Predicting Credit Union Mergers:

A longitudinal study of the key predictors of two credit unions merging

Sam Isaacman, MBA

Harrisburg University of Science and Technology

Author Note

Harrisburg University of Science and Technology

Correspondence concerning this article should be addressed to Sam Isaacman

437 Northstar Drive Harrisburg PA, 17112. E-mail: sisaacman@my.harrisburgu.edu

Abstract

Due to the ongoing trend of mergers in the credit union industry, there is significant value in creating a predictive model that can accurately and efficiently identify the credit unions most likely to merge with each other. The value exists in decreasing project timelines, avoiding consulting costs, and minimizing the opportunity costs associated with failing to merge. Past research identified factors contributing to general trends impacting any credit union's willingness to merge, but that research did not evaluate these factors at the individual credit union level. This research went a step further by exploring the probability of two specific credit unions merging. The purpose of this research was to create a predictive model that could accurately predict what credit union is most likely to pair with an acquiring credit union. To simplify this concept, the purpose of this research was to create a 'match-maker' predictive model that could accurately and efficiently predict credit union pairs (think couples). After training a model on all possible credit union merger combinations from years 2010 – 2016, a logistic regression model was able to accurately predict what credit union would merge with the acquiring credit union for years 2017-2018. This model correctly matched merger combinations 74% of the time when a merger prediction was made. The model was also over 99.9% accurate in predicting couples / merger pairs that did not merger together.

Predicting Credit Union Mergers: A longitudinal study of the key predictors of two credit unions merging

With economic uncertainties surrounding a once-in-a-century pandemic, diminished profit margins dating back to the Great Recession, and intensive competition from mega-banks, credit unions are under immense pressure to remain in business. While many people in the U.S. are familiar with credit unions, they may find it surprising to know that the typical credit union operates closer to a small mom-and-popshop than a mega-bank. The typical credit union only has around a dozen employees, and just as small businesses have shuttered their doors in the face of big-box retailers such as Walmart and Amazon, so too have credit unions closed shop in recent years. The number of credit unions has declined almost every year for the past several decades. Some have gone out of business entirely, but most have merged into larger credit unions.

This process of merging, occurring across an industry consisting of thousands of credit unions, is not unlike the process of dating. The two credit unions consider the attributes of each other when deciding whether to pursue courtship. Factors such as similarities in financial well-being, relative distance to each other (i.e., overlapping markets), and hobbies (i.e., products and services) come into play just as they do for people. This research aimed to better understand how factors such as these contribute to the odds of two credit unions merging. In doing so, a model was developed to predict the likelihood of two credit unions merging. In other words, and drawing on the dating metaphor, this research aimed to develop a machine learning predictive model that operates similarly to a person playing matchmaker in a room full of singles. The primary value of this model is in the reduction of employee hours and consulting costs needed to identify merger candidates. An additional measure of this value is in the opportunity costs associated with a credit union pursuing but failing to secure a successful merger (e.g., what someone's life could have been if they had married the one that got away).

Credit Unions

Credit unions are not-for-profit, member-owned financial institutions that offer savings and loan products nearly identical to those offered by banks. Although credit unions and banks offer similar products, credit unions differ from banks in that credit unions work in the interests of their customers whereas banks work in the interest of shareholders. Beneath their outward similarities, banks and credit unions differ drastically in their core missions. The traditional bank works to maximize its shareholder/owner wealth whereas a credit union strives to maximize both member value and the quality of service provided to their member-owners.

Credit unions came to the United States in the early 1900s and were modeled after the Canadian and German models. The first credit unions can be traced back to Germany during a potato famine where they acted more akin to charities than banks. The necessity and democratic nature of these institutions made them popular, and over the years, they morphed into democratic nonprofits offering a variety of banking services. The first U.S credit unions typically formed under the sponsorship of an employer or another organization that made up the credit union's field of membership (a requirement to join the credit union). Having a closely tied group of borrowers and savers provided an option for consumer credit during a time when banks were hesitant to lend. For these reasons and more, the credit union movement grew exponentially over the next century.

Industry Growth & Consolidation

The number of new credit unions surged during the first half of the 20th century. Crofton et al (2020) observed that the total number of credit unions tripled from 1930 to 1940, exceeding the number of banks by the 1950s, and since come to hold over a trillion dollars in total assets with more than 100 million U.S. members. However, the total number of new credit unions peaked in 1969. Since then, the number of U.S. credit unions has declined almost every year with the consolidation consisting of either mergers or liquidations. Goddard et al (2014) observed that the U.S. credit union industry declined from 14,549 to 7,335 between 1990 and 2010, much of which was due to mergers. These mergers have primarily consisted of larger, healthier credit unions acquiring smaller, failing credit unions. Credit union mergers are more favorable than liquidations for many reasons but primarily because they cause less disruption to the consumer members. Merging allows a failing credit union to continue serving their customers, and in many cases, avoid the type of layoffs seen with liquidation. Merging also offers a benefit in protecting the National Credit Union Administration (NCUA) Share Insurance Fund, which is a fund that operates akin to FDIC insurance (e.g., consumer protection against loss of funds in a checking account).

