Predicting bank failures by using banking performance and condition ratios

Submitted by: Utku Karagoz

Undergraduate Economics Program

Carnegie Mellon University

In fulfillment of the requirements for the

Tepper Senior Honors Thesis

Advisor: Şevin Yeltekin

May 2010

SUMMARY

I analyze the relationship between bank failures that occur in the financial sector and the banking performance and condition ratios. The performance ratio that I chose to use in my analysis is the return and equity and the condition ratios are the capital adequacy ratio, the leverage ratio and the loan-deposit ratio. To achieve this goal, I use Estrella's model (2000) as my main framework and observe the banking sector over the recent credit crisis. I apply logit regression analysis to see if making predictions about future bank failures is possible with the available past data. In the regression analysis, I use both three-factor models and single-factor models to assess the efficiency of more previously collected data. In order to see the see the motivators behind the banking firms' decisions, I also apply correlation tests between each performance and condition ratio.

1 INTRODUCTION

Over the last decade, numerous papers have been written on the analysis of predicting possible bank failures before banks announce their bankruptcies or call for bailout funds. Meyer (1970) uses the corresponding banking data between 1948 and 1965 both to look for the reasons behind bank failures and the predictability of future failures with the given dataset. He uses four groups of factors to explain bank failures which include local economic conditions, general economic conditions and quality of management. He concludes by claiming that even when failure frequently results from embezzlement and other financial irregularities, financial measures can evaluate the relative strengths of the banking firms. He also argues that looking only at the financial position of a firm is not enough to discriminate among bank groups. Thus he works with nine variables in his paper. Another relevant research was done by Thomson (1991) on bank failure prediction in the 1980s. His study shows that bank failure probability is a function of variables related to its solvency, including capital adequacy, asset quality, earnings performance and the asset liquidity. Estrella (2000) on the other hand emphasizes capital ratios, which measure the amount of capital that the banking firms hold in case of a financial crisis, as predictors of bank failure. He asserts that bank regulators may find a useful role for the simple ratios in the design of regulatory capital frameworks, particularly as indicators of the need for prompt supervisory action.

Many of these papers deal with bank failure reasons within an empirical model. The main purpose of this paper is to build upon the existing empirical analyses and to analyze the relationship between bank performance and condition ratios and probability of failure. To accomplish this, I use data on these ratios for all active and failed U.S. banks between 2003 and 2009.

1.1 Financial Crisis and the Real Economy

The following quotation by Ovanhouser (2009) provides a motivation for studying financial crisis.

> *"Disruptions in financial markets rise to the level of a crisis when the flow of credit to households and businesses is constrained and the real economy of goods and services is adversely affected."*

This definition states a financial crisis in a cause-and-effect relationship. The diminished flow of credit to households and businesses initiates an economic crisis in the real sector of the economy. Because credit decisions are mostly made by banks and financial institutions, the question suggests that the banking sector is directly involved in the initiation of a financial crisis process.

Another quotation provided by Paul Krugman (2000), relates the banking crisis to real economic activity;

> *"There are two ways in which problems in the banking sector can lead to a financial crisis in emerging market countries. First, the deterioration in the balance sheets of banking firms can lead them to restrict their lending in order to improve their capital ratios or can even lead to a full-scale banking crisis which forces many banks into insolvency, thereby directly removing the ability of the banking sector to make loans. Second, the deterioration in bank balance sheets can promote a currency crisis because it becomes very difficult for the central bank to defend its currency against a speculative attack. Any rise in interest rates to keep the domestic currency*

from depreciating has the additional effect of weakening the banking system further because the rise in interest rates hurts banks' balance sheets."

Krugman claims that once the capital ratios of numerous banking firms decrease, the subsequent efforts to strengthen their positions can first limit the credit volume in the market and then initiate a financial crisis. In this process, several banks fail to restructure themselves and go. Thus, in order to have a better idea on the reasons behind crises and to be able to propose several solutions to help avoid them in the future, it is natural to focus on the structure of the banking sector in an economy.

