Does Technology Matter? Evidence from the Credit Union Industry

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ABSTRACT

Credit unions are unique not-for-profit financial institutions that share an association between members forged through a common bond, normally tied through employment. The resulting preferential tax treatment provides economic benefits which permit credit unions to charge lower rates on loans to members while paying higher deposit rates. Adoption of new technologies allows credit unions to further reduce the cost of providing services.

This paper investigates the financial performance differences between technology leaders versus laggards for credit unions below $100 million in asset size. Four time periods from 2002 through 2011 are examined. This includes periods of growth, financial turmoil and economic recovery. Using factor analysis to reduce 21 financial performance metrics to 8 underlying factors, a model is developed and tested using multivariate discriminant analysis.

The paper finds there are significant differences in the financial performance of credit unions that are technology leaders versus technology laggards. These relationships are relatively stable over time and across enormous business cycle variations.

INTRODUCTION

Credit unions are unique financial institutions that differ distinctly from commercial banks. They are not-for-profit enterprises that exist for the benefit of their members. By law credit unions must possess a common bond that is shared by members although this commonality is sometimes stretched, often to the chagrin of their competitors. (Koch & MacDonald, 2010) Often this required bond is forged through employment relationships. Credit unions such as Boeing and American Airlines include membership from within those companies. Governmental credit unions include employees of the Pentagon, the U.S. Navy or federal employees in general. Other credit unions include teacher organizations, universities and state and local government employees. According to the Credit Union National Association (CUNA) as of June 30th, 2011 there are 7,380 credit unions in the United States. Of these, 5,961 are under $100 million in assets. (CUNA, 2011) Credit unions in various, forms also exist in locales around the world. The World Council of Credit Unions in 2010 estimates that credit unions are found in 100 nations with over 188 million members and total assets of almost $1.5 trillion. (World Council of Credit Unions, 2011)

Because credit unions enjoy not-for-profit status, they are exempt from Federal income taxes, a distinct advantage over commercial banks and other for-profit financial institutions. While bank management focuses on profit maximization, maximization of market share and/or maximization of shareholder wealth, credit unions, by contrast, attempt to minimize borrowing costs for members while maximizing returns to depositors. In order to accomplish these dual objectives some credit unions have turned to applications of technology to reduce costs and extend services to customers in hopes of expanding their customer base. While the adoption of technology does not guarantee sustainable competitive advantage, the lack of technological applications may be associated with subpar financial performance. This is a focus of this paper.

The introduction of personal computers in the early 1980's followed later by the expansion of the Internet has expanded the applications of financial services by banks and non-bank financial institutions including credit unions. The introduction of smartphones and other mobile technologies including i-Pad type tablets has accelerated customer demands for financial applications and extended financial services.

Nicholas Carr, former executive editor of *Harvard Business Review* in his book, *Does IT Matter?,* stirred a debate over the role of information technology in creating sustainable competitive advantage. (Carr, 2004). Everett Rogers in his classic 1962 work, *Diffusion of Innovations* identifies four major elements in the diffusion of innovations: 1) innovation 2) communication channels 3) time and 4) the social system. (Rogers, 2003) Following Rogers, this paper examines the adoption of technology over an extended period of time from 2002 to 2011.

This paper investigates the financial performance of US credit unions that are "leaders" in the adoption of technology versus those that are "laggards". Because there is considerable evidence that the size of financial institutions affects the ability to acquire information technology we confine our analysis to credit unions that are $100 million or less in total assets.

Survey of the Literature

The financial institutions literature that is relevant to this paper is both extensive and diverse. For simplicity this research is clustered into four primary topics: 1) the economics of credit unions 2) economies of scale and scope in credit unions 3) the financial performance of credit unions and 4) technology and innovation in financial institutions including but not limited to the Internet. Other credit union topics including international applications, governance, strategic management issues excluding technology and an assortment of other topics are reserved for subsequent research papers.

The Economics of Credit Unions

Early research related to the economics of credit unions dates to the 1970's with the works of Flannery (Flannery, 1974) and Cargill (Cargill T. , 1977). In May 1981, three papers on credit unions appeared in the *Journal of Finance*. Smith, Cargill and Meyer created a model incorporating a function that includes the fundamental saver-versus-borrower conflict that exists for credit union managers. (Smith, Donald J.; Cargill, Thomas F.; Meyer, Robert A., 1981) Because credit unions are voluntary associations of members, traditional measures of financial institutions profitability lack the usual importance. Customers (members) expect lower loan rates and higher deposit rates than those normally available from for-profit competitors. Credit unions may display neutrality between savers and borrowers or, alternatively, may show a preference for either savers or borrowers.