Mergers

A credit union merger consists of one credit union acquiring another credit union. Whereas each credit union existed under its own charter prior to the merger, only the surviving credit union's charter remains after the merger finalizes. This practice has become increasingly more common in recent years, and despite the size and prevalence of the credit union industry, there have been relatively few academic studies on credit union mergers. Fried et al (1999) may have performed the first academic study on credit union mergers, astutely noting that credit union mergers need to be evaluated based on service-level provided to members, but erroneously failing to accurately measure loan service value as a result of an inadequate loan rate calculation. Fried et al (1999) failed to control for differences in credit union loan portfolios. This error is similar to someone stating their bank provide more value because they have a mortgage rate that is lower than someone else's credit card rate. The failure in that comparison is that mortgage rates are almost always lower than credit cards, because unlike a credit card, a mortgage is secured by a property. More recent research into the trend of mergers by Crofton et al (2020) suggested the introduction of regulatory share insurance in 1971 led regulators to permit more mergers to prevent liquidations, failures, and a cost to their share insurance fund. Looking at the wider banking industry, Critchfield et al (2005) attributed increase in mergers to deregulation (i.e., interstate bank competition), large swings in asset prices, and technology changes. As for the parties in a merger, Dopico et al (2014) showed that almost all credit union mergers consist of a larger credit union acquiring a smaller credit union.

Motivations to Merge

Smaller credit unions are often interested in merging with a larger as a means to remain in business. Merging offers credit unions employees the chance to save their jobs and continue serving their members. A merger can also be an attractive alternative to replacing a credit union CEO, and mergers can lead to higher compensation for all employees the acquiring credit union pays higher salaries. Another motivator for credit union mergers is the knowledge and product transfer that can occur when the merging credit unions offer different types of products and services. Unique products can include boat loans, RV loans, credit or debit card reward programs, youth savings accounts, retirement certificate or deposits and individual retirement accounts, insurance products, courtesy pay or overdraft protection, and online banking functionality. Similarly, mergers can provide a means to balance two credit union loan portfolios, offering diversification that protects the credit union from interest rate risk. Yet another motivation for merging can be increases to potential members via the combination of both credit unions' field of membership groups. Moreover, Bauer (2009) proved that the financial well-being of acquired credit unions increased substantially following the merger whereas the acquiring credit union showed very little improvement.

Larger credit unions are interested in merging with smaller credit unions as a growth opportunity. Ames et al (2014) stated that an acquiring credit union may receive a financial benefit from the National Credit Union Administration for pursuing a merger with a failing credit union and avoiding liquidation and its effect on the share insurance fund. Akkus et al (2013) found value in bank mergers was tied to cost efficiencies in overlapping geographic markets, network effects, and relaxed regulatory burden. Cerasi et al. (2019) evaluated Italian bank mergers and found that competition decreased when a bank merger led to a dominant player in each geographic region. While credit unions typically do not dominate markets, increases in total assets provides economies of scale that can help them better compete. DeYoung (2009) noted that executives are more likely to pursue fast growth when their compensation is tied to the asset size. Since credit union executive compensation is benchmarked to the title and size of the firm, credit union executives of larger credit unions are likely to gain a financial benefit from merging even if the merger offers no value to its members.

Benefits of Predicting Prospective Merger Candidates

The credit union industry spends millions of dollars on merger activities every year. A large portion of this cost includes managerial time and consulting fees tied to an acquiring credit union identifying merger candidates. Identifying credit unions willing to merge offers significant value in decreasing the time and effort required to identify these candidates. Moreover, there are opportunity costs in not selecting an ideal merger candidate. Training a model on past merger pairs gives insight into the quality of candidate an acquiring credit union can achieve. A model that solely looked at probability to merger without considering pairs would always recommend merging with failing credit unions. Looking at the probability of two credit unions merging based on historical mergers can inform a credit union of the matches that are either out of their league and a waste of time to pursue or failing so much that they would drag the acquiring credit union down. Using this historical data leverages the knowledge of past managers in evaluating candidates. Moreover, Alhenawi et al (2018) found that how two organizations relate to each other does affect the combined entities success in a market.

Factors Impacting Probability to Merge

Most of the studies evaluating factors linked to credit union mergers evaluate the probability of merging based on financials. Goddard et al. (2008) and Goddard et al. (2014) observed that credit unions with fewer assets, a high composition of liquid assets, low loan-to-asset ratios, and low profitability are more likely to merge or liquidate, and older lower capitalized credit unions are more likely to merge. Ames et al (2014) suggested that an acquiring credit union was less likely to seek out a credit union with a large portfolio of delinquent loans. In the context of pressures influencing probability to merge, Smith and Woodbury's (2010) indicated that credit unions may be impacted less by economic cycles than banks. Hernando (2008) identified high management cost to bank profitability as a driver of mergers. Worthington (2004) found asset size and liquidity to be variables impacting the probability of an Australian credit union engaging in a merger. While these studies establish a base understanding of factors driving mergers, no academic study has tried to predict the credit unions most likely to merge.

There is much less attention paid to non-financial variables linked to a credit union's probability to merge. Studies such as Barron et al (1994), Gordon (1987), and Kharadia (1981) found poor management, inadequate credit criteria, and field of membership related closures were associated with credit union failures, but these studies did evaluate these factors as they relate to mergers. Worthington (2004) found an association between regulatory variables and an increase in the probability of Australian credit unions to pursue a merger, but this analysis covered less than one decade. Erel et al (2012) identified geography as a factor for cross-border bank mergers but it is difficult to draw direct parallels between international banks and U.S. credit unions.

Predictive Model – Predicting Mergers

To the best of knowledge of the author, there have been no academic studies attempting to create a predictive model of merger pairs for credit unions or any other industry. The closest research to date appeared to be that of Routledge et al (2013) who attempted to predict the likelihood of individual organizations pursuing a merger based on regulatory text filings. As the credit union industry and others continue to consolidate, models predicting merger combinations are increasingly valuable. This research attempts to predict credit union mergers by identifying the factors with the largest effect on the probability of two credit unions merging. This insight will allow one to identify ideal candidates for a credit union merger, which could lower the industry cost of successful mergers. Success of this model is defined as obtaining a model with a high degree of predictability in determining which credit unions are most likely to merge.

