality and diversification is negative and weak (given that they are less than 0.5). This depicts an inverse relationship which implies that an increase in one of these variables would be associated or accompanied by a decrease in efficiency scores.

On the other hand, correlation between efficiency scores and profitability and size is positive but also weak. It is important to note that all correlations are less than 0.5 depicting non existence of multicolinearity. Multicollinearity exists when independent variables are highly correlated (r>=0.9), and tends to lead to a poor regression model (Dancey & Reidy, 2011).

Table 4: Correlation Analysis

	Bias Corr. TEFF	Asset quality	Diversification	Profitability	Size
Bias Corr. Teff.	1.000				
Asset quality	-0.197***	1.000			
	0.000	-----			
Diversification	-0.270***	0.239***	1.000		
	0.000	0.000	-----		
Profitability	0.039	-0.046	-0.055	1.000	
	0.434	0.352	0.268	-----	
Size	0.051	0.011	-0.433***	0.136***	1.000
	0.299	0.830	0.000	0.006	-----

***(**)(***) significant at 10%(5%)(1%).**

4.3 Regression Results

Regression results are presented in table 5 which has model 1 and model 2. Model 1 presents the results for all the control variables while model 2 presents the results for the full model. Evidently, model 2 has a higher value of adjusted R^2 (0.430) compared to model 1 (0.426). This is an indication that addition of income diversification increases the predictive capability of the model. Model 1 shows that there exists a positive relationship between intermediation efficiency and profitability and size. However an inverse relationship is depicted between efficiency and income diversification.

Model 2 is used to test a null hypothesis that: there exists no significant relationship between income diversification and financial intermediation efficiency of Deposit Taking Sacco societies in Kenya. The results show that income diversification has a negative significant coefficient $(\beta = -0.867, \rho = 0.0147)$. This result leads to rejection of the null hypothesis. The results imply that diversification hurts efficiency. An increase in the ratio of noninterest income to total assets by one unit results to a decline of mean efficiency by 0.867 units, holding other variables constant.

Table 5: Fixed-effects regression results

Variable	Model 1	Model 2
Constant	-2.167 (0.521)**	-2.072(0.489)**
Diversification		-0.867(0.353)*
Asset quality	-0.354 (0.057)**	-0.344(0.060)**
Profitability	0.941 (0.361)**	1.154(0.384)**
Size	0.283 (0.059)**	0.275(0.057)**
Model statistics		
R-squared	0.573	0.577
Adjusted R-squared	0.426	0.430
S.E. of regression	0.145	0.144
Sum squared resid	6.460	6.390
Log likelihood	271.419	273.649
F-statistic	3.906	3.929
Prob(F-statistic)	0.000	0.000

*Values in Parentheses are standard errors. * indicate that the variable is significant at 5 percent; and ** indicate that the variable is significant at 1 percent.*

The empirical results are consistent with those of Elyasiani and Wang (2012) and Huang and Chen (2006) but contradict those of Maghyereh and Awartani (2014) and Sufian (2009). The inverse relationship implies that income diversification hurts efficiency through more idiosyncratic risk and decreased incentives to monitoring. This may be seen to contradict the portfolio theory that posit that diversification into non interest income would reduce volatility and enhance returns. The logical explanation for this phenomenon is that as the management focuses on diversification, they reduce their attention on the core mandate of the DTS which is provision of credit to members.

The increase in the number of activities is generally associated with increased opaqueness and information asymmetry and agency problems (Elyasiani & Wang, 2012). The core mandate of DTSs is to collate deposit and advance loan to members at favorable terms. Diversification into other activities such as provision of ATM services, salary processing and over the counter operations, may hurt efficiency with which they undertake their core mandate. Additionally; the size of DTSs could act as a bottleneck, in small DTSs, no significant economies of scale are realized with income diversification. Goddard et al., (2008a) suggest that where credit unions neither have sufficient scale nor the requisite expertise to diversify, they should limit diversification and continue to operate as simple savings and loans vehicles.

Goddard et al. (2008a) found that, though much of the growth in US credit unions was via diversification into non-interest earning activities, this did not lead to enhanced returns for members. Among the motives for diversification, Santomero and Eckles (2000) cite growth, realization of efficiency gains via economies of scale and scope, reduction of idiosyncratic risk, and strengthening of the financial system. Evidently, the realization of efficiency gains is not evident in case of DTSs in Kenya.

5. Conclusion

The average efficiency of DTSs in Kenya was found to be relatively lower indicating that most DTSs were operating further away from the frontier. The results also show that diversification into non interest income hampers efficiency. Two plausible explanations could be extended for this phenomenon. With diversification, there is an increased opaqueness and information asymmetry which compound the agency problem. Additionally, diversification is only beneficial if economies of scale are realized. The fact that most DTSs are still small in size implies that no significant economies of scale are realized through income diversification. It is therefore recommended that DTSs in Kenya should first consolidate their operations by increasing the uptake of their existing product lines before venturing into other income streams.

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