1.2 Basel Accords

Ovanhouser (2009) and Krugman (2000)'s works suggest that bank risk behavior is important for the real economy. Some institutions are already in place to avert bank failures. Of these institutions, the most distinguished organization is the Basel Committee on Banking Supervision. The Basel committee is formed of representatives and regulatory authorities from twelve countries including United States, United Kingdom, France and Germany. The most commonly used works of the committee are the Basel Accords that has the purpose of creating an international standard for banking regulators to set the amount of capital that is required for banks to hold in case of a financial crisis. Of these accords, Basel II is the most recent one that is used by regulators throughout the world. In this accord, there are three main pillars;

1) Minimum Capital Requirements

2) Supervisory Review

3) Market Discipline

The first pillar of this accord directly concerns the main purpose of this paper because it provides several suggestions for regulators to carefully observe banking firms' decisions that cause a possible bank failure in case of an economic instability. According to this pillar, the minimum regulatory capital level is set at 8% based on the main components of risk faced by the banking firms; the credit risk, the operational risk and the market risk. A minimum capital requirement is needed because obtaining liquid assets is especially difficult during a financial crisis. And according to Memmel and Raupach (2007), a liquidity recession adversely affects the credit flow.

1.3 Why do banks prefer low capital ratios?

We should also understand the reason behind failed banks' choices of capital ratio levels. There are numerous existing papers on the relation between the capital ratio level and the profitability rates. One of these is the following work of Memmel and Raupach (2007):

> *Banks face a trade-off when choosing the appropriate level of their capital ratio. On the one hand, regulatory authorities and rating agencies force the banks to maintain a minimum capital ratio. The regulatory lower limit for the total-capital ratio is 8 percent, while rating agencies and other market participants insist that a bank holds a certain ratio of Tier 1 capital if it wants to obtain a certain rating. On the other hand, banks try to maximize their return on capital to satisfy their investors; in contradiction to Modigliani/Miller's irrelevance theorem (1958), it is believed that banks can increase their performance by substituting capital with debt. This view, however, is not the result of ignoring the risk impact of leverage. The economic literature provides a number of theoretical arguments why a high leverage is desirable for banks. Given the above reasons for the existence of a target leverage, the trivial fact that shocks change the leverage implies that the bank management has to adjust it from time to time.*

So I decided to test this academic view on my data to see if a low capital ratio is really desirable for banks. In order to run this test, I applied a correlation analysis on my independent variables for the data in every single year between 2003 and 2008. Hill (2005) explains correlation as a measure of the relation between two or more variables. The measurement scales used should be at least interval scales, but other correlation coefficients are available to handle other types of data. Correlation coefficients can range from -1.00 to +1.00. The value of -1.00 represents a perfect negative correlation while a value of +1.00 represents a perfect positive correlation. A value of 0.00 represents a lack of correlation. Of all the correlation coefficients, the most commonly-used version is Pearson r which shows linear correlation between multiple variables. It measures how proportional two variables are to each other. In this paper, the correlation results are given in Table 3. In years 2006-2008, there is a moderately strong correlation between the capital ratio and the leverage ratio, with coefficients 0.303, 0.204 and 0.373 respectively at 0.000 p-value level. The correlations between other variables are considerably weak with values less than 0.10. The signs of the correlation coefficients between ROE and the capital ratio and between ROE and the leverage ratio are negative as expected in 2006 and in 2007.