This research explored how past findings, which looked at industry trends as am whole, applied to the selection criteria used by individual credit unions when selecting a merger partner. My hypotheses evaluated whether the differences in credit union performance metrics impacted their probability to merge. These hypotheses were analyzed as part of the final model and they were accepted or rejected based on their significance in relation to a preset alpha-level.

As Bauer et al. (2009) found that the financial well-being of an acquired credit union increased substantially following a merger, hypothesis 1 was constructed to see if healthier credit unions were more likely to merge with unhealthy credit unions.

- *H1 – The absolute difference between two credit unions' net worth ratios has an impact on their probability to merge.*

Cerasi et al. (2019) found that scale can help banks compete better in a geographic market. To see if this relationship represented itself in a credit unions decision on a merger partner, hypotheses 1 and 2 were formed.

- *H2 – The absolute difference between two credit unions' total branches has an impact on their probability to merge.*
- *H3 – The absolute difference between two credit unions' total assets has an impact on their probability to merge.*

In response to DeYoung's (2009) finding that executives were more likely to pursue fast growth when their compensation was tied to asset size, the below hypotheses were formed to see if credit unions were more likely to merge with larger credit unions with higher average compensation and benefits.

- *H4 – The absolute difference between two credit unions' average benefits and salary has an impact on their probability to merge.*
- *H5 – The absolute difference between two credit unions' return on assets has an impact on their probability to merge.*

Methods

This analysis utilized a dataset covering nine years of state-chartered credit union mergers. The analysis focused on identifying factors influencing merger pairs via the creation of a merger combination predictive model. This model can predict what credit unions will merge in the future. This was performed by training predictive models on actual and possible merger combinations and then applying that model to years not included in the training dataset. The predictor variables used in this analysis were obtained from NCUA.gov custom query data.

Data

National Credit Union Administration (NCUA) data was used for this analysis. A historical dataset of charter conversions, liquidations, and buyouts was pulled from NCUA.gov. That dataset was filtered so that only mergers from 2009 to 2018 remained. A second dataset of credit union financials for the same timeframe was also pulled from NCUA.gov, and these two datasets were combined using the credit unions' unique charter numbers. The previous year-end financials of the merging (non-surviving) credit unions were used as the merged credit union no longer existed at the end of the merging year. The year-end financials of the acquiring credit unions were used on the year of the merger.

Additional pre-processing was performed to clean the dataset used. Federally chartered credit unions were removed from the dataset and about 20 intrastate credit union mergers across state lines were removed. This resulted in a set of 577 mergers over 9 years. Combinations of all possible credit union pairs for each state were performed. Those that merged or did not merge were indicated accordingly. The process of creating the combinations that could have merged but did not per state yielded an additional 114,883 records. An example of the output from this process is included in Table 1 for the 2010 merger between Mutual Credit Union and Hinds Community College Credit Unions.

Table 1
Example of All Possible Merger Combinations (Target Variable)

Acquiring Credit Union	**Potential Acquired Credit Union**	**Merged?**
Mutual Credit Union	Hinds Community College Credit Union	Yes
Mutual Credit Union	Member Exchange Credit Union	No
Mutual Credit Union	Mississippi Public Employee Credit Union	No
Mutual Credit Union	Mutual Credit Union	No
Mutual Credit Union	Navigator Credit Union	No
Mutual Credit Union	Stephens-Adamson Employees Credit Union	No
Mutual Credit Union	Credit Union South Credit Union	No

The financial data was further pre-processed to calculate industry key performance ratios. A total of 174 ratios were calculated for each merger combination. These financial ratios per merger combination consisted of 58 financial ratios for the acquiring credit union, 58 financial ratios for the candidate credit union, and 58 ratios measuring the absolute difference between the acquirer and acquired credit unions' ratios. The last group of calculations was performed to see if opposites attract in the credit union merger space. Moreover, the purpose for calculating these financial ratios was to adjust for differences in size between credit unions. This was needed to measure efficiencies of the credit unions such as operating expense over total assets. Without a ratio, measuring total costs would provide no indication of how well the credit union operates from an efficiency standpoint. Other reasons for these calculations included determining the loan portfolio mix as needed to determine the credit union's lending focus. A credit union with a high percentage of auto loans divided by total loans does a better job of indicating the credit union's lending focus than the total auto loans booked since the total auto loans booked differs greatly based on the size of the credit union.

Predictors

A total of 48 predictor variables were selected for analysis in building a model to predict credit union mergers. These 48 predictor variables represented 14 different ratios grouped as the acquiring credit union's ratios, the merger candidate credit union's ratios, and absolute difference between the two credit union's ratios. These 48 predictor variables were limited down to a set of six used in the final model selected to predict merger combinations. These six variables are shown in Table 2.

Table 2
Predictive Model Variable Descriptive Statistics

#	Credit Union (CU) Predictor Variable	Mean	Standard Deviation
1	Candidate CU's Total Assets	$569,924,703	$1,110,261,602
2	Candidate CU's Credit Card Loans / Total Loans	5.12%	3.74%
3	Candidate CU's Mortgages Loans / Total Loans	35.18%	17.55%
4	Candidate CU's Total Branches	10	11
5	Combo[1] CU's Total Compensation & Benefits	$23,554	$22,347
6	Combo[1] CU's Total Branches	8.74	11.12

[1] Combo represents the absolute difference between the acquiring credit union's metric and the acquired credit union's metric. It is intended to measure how similar or different the two are on the metric listed.

