**CAN STATISTICS BASED EARLY WARNING SYSTEMS DETECT
PROBLEM BANKS BEFORE MARKETS?**

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by

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**CAN STATISTICS BASED EARLY WARNING SYSTEMS DETECT
PROBLEM BANKS BEFORE MARKETS? (86 pp.)**

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Many statistical early-warning models have proven to have some predictive power. These models involve five basic approaches: logit, discriminant analysis, proportional hazard models, trait, and robust regression.

If markets are at least semi-strong form efficient, then prices must already incorporate any information that could be obtained by using these statistical early warning systems. In this case, either early warning systems do not have special predictive power, or the information they provide is quickly obtained by markets, probably through industry analysts who utilize such models in their analysis. If these systems can be used to earn abnormal profits, then the efficiency of equity markets is called into question.

In this dissertation, I utilize these five early warning systems to find problematic banks using data from 1986 through 2009. A zero cost arbitrage portfolio is formed each quarter by shorting the banks identified by the models as potential problems and going long the remaining non-problematic banks in the sample. The risk adjusted returns on the arbitrage portfolio and its long and short components is compared to risk adjusted returns on a long portfolio of all banks in the sample. If the returns on any of these portfolios are statistically greater than the “all bank” we can infer that the early warning system is able to provide information not available to investors and can conclude that the market is not semi-strong form efficient.

I find that using market returns for portfolios formed by bank EWS is a viable universal standard to judge their ability to discern problematic banks and conclude that newer and/or more complex EWS do not perform better than older and/or simpler models over long periods of time. Only two of the models are able to beat the naïve all bank portfolio on a risk adjusted basis over the entire term and none are able to beat the market on a risk adjusted basis, but all are able to form a long portfolio able to screen out some underperforming stocks and so beat a naïve strategy on an unadjusted for risk basis. From this, I conclude that the market for publicly traded commercial banks is highly, but not perfectly, semi-strong form efficient.

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1 Introduction

Almost as long as there have been banks, people have been trying to predict their failure. Bank regulators want to prevent the failure from occurring, and investors and depositors want to keep from losing their money. Many early-warning systems (EWS) or statistical models have proven to have some predictive power. These models involve six basic approaches: logit analysis (logit), multiple discriminant analysis (MDA), proportional hazard models (PHM), trait recognition (trait), robust regression, and intelligent systems typified by neural networks (NN). The methodology used in the first five models are widely accepted and these models are now used to analyze which characteristics are most closely associated with problematic banks, while the sixth, NN, is still under development and most research in the area is focused on refining the model rather than utilizing it.

If markets are at least semi-strong form efficient, then prices must already incorporate any information that could be obtained by using these statistical early warning systems. In this case, either early warning systems do not have special predictive power, or the information they provide is quickly obtained by markets, probably through industry analysts who utilize such models in their analysis. If these systems can be used to earn abnormal profits, then the efficiency of equity markets is called into question. By comparing the ability of various EWS to form portfolios that earn abnormal profits, we have established a “universal standard” with which to judge the various models. We use this universal standard to determine if newer and/or more complex EWS perform better than older and/or simpler models.

In this dissertation I utilize the five “established” or “archetypical” EWS to find problematic banks using data from 1986 through 2009. A zero cost arbitrage portfolio is formed each year by shorting the banks identified by the models as potential problems and going long

the remaining non-problematic banks in the sample. The risk adjusted returns on the arbitrage portfolio and its long and short components are compared to risk adjusted returns on a long portfolio of all banks in the sample, which represents a “naïve” strategy. If the returns on any of these portfolios are statistically greater than the “all bank, naïve strategy” long portfolio we can infer that the early warning system is able to provide information not available to investors and can conclude that the market is not semi-strong form efficient.

To utilize some of these models over the above time span, which includes a long period of time when relatively few bank failures occur, I have to utilize a novel method of accumulating data over time which also tests the stability of the predictive power of the variables used.

I find that using market returns for portfolios formed by bank EWS is a viable universal standard to judge their ability to discern problematic banks. Based on this standard and their ability to predict the failure of specific banks, I conclude that newer and/or more complex EWS do not perform better than older and/or simpler models over long periods of time. Over the period from 1986 through 2009, the financial variables used in this study remain stable and do not lose their ability to predict bank failure during the financial crisis of 2008. Only two of the models are able to beat the naïve all bank portfolio on a risk adjusted basis over the entire term and none are able to beat the market on a risk adjusted basis, but all are able to form a long portfolio able to screen out some underperforming stocks and so beat a naïve strategy on an unadjusted for risk basis. From this, I conclude that the market for publicly traded commercial banks is highly, but not perfectly, semi-strong form efficient.