2 EMPIRICAL FRAMEWORK

The framework of the empirical analysis mainly relies on the logistic regression model (logit model) with binary responses. The binary response model's main function is to assess the response probability. In Introductory Econometrics, Wooldridge(2009) shows this model as below;

$$P(y = 1|x) = P(y = 1|x_1, x_2, \ldots, x_k) \tag{1}$$

In this setup, 'x' stands for the explanatory variables that were used in the empirical research. These variables are used as predictors in this paper. In addition, the linear probability model assumes the response probability to be linear in a set of parameters B_j;

$$P(y = 1|x) = \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k \tag{2}$$

The probability of success is a function of the x_j. The main disadvantage of relying on a linear probability model however is that the fitted probabilities can have a value less than zero or greater than one. To avoid this circumstance, I consider a class of binary response models of the form;

$$P(y = 1|x) = G(\beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k) = G(\beta_0 + x\beta) \quad (3)$$

This makes sure the function G takes on values between zero and one such that;

$$0 < G(z) < 1 \text{, for all real numbers } z.$$

This class of models therefore makes sure that the estimated probabilities at the end are between zero and one. Taking this approach as the basis in the logit model, G is the nonlinear logistic function;

$$G(z) = \exp(z)/[1 + \exp(z)] = \Lambda(z) \quad (4)$$

which is again between zero and one. This is the cumulative distribution function for a standard logistic random variable.

This logit model can also be derived from an underlying latent variable model. If we let y^* to be an unobserved variable;

$$y^* = \beta_0 + x\beta + e, \; y = 1[y^*>0] \quad (5)$$

1[.] defines the binary outcome of the indicator function. If the event in the bracket is true, the function takes on the value one, and zero otherwise. Thus, y is one if $y^*>0$ and y is zero if $y^*\leq 0$. It is also assumed that e is independent of x and has the standard logistic distribution in this paper. Continuing on, we can derive the response probability for y;

$$P(y = 1|x) = P(y^* > 0|x) = P[e > -(\beta_0 + x\beta)|x]$$

$$= 1 - G[-(\beta_0 + x\beta)]$$

$$= G(\beta_0 + x\beta) \tag{6}$$

which is exactly the same as the equation (2). So the fundamental goal of the binary response model is to explain the effects of the x_j on the response probability $P(y = 1|x)$. The latent variable formulation is thus very important to observe the effects of each x_j on y^*.

3 EMPIRICAL STRATEGY

In this paper, three banking condition ratios have been selected to make bank failure predictions. The strategy of selecting the right indicators was mainly based on the first pillar of the Basel II accord.

i. *Loan-Deposit Ratio*: Loans and lease financing receivables net of unearned income, allowances and reserves as a percent of total deposits.

ii. *Leverage Ratio*: Core capital as a percent of average total assets minus ineligible intangibles.

iii. *Capital Adequacy Ratio*: Capital as a percent of risk-weighted assets defined by the federal regulator.

iv. *Return on Equity (ROE) Ratio*: Annualized net income as a percent of average equity on a consolidated basis.

v. *Asset Size*: The sum of all assets owned by the institution including cash, loans, securities, bank premises and other assets.

The first three variables listed above are used both in the regression analysis and in the correlation test. The last two variables however are used only in the correlation tests to look for the relationships between asset size, profitability and the banking firms' condition ratio choices.

As explained in the model strategy, logistic regression analysis is applied to the related years of data and four models are used to make predictions on bank failures. While Model 1-3 looks for relationships between bank failure and each single variable, Model 4 includes all the variables.

Model 1: P(Bank Failure) = G[intercept + loan-deposit ratio effect x (observed loan-deposit ratio)]

Model 2: P(Bank Failure) = G[intercept + leverage ratio effect x (observed leverage ratio)]

Model 3: P(Bank Failure) = G[intercept + capital ratio effect x (observed capital ratio)]

Model 4: P(Bank Failure) = G[intercept + loan-deposit ratio effect x (observed loan-deposit ratio) + leverage ratio effect x (observed leverage ratio) + capital ratio effect x (observed capital ratio)]

4 EMPIRICAL RESULTS

The data are provided by the Federal Deposit Insurance Corporation (FDIC) database which includes 8974 active and 216 failed U.S banks. Every single bank that has available information in the database is added to the analysis regardless of any categorizations such as asset sizes or institution types.