Metrics measuring the credit union's total assets and total branches were included as part of a set of ratios measuring the size of the credit unions. Credit unions with larger total assets are generally healthier and not in need of merging. Total branches were also selected as a measure of a credit union's size but also a measure of business model (digital vs branches) and market footprint. After analyzing the variables, the candidate credit union's total assets, total branches, and the absolute difference between the acquiring credit union and acquired credit union's total branches were selected as the three size-related predictor variables used in this model.

Several measures of the credit union's loan concentration were also included in the analysis to determine if credit unions merge based on similarities or differences in these values. These measures included concentrations in auto loans, real estate loans, 1st mortgage loans, and credit card loans. After analyzing the metrics, the candidate credit unions' proportion of credit card loans to total loans and the credit unions' proportion of mortgage loans to total loans were selected as the two loan concentration variables used in this model. Additional measures of loan quality (e.g., delinquency rations and charge-off ratios) were also considered for use but discarded due to their poor performance in predicting mergers.

The final variable of interest for this analysis consisted of a measure gauging differences in the credit union's level of compensation. The absolute difference between the acquiring credit union's average compensation and benefits and candidate credit union's total compensation and benefits was used to evaluate if a jump in salary was a motivating factor for the merger. The basis behind this idea is that if the acquiring credit union paid higher salaries, the acquired credit unions' employees may be motivated out of self-interest to merge.

Outcome

The intended outcome of this analysis was a predictive model that accurately predicted credit unions likely to merge. This was measured by training a model on past credit union merger data and testing it on more recent merger data. The model provided a high degree of accuracy in predicting actual mergers with minimal false positives. Hypotheses testing was performed on the metrics used to predict these scores.

Data Analytic Plan

The initial step of this research consisted of pulling the historical merger and financial datasets. These two datasets were combined using the credit union's charter number. After the datasets were combined, combinations of all credit union potential mergers per state were determined by combining the datasets back onto itself by state and year. This resulted in a list of all potential combinations for the credit unions that existed in the state where the merger occurred. After obtaining the full list, calculations were performed to determine the acquiring credit union’s ratios, merger candidate credit union’s ratios, and the difference between the two credit union’s ratios.

Exploratory analysis was then performed on the dataset to include a series of side-by-side boxplots split by two groups: merged or did not merge. This was performed to see if there were visually discernable differences in the data between the merged pairs and did not merge pairs. Other visualizations were performed to check for variable normality and multicollinearity.

Several models were created and analyzed before selecting a logistic model as the best model for predicting credit union merger pairs. The model was trained on mergers between 2010 and 2016 and tested against mergers that occurred from 2017-2018. Due to the skewed datasets, backwards step pseudo-R2 was performed to filter down from 48 variables to the final six used in the model. The accuracy of the predicted mergers, as opposed to the overall accuracy, was used as a primary measure of success.

Results

Statistical assumptions testing was performed to check for normality and linearity of the predictor variables and the variables evaluated as part of the hypothesis testing. Most of these variables, and all that were included in the final predictive model, were highly right skewed. This was noted in developing the logistic regression model. To overcome this challenge, backwards pseudo R2 methodology was used to optimize the model. The statistical assumption testing for multicollinearity showed that none of the final six predictor variables exhibited any singularities as defined by a threshold of +/- 0.9 (See Attachment A).

Table 3 provides an overview of the hypotheses that were supported and were not supported as part of this research. Support or not supported was based on the p-values falling above or below an alpha value of 0.05.

Table 3
Hypothesis Testing

Hypothesis	Results	Intercept / Variable	Estimate	Z-Score	P-value
Hypothesis 1	Supported	Combo CU's Net Worth Ratio	2.38	2.32	0.02
Hypothesis 2	Supported	Combo CU's Total Branches	1.12	28.82	0.00
Hypothesis 3	Supported	Combo CU's Total Assets	-0.25	-7.49	0.00
Hypothesis 4	Supported	Combo CU's Total Comp. & Benefits	0.00	-7.88	0.00
Hypothesis 5	Not Supported	Combo CU's Return on Assets	-0.02	-0.21	0.83

Support was found for hypotheses 1 as the variable was shown to be significant and contributed to the accuracy of the model. This relationship, that a greater difference between the two credit unions' net worth ratios increases their likelihood to merge, makes sense from a business perspective as credit unions with higher net worth ratios are more likely to acquire smaller credit unions with lower net worth ratios. This is a typical growth strategy seen in the industry. The smaller credit unions motivation to merge is often linked to a need to serve as documented by previous research.

Hypothesis 2 was supported as credit unions with similar total number of branches were more likely to merge than credit unions with a larger difference in total number of branches. This suggests that credit unions prefer to merge with other credit unions that share a similar branching vs. digital business model.

Hypothesis 3 was accepted as credit unions with similar assets were much more likely to merge than credit unions with greater differences in asset size. This was contrary to what one would typically expect.

Hypothesis 4 was accepted as credit unions with similar average benefits and salary were more likely to merge than credit unions with a greater difference in the metric. A surprising finding here was that similarities in average compensation and benefits contributed more to the likelihood of merging that differences.

Hypothesis 5 was the only hypothesis to be rejected. While it was hypothesized that credit unions with greater profitability would likely merge with credit unions with smaller return on assets, the difference in the credit unions' return on assets was not a good predictor. This may be due to some credit unions following a low return on assets operating model. Those credit unions are healthy but operate with a low return on assets, returning profits to members before they make it to the financial statements.