2 A Survey of Relevant Literature

2.1 Early Warning Systems

Some of the earliest attempts at predicting bank failures utilize univariate ratio analysis. Secrist (1938) studies bank failures over 10 years using univariate analysis of 4 ratios and concludes that more sophisticated statistical methods would be required to predict likely bank failures. Sinkey (1974) conducts perhaps the most complete univariate study by using a matched sample of 110 problem and non-problem banks over 7 years to identify performance characteristics that might be used in an early warning system. He analyzes 21 size related ratios, 18 ratios related to the sources and uses of revenue, 2 measures of profitability, 2 ratios for capital adequacy, and 1 measure of managerial quality. He concludes that there are significant differences in the studied characteristics between the problem and nonproblem banks, and that the differences increase slowly over time as a sound bank becomes problematic.

One of the first attempts in constructing an early warning system, by Meyer and Pifer (1970), is a precursor of the logit regression method using untransformed variables. They examine a matched sample of 30 banks over 18 years using 32 variables and the rate of change of these variables over the period. Their study finds that failure can be predicted with reasonable accuracy (80 percent of failed banks are flagged) for up to 2 years prior to failure, even when embezzlement or other financial irregularities contribute to the failure, but trends in the data must be considered for the model to work.

Martin (1977) refines the work of Meyer and Pifer (1970) by using logit regression to analyze 5,700 banks over 6 years. He draws from a set of 25 ratios from four broad groups: asset risk, liquidity, capital adequacy, and earnings. He compares results using logit and discriminant

analysis, finding that discriminant analysis works better when the sample size is small, but otherwise both models produce similar results. Unlike MDA, logit analysis provides an estimate of the probability of failure during the next 1 or 2 year period, which may be of considerable importance to bank authorities and business.

During the same period (1975 – 1980), Sinkey (1975, 1977, and 1978) and Pettway and Sinkey (1980) use MDA to successfully screen for problem banks. In the 1975 study, Sinkey use MDA on a matched sample of 110 banks with 4 years of data and 10 ratios representing asset composition, loan characteristics, capital adequacy, sources and uses of revenue, efficiency, and profitability and conclude that they are “good discriminators.” In the 1977 study, Sinkey modifies the discriminant analysis to use only one group instead of the usual two because of the extremely small number of failed large banks with which to form a sample. Using data on the 50 largest US banks over 5 years with 7 variables he shows that such an “outlier” model is able to detect potentially problematic banks. In their 1980 study, Pettway and Sinkey use a paired sample of 66 banks over 6 years with a two-variable linear discriminant function and are able to detect problematic banks a little over a year before failure.

Both logit regression and MDA are subject to the effects of outliers, especially for large bank studies where sample sizes are small and the population is not normally distributed. Booth (1980) shows that a non-parametric statistical method, M-estimator robust regression, can be used to identify problem banks as outliers without the need to identify problem banks a priori or to meet the more stringent assumptions of discriminant analysis and logit regression. In addition, the method is much less computationally intensive than the outlier identification method which Sinkey uses in 1977.

Subsequent research on EWS concentrates on improving the predictive power of the model or finding additional risk factors associated with bank failures. Sinkey (1977) combines discriminant analysis with a second screen based on stock market performance using a capital asset pricing model (CAPM) and finds that the market screen performs nearly as well as discriminant analysis on financial ratios. Booth (1982) combines M-estimator robust regression, robustified Mahalanobis distance analysis, and principal component analysis on a sample of 50 large banks using 3 years of data with 3 accounting ratios. He finds that the combination may provide earlier warning than methods using a single identification method.

Tam and Kiang (1992) use a NN approach to nonlinear discriminant analysis (see section 2.1.B for more on their research). Yeh (1996) uses data envelopment analysis with twelve financial ratios to study the efficiency of 54 Taiwanese banks in converting inputs into outputs. The method categorizes banks into high, medium and low efficiency and is able to find problem banks and link their performance to operating strategies.

