AN APPLICATION OF RANK TRANSFORMATION: MERGER TARGET PREDICTIONS

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Abstract

This study attempts to predict merger targets among banks, and also investigates the predictive power rank transformation adds to the prediction models. Rank transformation has been suggested as a robust and powerful tool for financial problems. Multiple discriminant analysis (MDA) and logistic regression have been applied to selected ranked and unranked financial ratios. Then, the classification results of MDA and logistic regression on both ranked and unranked data sets are compared. The results have indicated that rank transformation does improve the predictive power of MDA and logistic regression.

INTRODUCTION

This study attempts to predict merger targets among banks, and also investigates the predictive power the rank transformation method adds to the prediction models. The rank transformation method has been suggested as a robust and powerful tool for financial problems, yet it has not been utilized in the context of predicting takeover targets in the banking industry.

In this paper we identify a sample of acquired and non-acquired banks for the period 1996-1999. We applied multiple discriminant analysis (MDA) and logistic regression to ranked and unranked selected financial ratios for these banks. Then we compared the classification results of MDA and logistic regression on both ranked and unranked data sets. Our analyses indicate that the rank transformation method does improve the predictive power of MDA and logistic regression.

Financial ratios have successfully been used as vehicles to predict insolvent firms and merger targets. Altman (1968) was one of the pioneers in optimizing the uses of MDA and financial ratios to determine bankrupt firms. Barnes (1990) and Cheng (1989) employed factor analysis and MDA to predict merger targets. Cudd and Duggal (2000), Palepu (1986), and Barniv (1989) compared MDA to logistic analysis in predicting merger targets, while Thompson (1997) and Dietrich (1984) only applied logistic analysis. The results from these studies illustrate evidence of a significant and useful predictive power of financial ratios in the prediction of merger targets.

Besides MDA and logistic regression, the rank transformation method has been applied to financial ratios in other related literature. Kane et al. (1998) employed rank transformation to the prediction of corporate failure. Perry et al. (1986) proposed rank transformation as an alternative approach for classifying bank holding companies' commercial paper ratings. Skomp et al. (1986) investigated bond ratings using rank transformation. Unlike MDA and logistic regression, rank transformation does not require a multivariate normal distribution and equal variance, which normally do not occur in financial applications. This study attempts to examine a synergy of combining MDA and rank transformation in predicting merger targets among banks.

Banks play an important role in the economy. Investors and researchers can formulate a profitable investment strategy if they can construct a model for analyzing merger and acquisition activities and for predicting merger targets. This study also investigates an incremental predictive power that rank transformation contributes to parametric approaches in predicting merger targets within banks. Merits that distinguish this paper from previous studies are: (1) This study incorporates multiple financial ratios representing profitability, size, market valuation, leverage level, liquidity, and growth; (2) This study reexamines the usefulness of rank transformation in one of the financial problems; and (3) this study also analyzes the probability of getting acquired for banks.

Hypotheses Development for Merger and Acquisition and Variable selection

Palepu (1986) proposed six hypotheses in explaining mergers: inefficient management hypothesis, growth resources-mismatch hypothesis, industry disturbance hypothesis, size hypothesis, market-to-book hypothesis, and price-earnings hypothesis. The inefficient management hypothesis argues that a firm with an inefficient management team is a takeover target. The firm's efficiency is measured through financial ratios related to profitability, such as return on equity (ROE) and return on assets (ROA). Low values of these ratios indicate the inefficiency of the management team. Thus, according to the inefficient management hypothesis, a ratio representing profitability is expected to have a negative sign.

The growth resources-mismatch hypothesis predicts that the targeted firm's growth and resource availability are in imbalance. A high growth, scarce resources firm, as well as a low growth, wealthy resources firm are likely to be targeted. The growth resources-mismatch hypothesis involves four dummy variables: leverage, liquidity, growth, and a mismatch growth-resource dummy. An observation that has a value greater than the mean for each variable is considered as high and is assigned a value of 1, and 0 otherwise. Accordingly, the mismatch growth-resource dummy is reassigned. An observation that has either high growth and leverage but low liquidity, or low growth and leverage but high liquidity, is assigned a value of 1 and 0 otherwise. The mismatch growth-resource dummy is expected to have a positive sign.

The industry disturbance hypothesis hypothesizes that an acquisition is caused by an economic shock in the industry. If an acquisition occurs within an industry, the probability of a merger arises for other firms in the industry. Since this study deals with only one industry, the banking industry, this hypothesis is left untested.