As I briefly explained in my model strategy, the empirical analysis results are provided by the logit regression model. The probability of success $P(y = 1|x)$ that is explained in equation (2) explains the bank failure probability and the x_k stand for the indicators which are the capital ratio, the leverage ratio and the loan-deposit ratio. The regression data is presented in two separated tables. While the results for 2007 and 2008 (Table 1) explain the bank failure probabilities only in 2008 and 2009 respectively, the results corresponding to 2003, 2004, 2005 and 2006 (Table 2) covers all the bank failures that took place in 2007, 2008 and 2009.

TABLE 1
LOGIT REGRESSIONS
Dependent Variable: Failure in the subsequent year
Source: Federal Deposit Insurance Corporation Database

	2008			
	Model 1	Model 2	Model 3	Model 4
Intercept	-4.09063	1.44092	1.5155	1.59655
	(0.000)	(0.000)	(0.000)	(0.000)
Loan-Deposit Ratio	-0.0000002			-0.0000023
	(0.830)			(0.955)
Leverage Ratio		-0.696277		-0.579096
		(0.000)		(0.000)
Capital Ratio			-0.470967	0.0885841
			(0.000)	(0.085)
Concordant (Percent)	0.0	92.1	92.5	92.8
Discordant (Percent)	0.0	6.7	6.3	6.2
Tie (Percent)	100.0	1.2	1.3	1.1
Failures	139			
Nonfailures	8303			

	2007			
	Model 1	Model 2	Model 3	Model 4
Intercept	-5.83341	0.781629	1.68972	1.73557
	(0.000)	(0.312)	(0.088)	(0.053)
Loan-Deposit Ratio	-0.0000002			-0.0000175
	(0.927)			(0.961)
Leverage Ratio		-0.774627		-0.453726
		(0.000)		(0.010)
Capital Ratio			-0.608514	-0.293987
			(0.000)	(0.033)
Concordant (Percent)	0.0	73.2	82.4	78.1
Discordant (Percent)	0.0	11.6	9.2	9.4
Tie (Percent)	100.0	15.2	8.4	12.4
Failures	25			
Nonfailures	8531			

TABLE 2
LOGIT REGRESSIONS
Dependent Variable: Failure until January 2010
Source: Federal Deposit Insurance Corporation Database

	2006			
	Model 1	Model 2	Model 3	Model 4
Intercept	-3.69414	-3.6426	-3.36489	-3.30129
	(0.000)	(0.000)	(0.000)	(0.000)
Loan-Deposit Ratio	-0.0000006			-0.0000099
	(0.825)			(0.847)
Leverage Ratio		-0.0041725		0.0121482
		(0.535)		(0.004)
Capital Ratio			-0.0183141	-0.030073
			(0.019)	(0.003)
Concordant (Percent)	0.1	4.7	51.5	58.4
Discordant (Percent)	0.0	4.9	16.7	20.1
Tie (Percent)	99.9	90.3	31.8	21.6
Failures	216			
Nonfailures	8677			

	2005			
	Model 1	Model 2	Model 3	Model 4
Intercept	-3.73960	-3.70859	-3.33821	-3.32234
	(0.000)	(0.000)	(0.000)	(0.000)
Loan-Deposit Ratio	-0.0000026			-0.0000166
	(0.726)			(0.823)
Leverage Ratio		-0.0025478		0.0012508
		(0.693)		(0.124)
Capital Ratio			-0.0228334	-0.0244861
			(0.011)	(0.009)
Concordant (Percent)	0.1	27.2	53.8	53.2
Discordant (Percent)	0.0	18.6	23.2	23.4
Tie (Percent)	99.9	54.2	23.1	23.4
Failures	216			
Nonfailures	8688			