Lane, Looney, and Wansley (1986) use a PHM, a semiparametric model, that does not require distributional assumptions for the estimation of the baseline hazard function or probability that an average bank will fail. The model is designed to estimate of the probable time to failure, providing more information than models that only predict how likely banks are to fail. They use a sample of 130 failed banks and 334 matched nonfailed banks with a set of 21 financial ratios over five years and find that different variables work better when used over a one year prediction period versus a two year period. Wheelock and Wilson (2000) use a PHM with time-varying covariates to study which characteristics are likely to lead banks to fail or be acquired. They use three measures of managerial efficiency, 10 financial ratios and five other factors (total assets, holding company affiliation, branching, and age) on a 9 ½ year sample of

4,022 banks. They find that the characteristics associated with failure (high leverage, low earnings, low liquidity, and risky asset portfolios) are different from those associated with being acquired (small size, branching legal, low capitalization).

Kolari, Glennon, Shin, and Caputo (2002) use a nonparametric trait recognition model that allows for complex two- and three-variable interactions between financial and accounting variables. They use 23 financial ratios and 12 measures of the rate of change for most of these variables on a sample of 55 large failed banks that are matched to over 1,000 large unfailed banks over a 4 year period. They find that the model is able to outperform logit analysis in predicting out of sample bank failures.

Tung, Quek, and Cheng (2004) use a Generic Self-organizing Fuzzy Neural Network (GenSoFNN) based on the compositional rule of inference (CRI) to both predict bank failure and determine financial traits associated with bank failure (see section 2.1.B for more on their research). Curry, Elmer and Fissel (2007) add stock market factors to financial ratios in a logit regression utilizing a sample ranging from 75 to 99 banks and thrifts combined over a seven year period with 6 accounting ratios, five market variables and 3 risk related variables. They find the addition of market factors improve the predictive accuracy of the model.

Kimmel, Booth and Booth (2010) use a nonparametric LOESS model with a single financial ratio to analyze the performance of 46 large banks over 3 years. The model is similar to Sinkey's 1977 model in that it does not require the a priori identification of failed banks, but rather identifies banks that are significantly different from peer banks on one key dimension (three ratios are examined) while being similar along other dimensions, such as size (total assets or deposits). They find that the model works as well as earlier parametric models in predicting

failures among the sample of large banks and has the potential to provide superior performance during period when bank failures are uncommon.

2.1.A. Current Practice in the use of bank Early Warning Systems

Research using bank EWS is following a very different path than research on bank EWS. Research using bank EWS, for example to understand the causes of so many bank failures during the financial crisis of 2008, is largely being conducted using some of the simplest and oldest statistical models. A survey of recent literature turned up 5 studies using logit¹ (one of them combined with binary tree analysis²), one using a variant of the PHM³, and one using MDA⁴. Researchers probably use these methods because they are proven and widely accepted, while newer, more complex models are still under development and no clear consensus exists as to which version or implementation is best.

Barrell, Davis, Karim, and Liadze (2010) use logit analysis to examine some of the causes of 14 systemic and 14 non-systemic financial crises in 14 OECD countries from 1979 through 2007. They use a set of six variables that earlier research has shown effective in predicting bank crises and add three new variables: liquidity ratio, unweighted capital adequacy ratio and real property price growth to the model and find that the new variables better predict crises than the variables from prior research.

Caporale, Matousek, and Stewart (2009) use ordered logit and probit regression models in an effort to reverse engineer the Fitch Ratings of banks before and during the financial crisis of 2008, add a country specific variable and then compare the accuracy of their model to actual

¹ Barrell, Davis, Karim, and Liadze (2010), Caporale, Matousek, and Stewart (2009), Cole and White (2010), and Poghosyan and Čihák, (2009).

² Davis and Karim (2008)

³ Demyanyk and Van Hemert (2009)

⁴ Jordan, Rice, Sanchez, Walker, and Wort (2010)

ratings given by Fitch of three of the first banks to fail during the crisis. They examine 681 international banks over seven years using seven lagged (up to four years) financial variables. They find that capital adequacy, size, return on assets, and the stability of the home country have positive effects on a bank's rating, while the ratio of operating expenses to total operating income has a negative effect on the bank's rating.

Cole and White (2010) run 10 different logistic models on data from 2004 through 2008 using "standard proxies for the CAMELS components" as well as various measures of real estate loans. 117 commercial banks failed in 2009 and they conjecture that many more will fail during 2010 – 2012. To account for this, they create a measure of "technical failure" and add banks that meet this requirement to the sample of failed banks, yielding 265 failed banks. They find that traditional CAMELS measures do an excellent job in explaining the failures of banks but the real estate measures do a better job at long lead times. They also find that residential mortgage-backed securities played little role in determining which banks failed.