The size hypothesis suggests that a larger firm is less likely to be acquired. Costs associated with acquiring a firm are positively related to the size of a target. In addition, the number of bidders is small when the target firm is large because many bidders cannot afford the competition. Therefore, the expected sign for the variable representing size is negative.

The market-to-book (MTB) hypothesis argues that acquirers consider a firm with a low market-to-book ratio as an undervalued and attractive firm. The acquirers expect to find a firm with a low MTB and to optimize the ratio eventually. Thus, this hypothesis suggests a negative relationship between MTB and the probability of being acquired.

The price-earnings hypothesis hypothesizes that an acquiring firm with a high price-earnings ratio will likely experience price appreciation by acquiring a firm with a low price-earnings ratio because the market is valuing a combined firm with a price-earnings ratio of the acquirer before the acquisition. As a result, the acquisition elevates the price of the targeted firm. Therefore, the sign for a variable representing the price-earnings ratio should be negative.

Beside Palepu's six hypotheses, Dietrich (1984) added that trading volumes for the acquired firms were higher than usual in the year prior to the acquisition. Dietrich (1984) also stated that a high payout ratio was the result of a lack of investment opportunity and that a high payout ratio caused a lack of future cash flow. Thus, the possibility of being acquired arose.

Ownership and corporate structure have been widely investigated in conjunction with merger and acquisition activities. Israel (1991) found a negative relationship between financial leverage and the possibility of receiving a takeover bid. Jabbour (2000), Boardman (1998), Barnes (1996), Agrawal (1995), Eyssell (1993), and Allen (1991) investigated the relationship between insider ownership and merger and acquisition activity. The results suggest merger and acquisition activities relate positively to an insider's trading activities, and negatively to a percentage of insider ownership. However, Ambrose et al. (1992) did not find any evidence of a relationship between insider ownership and the possibility of being acquired.

Generally, variables used in previous research can be categorized into six groups: profitability, valuation, liquidity, financial leverage, growth, and size. In addition, this study inspects mismatch growth-resource (DDSGR), trading volume (VOL), payout ratio (PAYOUT), and percentage of shares owned by insiders (INSIDER). Multiple financial ratios for each group are collected. As a result, a total of 47 financial variables are analyzed. We then employ factor analysis to find the most representative variable for each group. Therefore, the final sample comprises 10 variables, which are as follows: The LIQ variable, which is the ratio of liquid assets (cash plus marketable securities, less current liabilities) to total assets, represents liquidity. Return on Assets (ROA), market-to-book ratio (MTB), a ratio of long-term liabilities to equities (LL_EQ), sales growth (SGR), and market value (MARKETVA) characterize profitability, market valuation, leverage, growth, and size. DLIQ, DLEV, and DSGR represent dummies for liquidity, leverage, and sales growth.

After we determine the variables using factor analysis, we perform MDA and logistic analysis on the modeling data set. Then the results of MDA and logistic analysis are compared. Subsequently, we rank all the variables in the modeling data set except the dummy variables. Leverage, growth, and liquidity are ranked based on their original data. We then calculate the means for leverage, growth, and liquidity. An observation that has a value greater than the mean for each variable is assigned a value of 1, and 0 otherwise. Finally, the mismatch growth-resource dummy is reassigned. An observation that has either high growth and leverage but low liquidity, or low growth and leverage but high liquidity, is assigned a value of 1, and 0 otherwise.

Multiple discriminant analysis (MDA), Logistic analysis and Rank Transformation

MDA generates discriminant rules to group similar observations together based on a specified number of groups. This method assumes that the sample is multivariate, normally distributed with equal variance (Johnson, 1998). However, these two assumptions are normally violated when we deal with applications in finance. Moreover, the efficiency of MDA decreases with discrete data. Another drawback of MDA dealing with probability is that the estimated value can be outside the 0 to 1 range. In this case, logistic regression becomes an alternative choice.

As discussed in Maddala (1999) and others, logistic regression works relatively well with discrete data and a combination of discrete and continuous data. Furthermore, the prediction by logistic regression always falls between 0 and 1, since logistic regression takes the following form:

$$\text{Probability of merger} = (1 + e^{-Y})^{-1}$$

where Y is a function of independent variables. Nonetheless, assumptions concerning normal distribution and equal variance must still hold. In finance, these two assumptions are sometimes unfeasible through parametric regressions, including MDA and logistic regression.