Of the 48 variables analyzed through backwards adjusted-pseudo R2 methodology for optimizing the model, the six variables listed in Table 4 were selected as having the largest contribution to the model's accuracy. To visually validate the effect of the variables included in the final model, side-by-side box plots were created for each variable (see Attachment B).

Table 4
Final Logistic Regression Model

Intercept / Variable	Estimate	Z-Score	p-value
(Intercept)	-4.60	-30.268	0.00
Combo CU's Total Branches	1.12	28.815	0.00
Combo CU's Total Compensation & Benefits	0.00	-7.877	0.00
Candidate CU's Total Assets	0.00	-17.383	0.00
Candidate CU's Credit Card Loans / Total Loans	-10.39	-5.479	0.00
Candidate CU's Mortgages Loans / Total Loans	-2.93	-5.843	0.00
Candidate CU's Total Branches	0.00	0.367	0.71

The adjusted Pseudo R2 for this model was .53, which indicates a good model. The accuracy of this model was further validated by training the model on 2010 through 2016 merger data and running it on 2017 and 2018 merger data. The test dataset consisted of 4,534 rows with each row representing a possible merger combination per state. That total was split between 130 actual merger combinations and 4,518 did not merge combinations.

The model proved very accurate in predicting 2017 – 2018 merger combinations. While the model's predictions were correct 98% of the time, its true measure of success was its ability to predict the merged combinations (rather than the 'did not merge' combinations that comprised 97% of the test dataset). The model correctly identified 28% of the merged combinations, and when a prediction was made that two credit unions would merge, the model was correct 74% of the time. In total, the model made 49 predictions of credit unions merging, and a total of 36 of those predictions were correct. While the model missed 72% of the merger combinations, it was very accurate when a prediction was made and its accuracy level of 28% was substantially greater than a random guess. In essence, the model was able to find the needle in the haystack.

This model may prove very valuable to the credit union industry in offering smaller credit unions, already struggling to stay in business, a tool to identify potential merger candidates. It can also help larger credit unions target candidates most likely to merge.

Discussion

The results of this analysis provide compelling evidence that different types of credit unions prefer different types of merger candidates. As shown in the results of the hypothesis testing performed for this analysis, the difference or similarity of several credit union financial ratios were statistically significant in predicting merger pairs. Those ratios included the absolute difference in net worth ratios, total branches, average compensation and benefits, and total assets. Findings by Goddard et al. (2008) and Goddard et al. (2014) that credit unions with fewer assets were more likely to merge are further supported by this research as smaller differences in asset sizes contributed to the probability of two credit unions merging. That smaller difference was driven by relatively smaller credit unions merging with slightly larger but still small in terms of industry-wide relative asset size. However, the results of the return on assets hypothesis was in contrast to findings by Goddard et al. (2008) and Goddard et al. (2014) in that credit unions with low return on assets were not more likely to merge with credit unions having high return on assets.

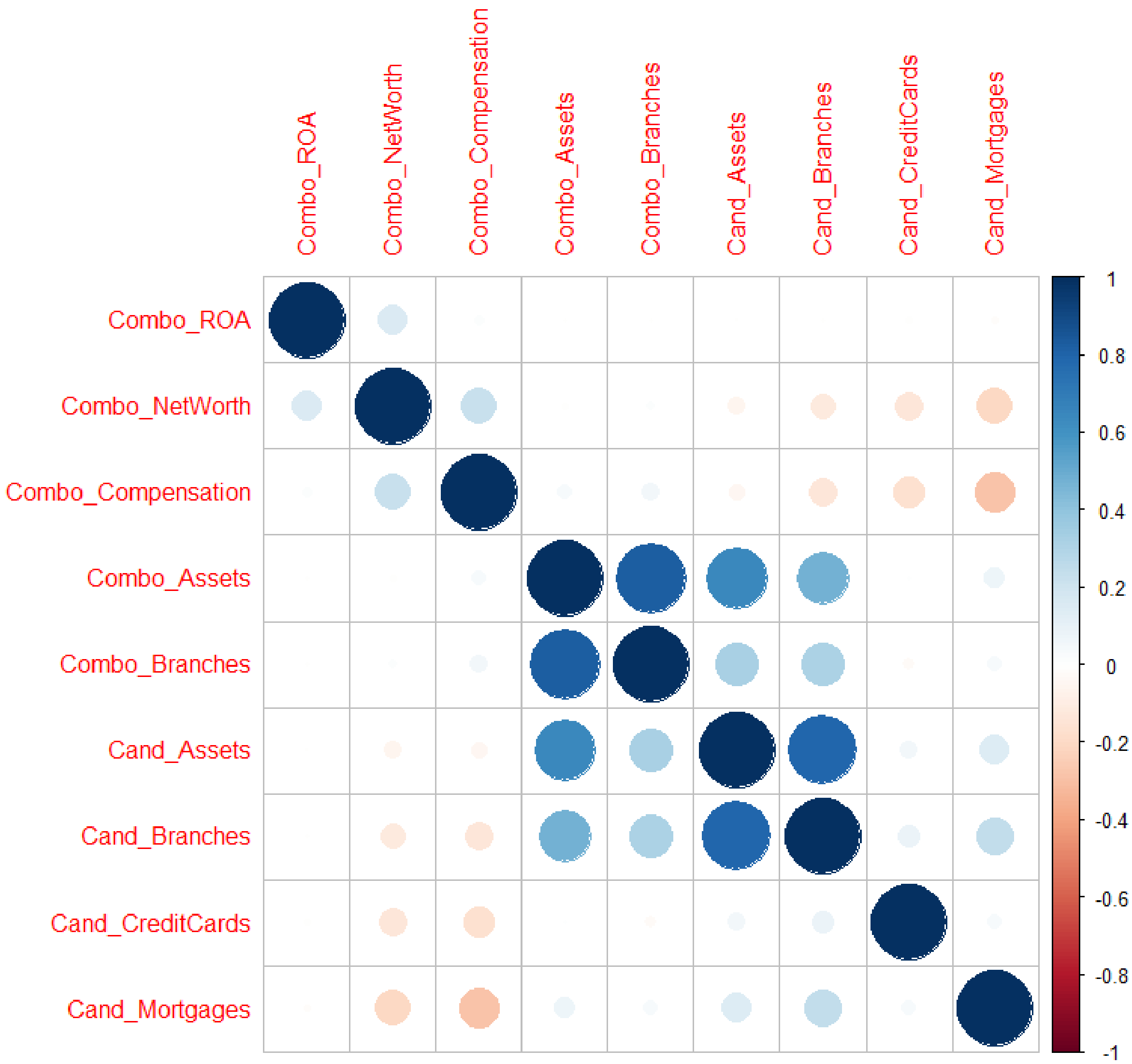
Limitations of this study included the exclusion of federally chartered credit unions and the number of ratios analyzed. Federally chartered credit unions were excluded from this study, but they operate very similarly to state-chartered credit unions and mergers between the two are permitted. In addition, the National Credit Union Administration (NCUA) Call Report data provides thousands of additional variables that could be analyzed to better understand the key drivers of two credit unions merging. This limitation could be overcome by pulling the additional data, which is made available to the public by the NCUA.