Black and Dugger's paper focuses on industry structure and regulatory issues faced by credit unions. (Black & Dugger, 1981) Navratil introduced a six-equation simultaneous model to investigate three different aggregate flows in the credit union industry: new loan extensions, net share flows and net change in financial investments. (Navratil, 1981) Smith contributed a theoretical model that determines optimal credit union loan rates and dividend rates as a function of balance sheet portfolios, operating costs, regulatory constraints and borrower-saver preference. (Smith, 1984)

An additional thread in credit union research encompasses elements of the industry structure-conduct-performance paradigm. Kaushik and Lopez trace the growth and development of US credit unions in the period since deregulation in 1980. (Kaushik & Lopez, 1994) Feinberg empirically examines the competitive effects that credit unions exert against banks in small local geographic markets. (Feinberg R. M., 2001) In a later study Feiberg et. al. find that credit unions and banks behave differently in local markets for consumer loans, reflecting the fundamental differences between not-for-profit and for-profit institutions. (Feinberg & Rahman, 2006) Ward and McKillop examine the extent to which the level of deprivation in the areas of the UK in which a credit union operates affects financial success of the organization. (Ward & McKillop, 2005)

Economies of Scale and Scope

Koot in the *Journal of Finance* provides an early investigation of economies of scale in credit unions. (Koot, 1978) Using a Benston-Bell-Murphy cost function and assuming an underlying Cobb Douglas production function, Koot finds that credit unions display decreasing returns to scale. Examining British Columbia credit unions, Murray and White find that most experience significant increasing returns to scale as well as economies of scope in mortgage and other lending areas. (Murray & White, 1983) Kim responded to Murray and White by distinguishing between economies of scale from overall production activity versus those from producing a particular product. (Kim, 1986)

Clark provides an extensive review of the earlier literature on economies of scale and scope in financial institutions. (Clark, 1988) Wilcox provides a more recent update. (Wilcox, 2005) Wheelock and Wilson find that information technology has favored larger institutions because of the relatively high fixed cost of equipment and software. Using non-parametric techniques, they find almost all credit unions operate with increasing returns to scale. (Wheelock & Wilson, 2011)

Financial Performance of Credit Unions

In 2001, Congress, determined to avoid a repeat of the Banking and Savings and Loan Crisis, passed legislation to provide for prompt corrective action in resolving problem institutions (organizations rated 4 or 5 on the CAMELS rating system.) (Rose & Hudgins, 2010) This resulted in a five category system ranging from 1=well capitalized to 5=critically undercapitalized. Credit unions as well as commercial banks are subject to these capital regulations. Sollenberger and Taggart discuss the consequences for management of having an undercapitalized credit union. (Sollenberger, Harold M.; Taggart, Colin, 2007)

In a subsequent article they examine long term credit union financial performance trends over the 20 year period from 1986 to 2006. (Sollenberger & Taggart, 2008) The trends include growth in size and profitability as well as capital. Consolidation has substantially increased average credit union size. Goddard, McKillop and Wilson examined US credit unions from 1991 to 2001 using variance decomposition analysis. (Goddard & McKillop, 2008). Some credit unions have evolved from niche players to full service retail institutions by embracing product and service flexibility.

Sollenberger and Stanecki have related credit union size with financial performance. (Sollenberger, Harold M.; Stanecki, Andrew W., 2009) They find that size is the most significant differentiating variable for credit unions. From 2003 to 2009 the number of credit unions decreased by more than 1,500. Smaller credit unions have decreased in numbers while large asset categories have increased. The generation of new members appears to be the biggest obstacle facing credit unions in the future.

Technology and Innovation in Financial Institutions

Technology has revolutionized the delivery of financial products to customers and has fundamentally changed competition in the financial services industry. Financial consumers, both young and old, use their smartphones, i-Pads and/or netbooks to transfer funds, check on account transactions or obtain loans from their local financial institution or from a competitor located hundreds or even thousands of miles away. Customers can access websites like LendingTree.com or Internetmortgage.com to obtain mortgages or bankrate.com to check on the best deposit rates. These are informational and, in some instances, transactional websites.

While technology intensifies competition, it also presents the possibility of significant reductions in operating costs by increasing economies of scale and reducing the average cost per transaction. For a discussion of the competitive impact of the Internet on banks using Porter's Five Forces Model the reader is referred to Siaw and Yu. (Siaw & Yu, 2004).