Davis and Karim (2008) use logit analysis as well as a nonparametric binary recursive tree technique to examine whether or not the US subprime crisis was predicted by ex ante macroeconomic and financial data from 105 countries during the period from 1979 through 2003 using 12 macroeconomic, financial and institutional variables. They are unable to predict the crisis using these models and the variables studied, so either the crisis is unpredictable from ex ante macroeconomic and financial data or, is unpredictable using these two models.

Poghosyan and Čihák (2009) use several version of the logistic regression model with a new dataset for 5,708 European banks from 1996 through 2007. They combine the usual financial variables with data on individual bank distress gathered by hand; searching a news database for selected keywords. By comparing their distress measure to CAMEL variables, they

find that capitalization, asset quality and profitability are good predictors of distress while cost-to-income ratios and basic liquidity indicators are not.

Demyanyk and Van Hemert (2009) use a discrete-time analogue to the PHM, called a proportional odds model, with a random sample of 1 million loans from the First American CoreLogic LoanPerformance database, as of June 2008, which includes loan-level data on about 85 percent of all securitized subprime mortgages; (more than half of the U.S. subprime mortgage market). They conclude that the crisis is “a classic lending boom-bust scenario with rapid market growth, loosening underwriting standards, deteriorating loan performance, and decreasing risk premiums.”

Jordan, Rice, Sanchez, Walker, and Wort (2010) use MDA to examine 225 banks that failed between February 2007 and April 2010, using a random sample of nonfailed banks as a control. They use six financial ratios and three institutional characteristic variables. Their model is able to predict failure up to four years in advance.

2.1.B. The future direction of research for bank Early Warning Systems

While some researchers are working to refine some of the older models, such as Cole and Wu's (2009, 2010) work with hazard models and Güvenir and Çakir (2010) with a variant of trait analysis called voting features based classifier with feature construction (VFCC), most research is being done in the area of artificial intelligence or neural networks.

Kunihiko Fukushima (1975) first proposed using a computer algorithm to mimic the processing of a biological neural network. A neural net is a set of interconnected computational nodes and are distinguished by the algorithms used by the nodes, the number of nodes, the complexity and direction of the interconnections, and the weights given to the inputs and outputs of the nodes. Tam and Kiang (1992) are among the first to apply the concept to the prediction of

bank failure. They use a multilayer NN with a backpropagation learning algorithm (a connectionist model) to perform discriminant analysis on a matched, 3 year sample of 118 Texas banks with 20 financial ratios. They find the NN model to be accurate, adaptable, and robust compared to earlier methods.

Tung et al (2004) use a Generic Self-organizing Fuzzy Neural Network (GenSoFNN) based on the compositional rule of inference (CRI). This model is based on a set of IF-THEN rules to model the problem which allows for better control and understanding of both the functioning and interpretation of the linkages between nodes and their weights. Ng, Quek, and Jiang (2008) modify the GenSoFNN model of Tung et al (2004) by allowing for localized learning in the training phase, calling their model “fuzzy cerebellar model articulation controller based on compositional rule of inference (FCMAC-CRI(S))”. They believe that their model prevents false or spurious associations from forming in the model and leads to better results. Ravisankar and Ravi (2010) add three additional variations of NN to the bank EWS literature: Group Method of Data Handling (GMDH), Counter Propagation Neural Network (CPNN) and fuzzy Adaptive Resonance Theory Map (fuzzy ARTMAP). Using datasets from Spain, Turkey, the UK and the United States, they find that the GMDH model outperforms the other models introduced in the paper as well as earlier NN models in terms of average accuracy, sensitivity, and specificity.

Can a perfect model for the prediction of bank failures exist? It is probably impossible to create a model that can eliminate type I errors, or false positives, at least as long as the model is designed to predict failure and not just underperformance. At best, a model can indicate, at the time of the forecast, that *ceteris paribus*, the bank will fail, but exogenous changes in the economy, or actions by bank regulators or bank management, can intervene and prevent the

failure of the bank. Type II errors, or false negatives, are also impossible to eliminate as between the time of the model's forecast and the bank's ultimate failure, exogenous changes in the economy, or bank management, such as fraud, can intervene in ways that would not have informed the model and still cause the bank to fail.