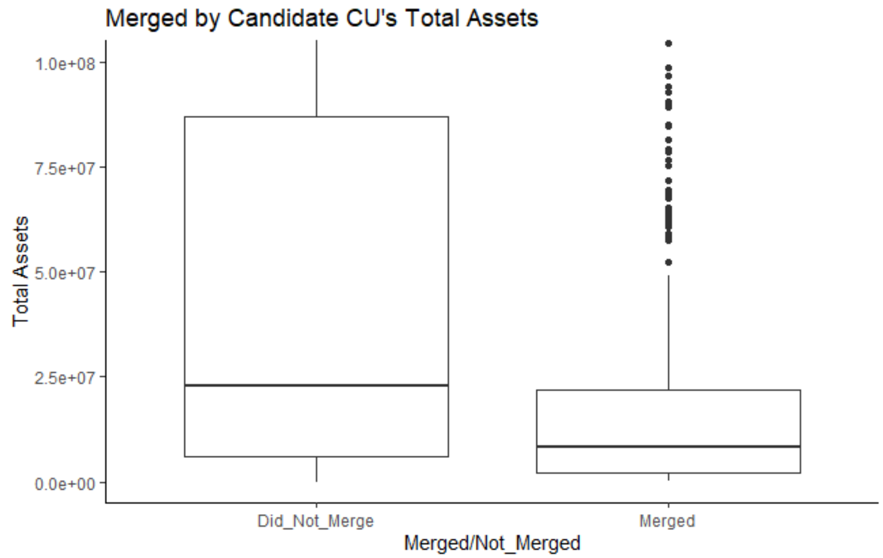
To obtain the true factors that compel credit unions to merge, variables beyond financial ratios should be analyzed. Surveying the credit union board and management staff involved in the merger decision may yield qualitative datapoints not available via public sources. The not-for-profit, ‘member helping member’ philosophy of credit unions, and the large number of small credit unions in the US, may make it easier for researchers to obtain this survey data. Moreover, this type of analysis could be extended to virtually any industry with public datasets and many historical mergers.\

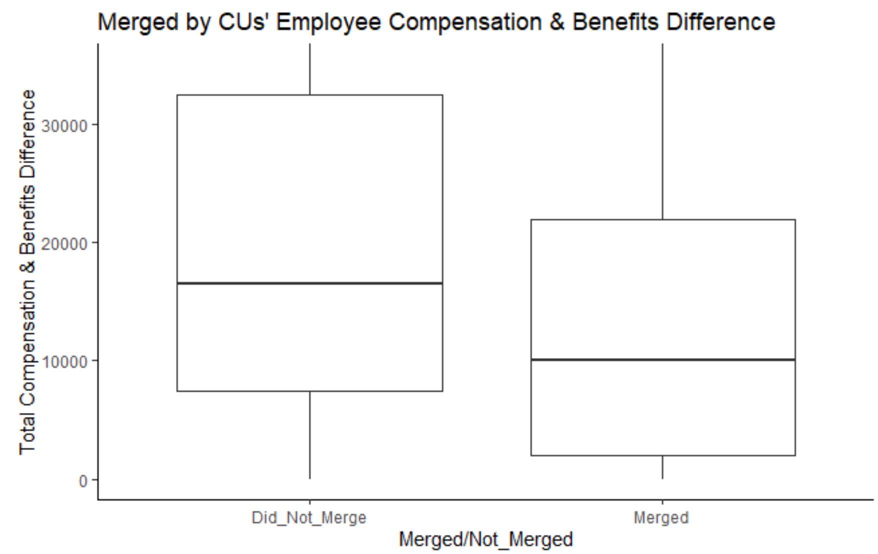
The framework for analysis established in this research offers a pathway for the development of similar merger models outside of the credit union industry. This may help researchers better understand organizational behavior as it pertains to consolidation. It may also help other industries save time and money in identifying merger candidates most likely to merge.