In a 2006 paper Dow found that larger credit unions are more likely to adopt new technologies, adopt them earlier and adopt more advanced versions. (Dow, 2006) Dow, using technology survey based data from the National Credit Union Administration from 2000 and 2003 develops a multiple regression model that includes the log of total assets, delinquent loans, non-interest expenses and fee income variables. These are generally statistically significant for all groups including non-adopters, late adopters and early adopters. We extend Dow's analysis is extended in this paper by examining different multivariate techniques, an alternative formulation of adoption versus non-adoption, a much more extensive examination of financial performance metrics and a much longer time frame that includes segments before, during and after the financial crisis of 2008.

Data and Research Design

This study examines the financial performance of credit unions that actively use technology related services versus those that are not active users of technology. Beginning in 2000 the National Credit Union Administration has collected quarterly survey data from credit unions in the form of a series of yes or no questions related to information system based financial services. In this paper four technology related credit union services are considered: WWW/Internet access, account balance inquiry, viewing account history and bill payment. A credit union that responds "yes" to all four questions is assigned a value of "1" and is deemed to be a technology leader; a credit union that responds "no" to all four questions is assigned a "0" value and is considered a technology laggard.

Recent years have been heavily influenced by the financial crisis. This paper therefore examines four different time periods: 1) 2002.4, a period well before the financial crisis 2) 2006.4, the end of a growth period before the crisis, 3) 2008.4, a period characterized by frozen financial markets and a "melt down" at the height of the crisis and 4) 2011.2, a period of slow recovery and the latest currently available data. The number of technology leaders versus laggards is shown in Table 1.

Table 1: Technology Leaders versus Laggards

	2002.4	2006.4	2008.4	2011.4
Technology Leader	**n= 739**	**n= 1734**	**n= 2202**	**n= 2332**
Technology Laggard	**n= 4472**	**n= 4269**	**n= 3708**	**n= 3408**

As discussed in the section on economies of scale and scope, the use of technology may be influenced by the size of the institution. To eliminate the effects of very large institutions, this study is limited to smaller credit unions below the $100 million total asset threshold. In addition, to eliminate the effects of *de novo* performance, all credit unions in the study have been in existence for at least five years. Furthermore, no defunct institutions are included. Data for this study are obtained through subscription to the proprietary SNL Corp. financial services database.

Descriptive Statistics and Significance Tests

This study utilizes 21 variables that are commonly used as metrics for the financial performance of financial institutions. Descriptive statistics for variables used in this model are presented in Table 2 along with test results for differences in the group means. The complete list of variables appears in Table 3.

In general, credit unions that are technology leaders have a total asset (TA) size of $40 million while those that are technology laggards are less than $10 million in assets. It is notable that the average asset size for both groups declined between 2002 and 2011; the drop in average size for the laggard group has declined substantially from over $17 million in 2002 to under $10 million in 2011. During the same period total assets in the technology leader group fell from about $46 million to around $39 million. The decrease in both groups reflects declines beginning before the financial crisis and continuing afterward.

The ratio of operating expenses to average assets (OE2AA) is higher for technology leaders versus laggards in all four time periods. The difference is statistically significant at the .000 level in each period. The *2010 Credit Union Technology Spending Survey* estimates that technology expenses account for 5-10% of total operating expenses for median credit union survey respondents. (Creditunions.com, 2010)

The ratio of total loans to total assets (TL2TA) is both a proxy for loan demand as well as an indirect proxy for liquidity since institutions facing greater loan demand have fewer remaining short term assets to provide liquidity. Conversely, falling loan demand, *ceteris paribus* increases liquidity. Technology leaders have consistently higher total loan to asset ratios than do laggards, a result that is statistically significant in all time periods.

Technology laggards consistently achieve higher yields on loans (YoL) than do technology leaders. This may in part be explained by scale or asset size differences. By contrast, the laggard group pays a slightly higher cost for interesting bearing liabilities (CIBL). The mean differences between groups for yield on loans is significant in all periods while the difference in the cost of interest bearing liabilities is statistically significant in all periods except in 2006 when the costs are virtually identical. These variations in YoL and CIBL may reflect the borrower-saver preference discussed by Smith. (Smith, 1984)