Rank transformation, a nonparametric approach, relaxes the two underlying assumptions. Another important benefit of rank transformation is that it is insensitive to outliers. Furthermore, rank transformation has been found to be robust and increasing predictive power in studies by Kane et al. (1998), Perry et al. (1986), and Skomp et al. (1986). These previous studies have introduced rank transformation to financial applications.

In this method, the *M* observations are ranked from the smallest, with a value of 1, to the largest, with a value of *M* (Conover, 1980). The ranking procedure is repeated for all desired independent variables. Then, MDA and logistic analysis are applied to the ranked sample. However, there are tradeoffs for employing rank transformation. First, estimated coefficients provided by the parametric approaches with rank transformation cannot be interpreted as marginal contributions to the dependent variable. Second, rank transformation disregards differences in nominal values. Therefore, it is up to researchers to decide whether or not these two drawbacks of rank transformation compensate for satisfying the underlying assumptions and gaining possible incremental accuracy.

Data

Data in this study have been collected from CompactDisclosure and Research Insight. Hence, the sample includes firms from the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the National Association of Securities Dealers Automated Quotation System (NASDAQ). Based on keywords such as merger, acquired, and acquisition, CompactDisclosure suggests that there were 186 acquired firms and 1,035 non-acquired firms within the banking industry (SIC code 67XX) between 1996-1999. Due to the incompleteness of some observations, there are only 56 acquired firms and 310 non-acquired firms left. Then, we separate the data set into two equal samples: modeling and holdout samples to validate the estimated parameters. Therefore, we randomly select 160 non-acquired firms - 80 for modeling and 80 for holdout samples. We also randomly separate acquired firms into two equal groups for modeling and holdout samples. Eventually, the holdout sample consists of 28 acquired and 80 non-acquired firms, and the modeling sample consists of 28 acquired and 80 non-acquired firms.

Table 1 displays means and means comparisons between acquired and non-acquired firms for both ranked and non-ranked data. The t-statistics indicate inequalities of means for the return on assets (ROA) and market-to-book (MTB) values in the non-ranked data set. The acquired firms illustrate higher ROA and MTB values than the non-acquired firms do. The inefficient management hypothesis justifies the differences in ROA but the market-to-book hypothesis suggests the opposite direction for the differences in MTB. In the ranked data set, the means for acquired and non-acquired firms are different for market value (MARKETVA) and market-to-book value (MTB). The acquired firms do have higher MTB than the non-acquired firms. Again, the findings regarding the differences in MTB oppose the market-to-book hypothesis. However, on average, the market value of an acquired firm is lower than it is for a non-acquired firm, which is supported by the hypothesis concerning size.

Results and Discussion

Table 2 summarizes the results of the model estimation. For the unranked data set, the results of MDA conform to almost all of the expected signs, except for ROA and MTB. Market value, market-to-book value, and volume are significant, and are consistent with the results of Barnes (1990) and Dietrich (1984). However, Barniv (1989) and Cudd (2000) did not find the variable representing market-to-book value significant. The findings from the logit model confirm the results from the MDA, except that the insider variable has a wrong sign. It is important to note that the market value volume, payout ratio, and mismatch growth dummy consistently possess the expected signs in both the MDA and logit model.

For the ranked data set, all variables except market value, MTB, and volume possess the expected signs in both the MDA and logit model. However, only volume and MTB are significant. Thus, the findings regarding profitability, mismatch growth, payout ratio and insider ownership reaffirm the hypothesis and findings of Dietrich (1984), Jabbour (2000), Boardman (1998), Barnes (1996), Agrawal (1995), Eyssell (1993), and Allen (1991). It is suspected that the attention of investors might be drawn to the industry once a firm in the industry announces a merger agreement. Investors then start accumulating shares of other firms in the same industry with expectations that those firms might be considering merger agreements in order to be in competitive positions. As a result, the volumes for the non-acquired firms are relatively higher than they are for acquired firms in the rank format, although the volume for all firms in the industry should be higher than normal. Therefore, volume is significant and negatively related to the probability of getting a merger bid when the data are ranked.

Most of the results are consistent with previous studies. The inefficient management hypothesis suggests that a firm that has low values of profitability ratios is likely to be a merger target. The variable representing profitability, ROA, is not significant in any model. Furthermore, the ROA variable possesses a negative sign in the ranked data set, and a positive sign in the unranked data set. The findings imply that an acquirer searches for a target with high market-to-book value, mismatch resources, and high payout ratio. In addition, a high level of insider ownership can prevent a firm from being acquired.