Instead of defining model perfection in terms of prediction accuracy, we could go back to the premise of this research and define the perfect bank EWS as one that is able to inform markets, and in doing so, makes the market informationally efficient. Given the results in sections 5 and 6, the market for publicly traded commercial banks became much more efficient after 1994. The fact that none of the models tested here is clearly able to beat the market after 1994 on a risk adjusted basis indicates that the market is informationally efficient (if not perfectly so), indicating that collectively bank EWS are able to inform markets, and do.

Simon (1955) argues that people (investors) can only make rational decisions to the extent that they have access to information and the computational capacities to make sense of the information they have. In terms of market efficiency, insiders and bank regulators will have better access to information than outside investors, and since they are forbidden to trade on this inside information, markets can at best be semi-strong form efficient. Per Simon (1955), better information and better computational models will result in more rational decisions, and therefore more efficient markets.

Arora, Barak, Brunnermeier, and Ge (2010) show that the proper pricing of financial instruments (derivatives) can be so computationally inefficient as to bound or limit market efficiency. Maymin (2011) shows that if $P=NP$, meaning that every computational problem whose solution can be verified in polynomial time can also be solved in polynomial time, markets must be at least weak form efficient. He also argues that if $P \neq NP$, then markets cannot

be weak form efficient (though questioned by this researcher, he modified this to “if $P \neq NP$, then markets cannot be proven to be weak form efficient.”) He argues that information is accumulating faster than computational power, and so markets will become more inefficient as time goes on. Applied to the problem of bank EWS, this would mean we could not be sure our model is perfectly efficient without trying every possible permutation and every possible alternative model. Even if we somehow stumbled on the perfect model, we couldn’t prove that we had, and lacking such proof, it would not be universally accepted, so could not completely inform the market, and therefore the market would remain inefficient, and the model should earn abnormal profits on a risk adjusted basis.

2.2 Winner and Loser Portfolios, and Market Efficiency

An efficient market is one in which prices always "fully reflect" available information (Fama 1970). Following Fama’s terminology, Φ_t is used to symbolize the set of information that is “fully reflected” in the price of a stock at time t . If the conditions of market equilibrium can be stated in terms of expected returns and equilibrium expected returns are formed on the basis of Φ_t , then trading systems based only on Φ_t cannot have expected profits or returns in excess of equilibrium expected profits or returns, or markets are not efficient. Mere disagreement among investors about the implications of Φ_t does not imply market inefficiency, but the existence of investors who can consistently make better evaluations of available information than are implicit in market prices does.

Jensen (1978) modifies this definition of efficient markets by noting that a trading rule would have to produce “economic profits” or a “risk adjusted return[s] net of all costs.” Fama (1991) interprets this to mean that prices reflect information to the point where the marginal benefits of acting on information (the profits to be made) do not exceed the marginal costs.

Berkowitz, Logue and Noser (1988) estimate the total transaction costs average 23 basis points measured against the principal value of trades.

Alexander (1961) postulates that information would diffuse through the market causing prices to follow a trend which could be recognized by a trading rule that would filter out noise. His rule calls for going long a stock if its price goes up $x\%$ and holding it until it subsequently drops the same percentage at which time the stock would be shorted and the position maintained until stock goes up $x\%$. Fama and Blume (1966) point out that Alexander ignores the effect of dividends on short sales and of transaction costs on all sales.

King (1966) improves on the work of Alexander (1961) in two ways. First, he includes the effect of dividends on short sales. Second, and more importantly, he recognizes that new information will affect the value of more than one stock so price changes are correlated across stocks. He uses a portfolio of 63 stocks from the NYSE and finds that about 31% of individual stock price change is explained by market movement and an additional 10% of total variance is explained by industry affiliation.

Levy (1967) creates a precursor to the winner and loser portfolios of Beaver and Landsman (1981) by using percentage changes in stock prices to rank them and then looks for serial correlation in the ranks to determine if the relative strength of a stock's performance persists over time. Levy feels that using relative ranks would filter out market and industry effects. Unfortunately, he does not check to see if his results are due to differences in risk.

Beaver and Landsman (1981) create the first research design using "winner" (whose risk adjusted abnormal (called residual in the paper) returns are systematically positive in the months prior to selection) and "loser" (whose risk adjusted abnormal returns are negative in the prior months) portfolios formed "directly and exclusively on the residual return behavior." They do so

by using the market model to estimate α and β for each security over 60 months and then compute abnormal returns by comparing expected and actual returns over the following 12 months. They use these to form the stocks into winner and loser portfolios. Setting the month of portfolio formation as $t=0$, they compute the risk adjusted abnormal returns for each stock in each portfolio from $t=-19$ to $t = 20$ using the market model. The portfolio abnormal return is the equally weighted mean of the excess return of the stocks in the portfolio, implicitly requiring the rebalancing of the portfolio each month. These average abnormal risk adjusted returns are summed to find the Cumulative Average [abnormal] Return (CAR).