Table 2: Descriptive Statistics and Significance Test

0= technology laggards; 1= technology leaders

	Operating Expenses to Average Assets (OE2AA)	**Total Loans to Total Assets (TL2TA)**	**Yield on Loans (YoL)**	**Members to Potential Members (Mem2PotMem)**	**Total Assets (TA)**	**Cost of Interest Bearing Liabilities (CIBL)**	**Return on Average Equity (ROAE)**	**Loan Growth Rate (LGR)**
2011- 0	3.64	45.59	7.50	53.91	9639.72	.78	.04	5.42
2011- 1	4.16	53.88	6.668	31.99	39112.38	.71	2.63	3.82
Signif. '11	.000	.000	.000	.000	.000	.004	.000	.347
2008- 0	3.92	53.17	7.90	49.96	9449.75	. 71	1.35	-2.01
2008- 1	4.53	62.44	7.31	32.62	37890.03	.68	1.46	3.14
Signif.' 08	.000	.000	.000	.000	.000	.000	.615	.000
2006- 0	3.76	58.50	7.49	50.01	11150.70	1.98	4.58	3.42
2006- 1	4.31	65.59	7.02	32.79	39961.17	2.00	6.34	4.93
Signif. '06	.000	.000	.000	.000	.000	.407	.000	.001
2002- 0	3.63	56.98	8.56	125.04	17089.24	2.41	7.41	2.68
2002- 1	4.15	62.06	8.07	40.18	46467.71	2.27	7.50	4.48
Signif. '02	.000	.000	.000	.311	.000	.000	.979	.008

The ratio of members to potential members (Mem2PotMem) is higher for technology laggards than leaders in all periods except 2002 when the ratio actually exceeds 100% for laggards. Membership growth is essential to the long-term financial performance of credit unions. As Sollenberger and Stanecki observe "generating new members is the Achilles heel that may limit credit unions competitiveness in the future". (Sollenberger, Harold M.; Stanecki, Andrew W., 2009).

Because of the unique nature of credit unions their objectives differ from other financial institutions, especially commercial banks. For banks, return on equity (ROE) is important and easily altered by the use of financial leverage. (Koch & MacDonald, 2010) For credit unions, a lower value for ROE may actually be an indicator of increased benefits to members, especially with lower costs to borrowers and greater returns to savers. (Smith, Donald J.; Cargill, Thomas F.; Meyer, Robert A., 1981) In two periods, 2002 and 2008 there was no statistically significant difference in ROE between technology leaders and laggards. In both 2006 and 2011 ROE was significantly higher for technology leaders.

Since loans are the primary earning asset for credit unions, loan growth (LGR) is important. In the period from 2002 to 2011 there have been historic business cycle swings. In three periods, 2002, 2006 and 2008 there is no statistically significant difference between technology leaders and laggards. In 2011 the loan growth rate for laggards substantially exceeds the rate for leaders.

Factor Analysis

Factor analysis is used to reduce the dimensionality of data sets. We initially examine 21 variables that represent a variety of financial performance metrics selected from the literature on financial institution performance. We utilize principal components factor analysis in SPSS to reduce the initial 21 variables down to a few underlying factors that explain a significant percentage of overall variance. The highest loaded variable on each factor is then utilized as a proxy variable for that factor. These proxies are subsequently used as independent variables in a multivariate discriminant analysis. For a thorough treatment of factor analysis the interested reader is referred to the classic work of Rummel. (Rummel, 1970)

Factors are extracted using an eigenvalue constraint of ≥ 1. Varimax rotation is used to produce the rotated factor matrix. (Hair, Black, Babin, & Anderson, 2010) The result is the extraction of eight underlying factors which are presented in Table 3.

Examination of the factor loadings for each individual factor allows us to identify and name each relevant factor. Typically one or more variables will load highly on a given factor with the remainder of the variables having low factor loadings. (Rummel, 1970) For example, in Table 3 entitled Rotated Component Matrix, the first factor is identified as Operating Expenses while subsequent factors represent loan demand, credit union size, cost of funds, earnings, yield on assets, growth and membership. The highest loaded variable on each factor is used as a proxy for that factor in a multivariate discriminant model.

Table 3 Rotated Component Matrix[a]