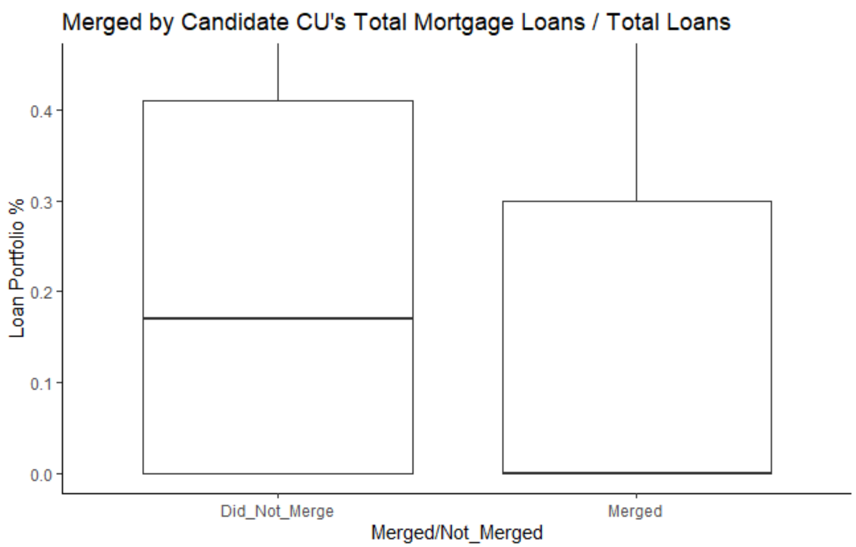
The practical implications of a merger model yielding the level of accuracy achieved by this model are substantial. The predictions provided by this model can save managerial time and increase the probability of a merger. This is achieved by directing managerial attention to credit unions most likely to merge with them. The model’s use of past merger combinations as its training dataset offers value in helping credit unions find the candidate most likely to merge with them versus most likely to merge in general. This can help a credit union identify the matches they are able to obtain versus identifying merger candidates most likely to merge in general, which would identify the worst performing credit unions. The value of this model is in its ability to lower project costs, consulting fees, and opportunity costs associated with missing an opportunity.

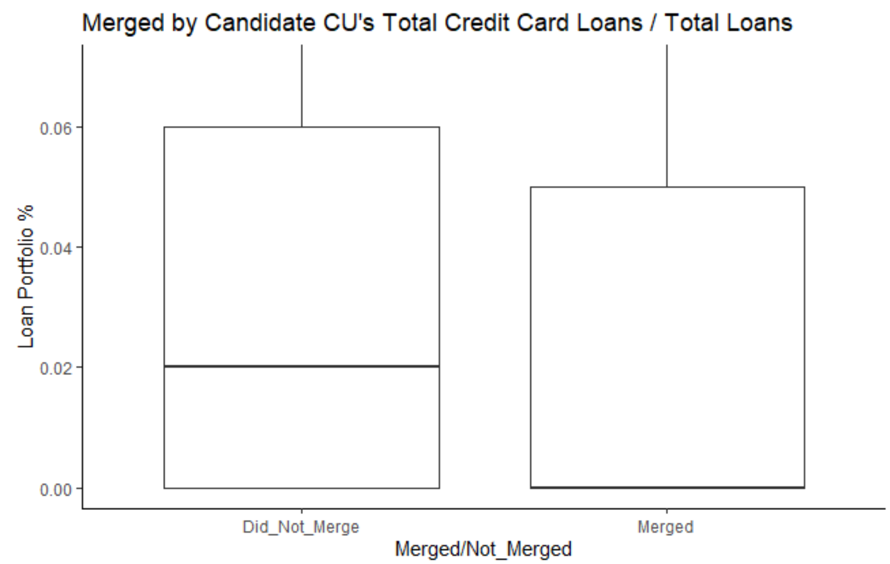
Correlation Matrix



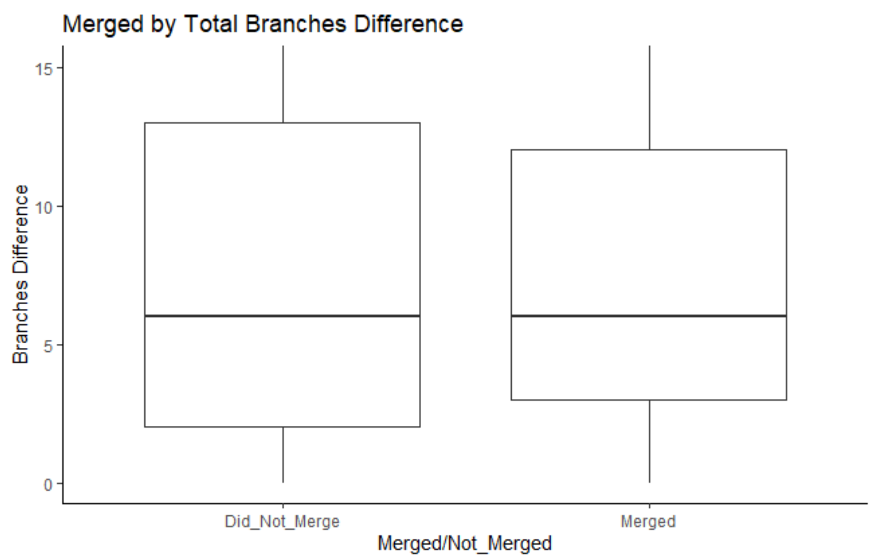

Merged by Candidate CU's Total Assets
Total Assets
1.0e+08
7.5e+07
5.0e+07
2.5e+07
0.0e+00
Did_Not_Merge
Merged
Merged/Not_Merged