	2004			
	Model 1	Model 2	Model 3	Model 4
Intercept	-3.79949	-3.81462	-3.79274	-3.79804
	(0.000)	(0.000)	(0.000)	(0.000)
Loan-Deposit Ratio	-0.0000021			-0.0000078
	(0.727)			(0.779)
Leverage Ratio		0.0012238		0.0013537
		(0.213)		(0.195)
Capital Ratio			-0.0003015	-0.0008106
			(0.858)	(0.746)
Concordant (Percent)	0.1	1.5	0.4	2.6
Discordant (Percent)	0.0	0.7	1.0	0.5
Tie (Percent)	99.9	97.8	98.6	96.9
Failures	201			
Nonfailures	8974			

	2003			
	Model 1	Model 2	Model 3	Model 4
Intercept	-3.86252	-3.87447	-3.78812	-3.81578
	(0.000)	(0.000)	(0.000)	(0.000)
Loan-Deposit Ratio	-0.0000018			-0.0000056
	(0.745)			(0.877)
Leverage Ratio		0.0010871		0.007255
		(0.852)		(0.140)
Capital Ratio			-0.0038402	-0.0065611
			(0.357)	(0.212)
Concordant (Percent)	0.0	0.5	37.7	14.9
Discordant (Percent)	0.0	0.3	16.7	6.0
Tie (Percent)	100.0	99.2	45.5	79.2
Failures	193			
Nonfailures	9176			

Table 1 reports the regression results of the banking firms based on the relationship between ratio data in 2007-2008 and the bankruptcy situation in the subsequent year. 2007 data for example explains the failures in 2008 only. In Table 1, the magnitudes of coefficients are dramatically decreased compared to the results in Table 2. The leverage ratio of Model 4 in 2008 and in 2007 has the coefficients of -0.579096 and -0.453726 with p-values of 0.000 and 0.010 respectively. Model 2 results are even clearer with coefficients of -0.696277 and -0.774627 respectively at the 0.000 p-value level. The reason why leverage ratio coefficients flip sign and become more significant in Table 2 is because Table 2 data uses the most recent data before a bankruptcy is announced. The time lag between the reported data and the bankruptcy result is less than or equal to one year.

The capital ratio data of Model 4 in Table 1 shows a little statistical insignificance with p-values of 0.085 and 0.033 in 2008 and in 2007 respectively. While in 2007, its coefficient shows expected relation with the dependent variable with a value of -0.293987, in 2008 the coefficient becomes 0.0885841 which is explained by a little high p-value. Model 3 results however with only capital ratio as the independent variable have coefficients of -0.470967 and -0.608514 at the 0.000 p-value level in 2008 and in 2007 respectively. The coefficient signs are as expected and their magnitudes are larger.

The reason for using slightly separate methods to assess bank failure probabilities is because in Table 2, the effectiveness of previous years' data on predicting the dependent variable was also tested. In 2006, both the leverage and the capital ratio are statistically significant with p-values of 0.004 and 0.003 respectively. Capital ratio has a negative coefficient -0.030073, suggesting that low capital ratios raise probability of bankruptcy. Leverage ratio coefficient on the other hand possesses a positive sign with a value of 0.0121482 unlike our expectations. This coefficient is positive for 2003-2005. In 2005, leverage ratio is 0.0012508 with a p-value of 0.124 which shows statistical insignificance. Capital ratio on the other hand is still significant with a coefficient of -0.0244861 and a p-value of 0.009. In 2004 and 2003, none of the variables are statistically significant. This is a result of the widening gap between the obtained year of data and the year of bank failure. Looking at models 1-3, the only variable that holds a significant effect on bank failure probability is again capital ratio with coefficients of -0.0244861 and -0.0228334 and p-values of 0.019 and 0.011 in 2006 and in 2005 respectively. Thus of the variables in Table 2, capital ratio has the most predictive power.