	Component							
	1 Operating Expenses	**2 Loan Demand**	**3 Size**	**4 Cost of Funds**	**5 Earnings**	**6 Yield on Assets**	**7 Growth**	**8 Membership**
TA11	.026	.087	.786	.035	.072	-.059	-.007	-.046
DelL2L	-.004	-.227	-.122	.006	-.156	.512	-.082	-.042
NCO2L11	.004	.045	-.156	.124	-.307	-.182	.075	-.175
ROAA11	-.471	.141	.044	-.084	.704	.093	.086	-.033
ROAE11	-.005	.113	.053	.005	.844	-.014	.068	-.011
CoF2AA11	-.034	.019	.051	.981	-.047	.010	.009	.007
OE2AA11	.980	.096	-.052	-.034	-.107	-.009	-.022	-.002
PLL2A11	-.128	.192	.127	-.006	-.774	.294	.031	.037
NIM2AA11	.095	.781	-.062	-.296	.077	.421	.034	.004
NII2AA11	.787	.018	.087	-.012	.126	.074	.090	-.019
NIE2AA11	.980	.096	-.052	-.034	-.107	-.009	-.022	-.002
TL2TA11	.072	.861	.149	.119	-.011	-.121	-.028	-.004
LiqA2A11	-.022	-.631	-.512	-.144	-.044	.151	.021	-.013
Mem2PotMem11	-.013	-.007	-.073	.013	.000	-.041	.008	.975
A2FTE11	-.154	-.466	.552	.138	.109	.089	.023	.117
LGR11	.048	.010	-.067	-.023	-.027	-.150	.808	-.026
AGR11	-.012	-.025	.061	.031	.072	.127	.786	.024
TREL2L11	.025	.060	.769	-.016	.006	-.168	-.075	-.044
YoL11	.058	.210	-.283	.025	.053	.774	.090	.003
CIBL11	-.022	-.023	-.019	.985	-.051	.005	-.001	-.005
C2A11	.013	-.214	-.460	.106	.102	.249	-.142	.019

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 7 iterations.

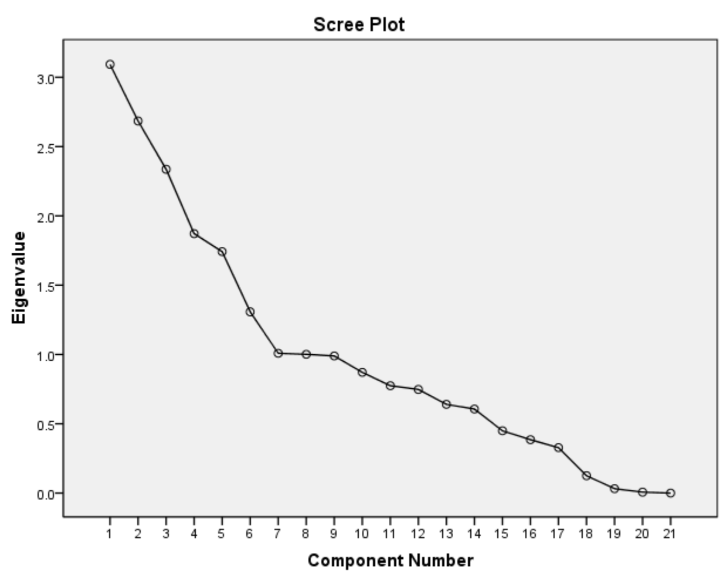
The cumulative variance explained by these eight factors is about 71.65%. The first factor, a measure of operating expenses explains about 13.5% of total variance. Each successive factor contributes an incrementally smaller amount of total variance. After extraction of the eight factor, the calculated eigenvalue falls below the unity threshold.

Table 4 Cumulative Variance Explained

Factor #	Eigenvalue	% of Variance	Cumulative % of Variance
1	2.825	13.453	13.453
2	2.212	10.531	23.984
3	2.183	10.397	34.380
4	2.113	10.064	44.444
5	2.012	9.583	54.027
6	1.352	6.440	60.466
7	1.342	6.389	66.856
8	1.006	4.791	71.647

The scree plot in Exhibit 1 provides a visualization of the incremental contributions to total variance. With the eighth factor the slope of the scree plot changes as successive factors make smaller marginal contributions to the explanation of total variance. Hair et.al. suggest in the social sciences that explanations of explained variance exceeding 60% are acceptable. (Hair, Black, Babin, & Anderson, 2010)

Exhibit 1 Scree Plot



Discriminant Analysis

To investigate the multivariate differences in financial performance between credit unions that are technology leaders and technology laggards a linear multivariate discriminant model is created with the form:

$$Z_i = \alpha + \beta_1 X_1 + \beta_2 X_2 \ldots\ldots\ldots\ldots + \beta_n X_n \quad (1)$$

Where Z_i = dichotomous dependent variable where:
1= technology leader
0= technology laggard

$$Z_i = \alpha + \beta_1 OE2AA + \beta_2 TL2TA + \beta_3 TA + \beta_4 CoF2AA + \beta_5 ROAE + \beta_6 YoL + \beta_7 LGR + \beta_8 Mem2PotMem \quad (2)$$

X_1= OE2AA= operating expenses to average assets= (**operating expenses)**
X_2= TL2TA= total loans to total assets= (**loan demand)**
X_3= TA=total assets= (**size)**
X_4=CoF2AA=cost of funds to average assets= **(cost of funds)**
X_5=ROAE=return on average assets= **(earnings)**
X_6=YoL= yield on loans to average loans=(**yield on assets)**
X_7=LGR=loan growth rate= **(growth)**
X_8=Mem2PotMem=members to potential members= **(membership)**

The variables in the discriminant model represent the highest loaded variables on the eight underlying factors derived from factor analysis of the initial 21 financial performance metrics.