Predictions in modeling sample

We identify cutoff points for MDA and the logit model in both non-ranked and ranked data sets. based on the procedure proposed by Palepu (1986). The cutoff points for MDA in non-ranked and ranked data sets are 0.236 and 0.298 chronologically. For

Table 1 Difference of means t-statistics

	Non-ranked Data			Ranked Data		
	Mean			Mean		
	Acquired	Non-acquired	t-statistics	Acquired	Non-acquired	t-statistics
ROA	0.011	0.008	-2.078**	61.821	51.938	-1.444
MARKETVA	1.889	2.555	0.287	49.938	67.536	2.629***
MTB	2.307	1.555	-3.189***	72.964	48.038	-3.852***
LIQ	-9.242	-6.363	0.511	48.107	56.738	1.258
LEV	0.673	0.700	0.098	56.464	53.813	-0.399
Sales Growth	9.907	14.466	0.730	52.589	55.169	0.374
VOL	0.334	0.145	-1.025	53.661	54.794	0.164
PAYOUT	0.103	0.090	-0.723	58.607	53.063	-0.805
INSIDER	0.129	0.164	1.098	48.786	56.500	1.126

*** significant at 0.01.
** significant at 0.05.
* significant at 0.10.

Table 2 Model Estimations

	Unranked		Ranked	
	MDA	Logit	MDA	Logit
Constant	-0.081	-2.490	0.111	-2.547***
ROA	7.486	80.101	-0.002	-0.013
Market Value	-0.015**	-0.358	0.002	0.027
MTB	0.117***	0.654**	0.005**	0.032**
Liquidity	0.016	-1.016	-0.007	-0.497
Leverage	0.058	0.614	-0.004	-0.487
Sales Growth	-0.046	-0.492	0.069	0.230
Mismatch Growth Dummy	0.041	0.337	0.060	0.452
Volume	0.203*	2.294*	-0.004**	-0.034**
Payout	0.339	2.006	0.002	0.015
Insider	-0.013	0.186	-0.001	-0.003
Chi-Square	17.959*	21.1**	22.041**	24.961***
R Square	0.163		0.196	
F-statistics	1.888*		2.366**	
-2 Log Likelihood		102.513		98.652

*** significant at 0.01.
** significant at 0.05.
* significant at 0.10.

the logit model, Palepu's (1986) procedure suggests 0.202 and 0.263 as cutoff points in non-ranked and ranked data sets. Table 3 displays the classification results. All approaches yield classification precisions better than a 50% chance at 0.01 level. As found in previous studies, the accuracies of the logit model seem higher than the accuracies of the MDA. MDA provides 65.74 and 69.44 % accuracies for non-ranked and ranked data sets respectively, while logit produces 66.67 and 69.44%.

Holdout Sample

The cutoff points computed in the previous section are also used in the holdout sample based on assumptions that both samples are drawn from the same population, and the model estimated in the modeling sample should be applicable to other samples drawn from the same population. Predictive accuracy results of the MDA and logit model in both ranked and unranked data sets for the holdout sample are shown in Table 4. All approaches have predicted with accuracies better than a 50% chance at 0.05 significance level. With the unranked data set, MDA seems to produce less accurate results than logit in predicting independent or non-merged firms. MDA is 50% accurate, while logit is 52.50% accurate. However, predicting merger targets, both MDA and the logit perform equally well. They 82.14% correctly predict acquired firms. Contradicting previous studies, the logit model does not statistically outperform MDA. With the ranked data set, MDA is more accurate in predicting acquired firms and less accurate in predicting non-acquired firms than logit is. Interestingly, MDA's performance level has increased substantially from 50% to 68.75% in predicting non-merged firms; so has the predicting accuracy of the logit model, which increases from 52.50% to 72.50%. However, the accuracies in predicting an acquired firm decrease from 82.14% to 75.00% for the MDA and from 82.14% to 64.29% for the logit.

Table 5 compares the classification accuracy of MDA and logit for ranked and non-ranked data sets. The results are very promising. Rank transformation increases classification accuracy significantly at 0.01 level for both the MDA and logit model. The findings have statistically proved that rank transformation does increase predictive power for both MDA and logit. The results also indicate that underlying assumptions of normal distribution and equality of variances are very important to predictive power. Thus, we suggest that a nonparametric approach, such as rank transformation, should be a crucial tool for research in finance, since most data samples present some non-normality of data.