In general, Table 1 data shows that Model 2 and 3 are statistically more significant and have larger coefficients and relatively lower p-values compared to Model 4. The reason why single factor models look more significant than the multiple factor model with less number of variables is because of the multicollinearity between the independent variables, especially between the capital ratio and the leverage ratio since both variables depend on the amount of capital that each banking firms hold. The situation can be observed in Table 3 that shows moderately strong correlation between the capital ratio and the leverage ratio. This result however does not hold for the data in Table 2 where coefficients in Model 4 are relatively stronger and more significant.

While both the capital adequacy ratio and the leverage ratio seem to be two successful bank failure indicators, the performance of the leverage ratio in the empirical analysis is slightly better as its effect on the predicted dependent variable is statistically more significant in Table 1.

In both tables, loan-deposit ratio fails to be a successful predictor for bank failures as it doesn't have any statistically significant data in any of the years and models. Its regression coefficients are very small and its large p-values indicate statistical insignificance in the model.

TABLE 3
CORRELATION TESTS
Variables: Return on Equity, Loan-Deposit Ratio, Leverage Ratio, Capital Ratio, Asset Size
Source: Federal Deposit Insurance Corporation Database

2008

	ROE	Loan-Deposit Ratio	Leverage Ratio	Capital Ratio
Loan-Deposit Ratio	0.017			
	(0.110)			
Leverage Ratio	0.065	-0.006		
	(0.000)	(0.594)		
Capital Ratio	0.023	0.001	0.373	
	(0.034)	0.934	(0.000)	
Asset Size	-0.003	0.015	-0.024	-0.005
	(0.766)	(0.160)	(0.030)	(0.638)

2007

	ROE	Loan-Deposit Ratio	Leverage Ratio	~~Capital Ratio~~
Loan-Deposit Ratio	-0.003			
	(0.782)			
Leverage Ratio	-0.078	-0.004		
	(0.000)	(0.703)		
Capital Ratio	-0.030	-0.000	0.204	
	(0.006)	(0.984)	(0.000)	
Asset Size	-0.001	0.012	-0.012	-0.005
	(0.922)	(0.275)	(0.265)	(0.645)

2006

	ROE	Loan-Deposit Ratio	Leverage Ratio	Capital Ratio
Loan-Deposit Ratio	-0.011			
	(0.297)			
Leverage Ratio	-0.131	-0.002		
	(0.000)	(0.867)		
Capital Ratio	-0.045	-0.001	0.303	
	(0.000)	(0.938)	(0.000)	
Asset Size	0.017	0.005	-0.013	-0.006
	(0.117)	(0.609)	(0.212)	(0.560)

	2005			
	ROE	Loan-Deposit Ratio	Leverage Ratio	Capital Ratio
Loan-Deposit Ratio	-0.000			
	(0.981)			
Leverage Ratio	-0.047	-0.001		
	(0.000)	(0.962)		
Capital Ratio	0.001	0.001	0.070	
	(0.956)	(0.950)	(0.000)	
Asset Size	0.018	0.007	-0.003	-0.004
	(0.093)	(0.515)	(0.748)	(0.697)

	2004			
	ROE	Loan-Deposit Ratio	Leverage Ratio	Capital Ratio
Loan-Deposit Ratio	0.030			
	(0.004)			
Leverage Ratio	-0.083	0.002		
	(0.000)	(0.879)		
Capital Ratio	0.031	0.001	0.184	
	(0.003)	(0.901)	(0.000)	
Asset Size	0.025	0.015	-0.009	-0.006
	(0.018)	(0.141)	(0.383)	(0.536)

	2003			
	ROE	Loan-Deposit Ratio	Leverage Ratio	Capital Ratio
Loan-Deposit Ratio	0.024			
	(0.020)			
Leverage Ratio	-0.135	0.002		
	(0.000)	(0.817)		
Capital Ratio	-0.044	0.004	0.390	
	(0.000)	(0.718)	(0.000)	
Asset Size	0.039	0.015	-0.023	-0.009
	(0.000)	(0.153)	(0.029)	(0.371)