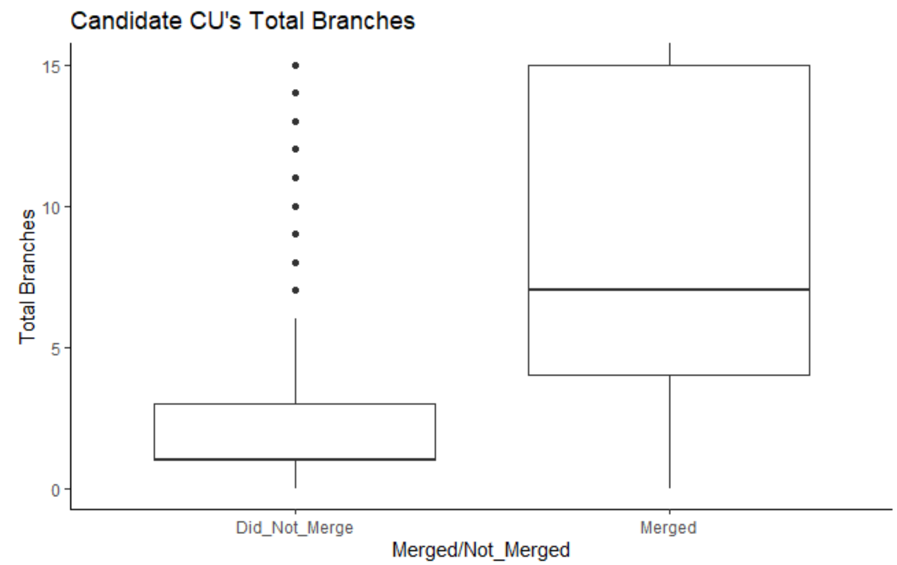

Merged by CUs' Employee Compensation & Benefits Difference
Total Compensation & Benefits Difference
30000
20000
10000
0
Did_Not_Merge
Merged
Merged/Not_Merged


Merged by Candidate CU's Total Mortgage Loans / Total Loans
Loan Portfolio %
0.4
0.3
0.2
0.1
0.0
Did_Not_Merge
Merged
Merged/Not_Merged


Merged by Candidate CU's Total Credit Card Loans / Total Loans
Loan Portfolio %
0.06
0.04
0.02
0.00
Did_Not_Merge
Merged
Merged/Not_Merged

`


Merged by Total Branches Difference
Branches Difference
15
10
5
0
Did_Not_Merge
Merged
Merged/Not_Merged


Candidate CU's Total Branches
Total Branches
15
10
5
0
Did_Not_Merge
Merged
Merged/Not_Merged

References

Alhenawi, &. S., Y. (2018). Toward a complete definition of relatedness in merger and acquisition transactions. Review of Quantitative Finance and Accounting, 53 (2), 351–396.

Ames, H., D. (2014). Credit union failures: Why liquidate instead of merge? Academy of 310 Business Disciplines Journal, 6 (1), 32–63.

Barron, E. W., D. N., & Hannon, M. T. (1994). A time to grow and a time to die: Growth and mortality of credit unions in new york city, 1914-1990. American Journal of Sociology, 100 (2), 381–421.

Bauer, M., K. J. (2009). The effect of mergers on credit union performance. Journal of Banking & Finance, 33 (22), 2267–2274.

Cerasi, C., V. (2019). A test of the impact of mergers on bank competition. Economic Notes, 48 (2), 1–27.

Critchfield, &. J., T. (2005). Consolidation in the u.s. Banking industry: Is the "long, strange, trip" about to end? Federal Deposit Insurance Corporation.

Crofton, D., S. (2020). Credit union capital insolvency and mergers before and after share insurance. In Press: Essays in Economic & Business History, 38, 1–29.

DeYoung, &. M., R. (2009). Mergers and acquisitions of financial institutions: A review of 323 the post-2000 literature. Journal of Financial Services Research, 36.

Dopico, L. G. (2014). Estimating the impacts of the activities of the office of small credit union initiatives (oscui) on small, new, low-income, rural, and minority credit unions. Impact Analysis Study (NCUA-14-R-0002), 36.

Erel, L., I. (2012). Determinants of cross-border mergers and acquisitions. The Journal of Finance, 67 (3), 1045.

Fried, L., H. O. (1999). The impact of mergers on credit union service provision. Journal of Banking & Finance, 23 (2-4), 367–386.PREDICTING CREDIT UNION MERGERS 16

Goddard, M., J. (2008). Consolidation in the us credit union sector: Determinants of failure and acquisition. SSRN Electronic Journal.

References

Goddard, M., J. (2014). U.S. Credit unions: Survival, consolidation, and growth. Economic Inquiry, 52 (1), 304–319.

Gordon, D. (1987). Causes of credit union failures 1981-85. NCUA Office of the Chief Economist, Research Study Number 4. 337 Hernando, N., I. (2008). Determinants of domestic and cross-border bank acquisitions in the european union. Journal of Banking and Finance, 33 (6), 1022–1032.

Kharadia, V. C., & Collins, R. A. (1981). Forecasting credit union failures. Journal of economics and business. The Journal of Finance, 33 (3), 147–145.

Oktay Akkus, A. H., J. Anthony Cookson. (2015). The determinants of bank mergers: A revealed preference analysis. Management Science, 62 (8), 335–362.

R Core Team. (2020). R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from https://www.R-project.org/

Routledge, S., B. (2013). Predicting merger targets and acquirers from text. Computer Science.

Smith, D. M., & Woodbury, S. A. (2010). Withstanding a financial firestorm: Credit unions vs. Banks. Filene Research Institute.

Worthington, A. C. (2004). Determinants of merger and acquisition activity in australian cooperative deposit taking institutions. Journal of Business Research, 57 (1), 47–57