The discriminant structure matrix in Table 4 can be used to assess the relative importance of individual independent variables. These discriminant loadings measure the simple linear correlation between each independent variable and the discriminant function. Hair et. al. have noted "…they can be interpreted like factor loadings in assessing the relative contribution of each independent variable to the discriminant function." (Hair, Black, Babin, & Anderson, 2010)

Total asset size (TA) is consistently the most important variable in all four time periods. This is consistent with the earlier discussion of the literature on scale economies as well as the work of Sollenberger (Sollenberger, Harold M.; Stanecki, Andrew W., 2009) and Dow. (Dow, 2006)

Total loans to total assets (TL2TA) has increased in relative importance from fourth in 2002 to third in 2006 and 2008 and up to second in 2011. By contrast, members to potential members (Mem2PotMem) has changed from seventh in 2002, all the way to second in 2006 and 2008 then back to sixth in 2011.

Table 4 Discriminant Structure Matrix

Variable	2011.2	2008.4	2006.4	2002.4
Total Assets (TA)	.939 (1)	.905 (1)	.936 (1)	.946 (1)
Total Loans to Total Assets (TL2TA)	.281 (2)	.302 (3)	.225 (3)	.202 (4)
Yield on Loans (YoL)	-.197 (3)	-.203 (5)	-.166 (5)	-.230 (3)
Operating Expenses to Total Assets (OE2AA)	.142 (4)	.221 (4)	.204 (4)	.238 (2)
Return on Average Assets (ROAE)	.083 (5)	.008 (8)	.079 (6)	.001 (8)
Members to Potential Members (Mem2PotMem)	-.082 (6)	-.375 (2)	-.378 (2)	-.026 (7)
Cost of Interest Bearing Liabilities (CIBL)	-.046 (7)	-.065 (7)	.014 (8)	-.127 (5)
Loan Growth Rate (LGR)	-.015 (8)	.167 (6)	.057 (7)	.068 (6)

The statistical significance of the discriminatory power of the discriminant functions are shown in Table using Wilks' Lambda. In all four time periods the overall goodness of fit is .000.

Table 5 Wilks' Lambda Statistics

Time Period	Wilks' Lambda	Chi-square	Degrees of Freedom	Significance
2002.4	.774	1332.0	8	.000
2006.4	.623	2805.9	8	.000
2008.4	.582	3189.0	8	.000
2011.2	.592	2995.3	8	.000

Table 6 presents data for Fisher's linear discriminant functions for each time period in the study. This data is used for classifying group membership. Each individual credit union would have observed values for each of the eight variables contained in the model. Using the data in

Table 6 a discriminant score can be computed for each credit union. This value is compared to the critical Z value to determine the estimated group membership.

Table 6
Fisher's Linear Discriminant Function

Variable		2002.4		2006.4		2008.4		2011.2
	Laggard	Leader	Laggard	Leader	Laggard	Leader	Laggard	Leader
Operating expenses to average assets (OE2AA)	.413	.731	.908	1.160	-.024	.337	.192	.355
Total loans to total assets (TL2TA)	.209	.214	.159	.167	.187	.337	.144	.161
Members to Potential Members (M2PotM)	9.57E-5	8.20E-5	.083	.072	.084	.072	.003	.002
Total Assets (TA)	.000	.000	7.21E-5	.000	9.38E-5	.337	4.71E-5	.000
Cost of Interest Bearing Liabilities (CIBL)	3.612	3.479	2.547	2.507	.363	.341	.538	.373
Yield on Loans (YoL)	4.473	4.376	2.685	2.586	2.946	2.767	1.248	1.173
Return on Average Equity (ROAE)	1.60E-5	.000	.010	.018	.004	.023	-.017	-.014
Loan Growth Rate (LGR)	-.060	-.060	-.005	-.006	-.070	-.067	.002	.001
Constant	-31.233	-35.733	-21.786	-25.212	-20.921	-23.682	-9.335	-12.639
Function at Group Centroids	-.220	1.329	-.496	1.219	-.652	1.098	-.688	1.002

Ultimately discriminant analysis is designed to classify observations into their correct group. This is accomplished using a discriminant classification matrix as shown in Table 7. The model used in this paper was derived from an initial set of 21 standard financial metrics that are frequently used in academic literature related to financial institutions. These were reduced to eight underlying factors. Proxy variables for these eight factors become independent variables in a multivariate discriminant model. That model produces the results shown in Table 7. The overall classification accuracy of the model ranges from over 86% in 2002 to just below 80% in

2011. Given the extreme changes in the economy and financial markets between 2002 and 2011, this appears to be remarkably stable. The model correctly predicts laggards at a 93% or better rate in all four periods.