Conclusion

The banking industry is an important sector among financial services. This paper tests some prominent mergers and acquisitions hypotheses for this sector. The study also verifies the usefulness of factor analysis in the variable selection procedure. The results mostly reaffirm previous studies that test these hypotheses in other industries. Size and insider ownership negatively influence the possibility of getting a merger bid. On the other hand, payout ratio and mismatch dummy positively affect the chance of being acquired. However, the estimated signs for ROA and volume are inconclusive. In the unranked data, ROA positively rather than negatively relates to the probability of being acquired. Volume inversely indicates the chance of getting acquired with the ranked data set. Insider ownership also can be a defensive device against a takeover threat.

The advantages of rank transformation have been reaffirmed in the context of merger targets predictions for banks. Rank transformation statistically improves predictive power of both MDA and logit, as it relaxes some of the normality assumptions that are necessary in parametric tests. Furthermore, rank transformation is insensitive to outliers. Thus, we suggest that this method can be used successfully to predict mergers and acquisitions in the banking industry.

Table 3 Prediction Results

			Frequencies			
			Acquired	Non-acquired	Prediction Accuracy	(t-value)
		Actual	28	80		
MDA	Non-ranked	Correct predictions	24	47	0.65741	3.272***
	Ranked	Correct predictions	21	54	0.69444	4.041***
Logit	Non-ranked	Correct predictions	25	47	0.66667	3.464***
	Ranked	Correct predictions	21	54	0.69444	4.041***

*** significant at the 0.01 level

Table 4 Prediction Results

			Frequencies			
			Acquired	Non-acquired	Prediction Accuracy	(t-value)
		Actual	28	80		
MDA	Non-ranked	Correct predictions	23	40	58.333%	1.732**
	Ranked	Correct predictions	21	55	70.370%	4.234***
Logit	Non-Ranked	Correct predictions	23	42	60.185%	2.117**
	Ranked	Correct predictions	18	58	70.370%	4.234***

** significant at the 0.05 level
*** significant at the 0.01 level

Table 5 Classification Accuracy Comparisons

	Classification Accuracy		
	Non-ranked	Ranked	Z-value
MDA	0.58333	0.70370	3.694***
Logit	0.60185	0.70370	3.144***
Z-value	0.55391	0.00000	

**significant at 0.01 level

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Appendix I
Variables Included in the Study

Number	Variable
1	C/F Operational Income
2	Cash
3	Current Debt / Equity
4	Current Dividend
5	Current Share[s?] Outstanding
6	Earnings per Share
7	Earnings Growth
8	Earnings per Share
9	Exchange
10	Income Before Depreciation & Amortization
11	Income Growth
12	Interest Expenses
13	Long-term Debt / Equity
14	Market Value
15	Marketable Securities
16	Net Income
17	Net Income / Common Equity
18	Net Income / Investment Capital
19	Net Income / Net Sales
20	Net Income / Total Assets
21	Net Sales
22	Net Sales / Assets
23	Net Sales / Current Assets
24	Net Sales / Employees
25	Net Sales / Plant
26	Net Sales / Working Capital
27	Number of Shareholders
28	PreTax Income / Common Equity
29	PreTax Income / Investment Capital
30	PreTax Income / Net Sales
31	PreTax Income / Total Assets
32	Price / Earnings Ratio
33	Sales Growth
34	Selling, General, Administration Expenses
35	Shareholder Equity
36	Shares Held by Officers and Directors
37	Times Interest Earned
38	Total Assets
39	Total Assets / Equity
40	Total Current Liabilities
41	Total Debt / Equity
42	Total Liabilities
43	Total Liabilities / Common Equity
44	Total Liabilities / Investment Capital
45	Total Liabilities / Total Assets
46	Total Liability Net Worth
47	Volume

Appendix II
Final Variables and Hypotheses

Hypothesis	Variable	Expected Sign
Inefficient management	ROA	-
growth-resources-mismatch		+
	Long-term Liability to Equities	?
	Liquid assets (cash + marketable securities - current liabilities)	?
	Sales growth	?
Industry disturbance	N/A	+
Size	Market value	-
Market-to-book	MTB	-
Price-earnings	PE ratio	-
Trading volumes	Volumes	+
Payout ratio	Payout ratio	+
Insider ownership	Shares held by officers and directors	-