In these separately tested years of data, there are statistically significant correlations between the ROE and the capital ratio and between the ROE and the leverage ratio. While the signs of both coefficients suggest a negative correlation between the ROE and the other two variables, the coefficient sizes reflect that there is a moderately negative correlation between the ROE and the leverage ratio. The correlation between the ROE and the capital ratio however is considerably small. Also the correlation between the ROE and the loan-deposit ratio is statistically insignificant both for 2005 and 2006 and in 2004 the correlation size is too small to be considered.

5 ASSESSMENT

The empirical study clearly shows that while capital and leverage ratio are very successful indicators, the loan-deposit ratio does not reflect any statistical importance in the logistic regression model. The loan-deposit ratio is referred by Roubini (1998) as an important factor to assess the strength of the banking sector. It reflects the amount of cushion that a banking firms has in case of a recall of its funding. In spite of this commonly held view, the given result does not reflect any significantly moderate relationship between bank failure possibility and the loan-deposit ratio.

The coefficients of the capital and leverage ratios support the hypothesis that banks that have low condition ratios are the riskier ones in terms of bank failure probabilities. This hypothesis is also supported in terms of statistical significance within the 95% confidence interval when the most up-to-date date is used.

We should also take into consideration the fact that the Basel II accord and the federal agencies require all banks to adopt a minimum capital ratio level of 8%. Based on the empirical results, the banks that have a capital ratio of 10% or less face significant threat of bank failure according to the empirical study. Thus, when inspecting the financial firms above the critical risk threshold, the results highly suggest the authorities to rely more on the leverage and the capital ratios and not as much on the loan-deposit ratio. As the Basel II accord sets the suggested minimum capital ratio level, it would be wise to closely monitor banks that have capital ratios close to this minimum regulated level.

5.1 Further Improvements

One of the possible improvements that can be made to this research paper is a panel data analysis. With multiple years of observations for every single banking firm, a researcher may look for the fixed and random effects in the model. Unfortunately, the FDIC database cannot provide adequate information for this analysis because the ratios for certain banks are missing in some years and the rows in the dataset for single banking firms do not match with each other for the consecutive years. This result may be seen in Table 1 and Table 2 by looking at the changing number of observations for different years.

Another improvement to the logit model that was used in this paper could be made by looking not at the ratio levels but at the absolute percent changes in the variables between consecutive years. This strategy may be very useful especially for observing banking firms' decisions at the time of a financial crisis. Unfortunately, for the same reason that the panel data analysis could not be used, the limited FDIC database does not provide sufficient information for the researcher to look for the absolute changes in the variables.

6 REFERENCES

Estrella, A., Park, S., Peristiani, S.: Capital Ratios as Predictors of Bank Failure. Economic Policy Review July, 33-52 (2000)

Wooldridge, J.: Introductory Econometrics. Ed. 4e.South-Western Cengage Learning: 574-622 (2009)

Memmel, C., Raupach, P.: How do banks adjust their capital ratios? J. Finan. Intermediation, 1-6 (2009)

Ovanhouser R.: Financial Crisis in America. Nova Science Publishers, Incorporated (2009)

Krugman, P.: Currency Crises. National Bureau of Economic Research: 154-159 (2000)

Basel Committee on Banking Supervision. International Convergence of Capital Measurement and Capital Standards. Bank for International Settlements, July, 1988.

Thomson, J. B.: Predicting Bank Failures in the 1980s. Federal Reserve Bank of Cleveland Economic Review **First Quarter**, 9-20 (1991)

Meyer, P., Pifer, H. W.: Prediction of Bank Failures. Blackwell Publishing for the American Finance Association September, 3-17 (1970)

Hill, T., Lewicki, P.: Statistics: Methods and Applications. StatSoft, Inc. November (2005)