Technology leaders by contrast are correctly predicted about 59% of the time in the two most recent periods, 2008 and 2011 and about 53% in 2006. Predicting leaders in 2002 was difficult with less than 37% of leaders correctly classified. There are several possible explanations. The number of laggards in 2002 exceeded leaders by almost ten-fold. Some technologies in 2002 were relatively new to credit unions. The adoption of these technologies may follow a time path along the lines described by Rogers work on diffusion of innovation. (Rogers, 2003) Over time the differences in financial performance of leaders may have become clearer and more distinct.

Table 7 Discriminant Classification Matrix

	Laggard (0)	**Leader (1)**	**Total**
2011.2 Laggard (0)	3184 (93.4%)	224 (6.6%)	3408
Leader (1)	949 (40.7%)	1383 (59.3%)	2332
Overall accuracy 2011.2			79.6%
2008.4 Laggard (0)	3463 (93.4%)	245 (6.6%)	3708
Leader (1)	894 (40.6%)	1308 (59.4%)	2202
Overall accuracy 2008.4			80.7%
2006.4 Laggard (0)	3981 (93.3%)	288 (6.7%)	4269
Leader (1)	816 (47.1%)	918 (52.9%)	1734
Overall accuracy 2006.4			81.6%
2002.4 Laggard (0)	4214 (94.2%)	258 (5.8%)	4472
Leader (1)	466 (63.1%)	273 (36.9%)	739
Overall accuracy 2002.4			86.1%

Summary and Conclusions

Credit unions are unique not-for-profit financial institutions that exist for the benefit of members who are bound together by a common bond. In the absence of a strong profit incentive, credit unions serve their members by providing loans at rates below their non-bank competitors while rewarding depositors with above market rates on funds. Some credit unions have responded by making greater use of information technology to create customer friendly products and services while reducing the average costs of providing them.

In this paper we investigate the financial performance of small US credit unions (less than $100 million in total assets) from 2002 to present. We examine credit unions that are technology leaders versus laggards using categories created from using survey data on information systems provided by the National Credit Union Administration.

Using factor analytic techniques we reduce 21 generally accepted financial performance metrics into 8 underlying factors. Using the highest loaded variables on each factor, we create a multivariate discriminant model for the purpose of predicting whether a given credit union is likely to be a technology leader versus a technology laggard. The model correctly classifies credit unions approximately 80% of the time in four different time periods.

The earliest period includes year-end 2002, a period when technological applications were relatively novel in credit unions. Year-end 2006 represents the end of a period of growth. Fall 2008 witnessed frozen credit markets worldwide, the financial collapse of financial institutions such as Lehman Brothers and AIG, and emergency rescue packages from Congress and the Federal Reserve System. Finally, we examine 2011.2 data, the latest available. This is a period of weak economic recovery.

The study finds that asset size is the most important variable in explaining performance differences between technology leaders and laggards. While this study eliminates large credit unions by restricting the sample to credit unions with under $100 million in assets, it nevertheless finds substantial variation in asset size between leaders and laggards with a mean difference of about $30 million between the groups. This finding is consistent with research on economies of scale in credit unions and banks.

In the end there are clear and discernible differences in the financial performance of technology leaders versus technology laggards. This suggests that perhaps technology does, in fact, matter. This may pose the question of whether scale matters as well. If technology is unaffordable to smaller credit unions, does that create an incentive to consolidate? Does consolidation blur the common bond requirement? Does the blurring of the common bond present policy issues about the continued differential tax treatment of credit unions relative to their for-profit counterparts. These are some of the many issues that must be answered in future research.

References

Credit Unional National Association. (2011, September). Retrieved November 27, 2011, from CUNA: http://cuna.org/research/fownload/USCU_profile_2q11.pdf

CUNA. (2011, September). Retrieved November 27, 2011, from Credit Union National Associaton: http://cuna.org/research/download/USCU_profile_2q11.pdf

World Council of Credit Unions. (2011, December 5). Retrieved December 5, 2011, from World Council of Credit Unions: http://www.woccu.org/memberserv/intlcusystem

Black, H., & Dugger, R. H. (1981). Credit Union Structure, Growth and Regulatory Problems. *Journal of Finance*, 529-538.

Cargill, T. (1977). Recent Research on Credit Unions: A Survey. *Journal of Economics and Business, 29*(Winter), 155-162.

Carr, N. G. (2004). *Does IT Matter?* Boston: Harvard Business School Publishing.

Clark, J. A. (1988). Economies of Scale and Scope at Depository Financial Institutions: A Review of the Literature. *Economic Review-Federal Reserve Bank of Kansas City*, 16-33.

Creditunions.com. (2010). *Member Service Technologies are a Priority for Credit Unions: 2010 Credit Union Technology Survey.*

Dow, J. P. (2006). The Adoption of Web Banking at Credit Unions. *Quarterly Review of Economics and Finance*, 435-448.

Feinberg, R. M. (2001). The Competitive Role of Credit Unions in Small Local Financial Services Markets. *The Review of Economics and Statistics*, 560-563.

Feinberg, R., & Rahman, A. A. (2006). Are Credit Unions Just Small Banks? Determinants of Loan Rates in Local Consumer Lending Markets. *Eastern Economic Journal*, 647-659.

Flannery, M. (1974). *An Economic Evaluation of Credit Unions in the United States.* Boston: Federal Reserve Bank of Boston Research Report.

Goddard, J., & McKillop, D. a. (2008). What Drives the Performance of Cooperative Financial Institutions? Evidence from US Creit Unions. *Applied Financial Economics*, 879-893.

Hair, J., Black, W., Babin, B., & Anderson, R. (2010). *Multivariate DataAnalysis.* Upper Saddle River, NJ: Prentice Hall.

Kaushik, S., & Lopez, R. H. (1994). The Structure and Growth of the Credit Union Industry in the United States: Meeting Challenges of the Market. *American Journal of Economics and Sociology*, 221-243.

Kim, H. Y. (1986). Economies of Scale and Economies of Scope in Multiproduct Financial Institutions: Further Evidence from Credit Unions. *Journal of Money, Credit and Banking*, 220-226.

Koch, T., & MacDonald, S. (2010). *Bank Management.* Thomson South-western.

Koot, R. S. (1978). On Economies of Scale in Credit Unions. *Journal of Finance*, 1087-1094.

Murray, J. D., & White, R. W. (1983). Economies of Scale and Scope in Mutiproduct Financial Institutions: A Study of British Columbia Credit Unions. *Journal of Finance*, 887-902.

Navratil, F. J. (1981). An Aggregate Model of the Credit Union Industry. *Journal of Finance*, 539-549.

Rogers, E. M. (2003). *Diffusion of Innovations* (5th ed.). New York: Free Press.

Rose, P., & Hudgins, S. (2010). *Bank Management & Financial Services.* New York: McGraw-Hill.

Rummel, R. (1970). *Applied Factor Analysis.* Evanston, IL: Northwestern University Press.

Siaw, I., & Yu, A. (2004). An Analysis of the Impact of the Internet on Competition in the Banking Industry using Porter's Five Forces Model. *International Journal of Management*, 514-523.

Smith, D. J. (1984). A Theoretic Framework for the Analysis of Credit Union Decision Making. *Journal of Finance*, 1155-1168.

Smith, Donald J.; Cargill, Thomas F.; Meyer, Robert A. (1981). An Economic Theory of a Credit Union. *Journal of Finance*, 519-528.

Sollenberger, H. M., & Taggart, C. (2008). Credit Unions Then and Now: Performance Analysis Shows Long-Term Trends. *Bank Accounting and Finance*, 16-28.

Sollenberger, Harold M.; Stanecki, Andrew W. (2009). Credit Union Financiaal Performance: The impact of Asset Size. *Bank Accounting and Finance*, 3-14.

Sollenberger, Harold M.; Taggart, Colin. (2007). What Happens to Undercapitalized Credit Unions? *Bank Accounting and Finance*, 25-48.

Ward, A.-M., & McKillop, D. G. (2005). An Investigation Into the Link Between UK Credit Union Characteristics, Location and Their Success. *Annals of Public and Cooperative Economics*, 461-489.

Wheelock, D. C., & Wilson, P. W. (2011, November). Are Credit Unions Too Small? *Review of Economics and Statistics*, 1343-1359.

Wilcox, J. A. (2005, November). Economies of Scale and Continuing Consolidation of Credit Unions. *FRBSF Economic Letter*, 1-3.