Chan (1988) finds that DeBondt and Thaler (1985), whose work is based on the winner/loser portfolios of Beaver and Landsman (1981), fail to account for variation in the systematic risk of the winner and loser stocks. For a variety of reasons (see Chan (1988), page 150), loser stocks naturally tend to become more risky, for example, as stock price falls, if the firm does not rebalance debt, debt becomes a larger part of its capital structure which increases the risk of the firm. At the same time, and for similar reasons, winner stocks tend to become less risky. This failure to account for time varying risk premia as measured by β causes their results to overstate the potential returns to contrarian strategies. Chan uses the market model to find winner and loser portfolios but then uses CAPM to test for abnormal returns in the resulting portfolios.

Beaver and Landsman (1981) and DeBondt and Thaler (1985) use β estimated during the selection phase of portfolio formation to determine the expected return during the test period, but Chan (1988) argues that the market risk of the firm is likely to change and so estimates β during the test period, assuming that the β measured over that period is the mean of the actual time varying β during the period. He calculates a self-financing arbitrage portfolio (loser – winner)

which consists of long positions in the losers and short positions in the winners (since he assumed reversion to the mean). Chan finds that losers are less risky (smaller β) than winners during the rank period but become more risky than winners after portfolio formation, ie in the test period.

Chopra, Lakonishok and Ritter (1992) find that loser stocks tend to have lower capitalizations than winner stocks, and since Banz (1981) found that smaller stocks have higher risk adjusted returns, Chopra et al (1992) adjust for both size and time varying beta and still find an economically-important overreaction effect.

Kothari, Shanken, and Sloan (1995) and Kothari and Shanken (1999) find that size and beta are necessary to explain returns, but while statistically significant, size provides little economic benefit. They also find that book to market as used by Fama and French (1992, 1993) has little explanatory power and its seeming explanatory power came from selection bias, data mining and is period specific to the Fama French data. Jegadeesh and Titman (2001) revisit their 1993 work using both CAPM and the Fama French three factor model to adjust returns for risk and find that the Fama French model returns slightly higher risk adjusted returns in momentum portfolios.

2.3 Two-Factor Model

Merton (1973) believes that the CAPM is used, despite its proven theoretical and empirical flaws, because it is easy to understand and does explain much of the variation in asset returns. He proposes an extension of the CAPM, the Intertemporal CAPM which shows that investors are rewarded for bearing market risk and the risk of unfavorable shifts in the investment opportunity set, which is associated with, and therefore can be proxied by, changes in the interest rate. Stone (1974) takes a more direct approach and proposes a two factor model with

the usual stock market index and a well diversified bond index for interest rate risk. Lloyd and Shick (1977) provide some support for Stone's 2-factor model, though they use a different, unmanaged, bond index and use a different correction for multicollinearity (though they found correcting for multicollinearity does not affect the results of their study). However, Chance (1979) shows that Lloyd and Shick probably use bad data and bad statistical methods. He finds no support for Stone's 2-factor model in his study.

Lynge and Zumwalt (1980) revisit Stone's 2-factor model using a different data set, different bond index, and different correction for multicollinearity between the stock and bond indexes and find that the addition of the bond index provides greater explanatory power than a 1-factor equity model (CAPM). Fogler, John and Tipton (1981) propose a 3 factor model with two bond indexes, one of 3-month U.S. Government bonds and the other of corporate bonds. They argue that the usual correction for multicollinearity, orthogonalization, does not add to the explanatory power of the model and the choice of variables to be orthogonalized is arbitrary, and so they do not orthogonalize any of the indexes. They find that most of the variation in stock returns is explained by the market variable with some additional influence by the government bond index, but that the corporate bond index does not provide any additional explanation of the stock returns.

Flannery and James (1984) test Stone's 2 factor model using 1-year Treasury Bills, 7-year Treasury Bonds, and 8% Government National Mortgage Association (GNMA) bonds. They use only US government or government agency issued bonds to insure that only interest rate risk is being captured by the bond data, and not changes in risk premia. Supporting Fogler et al (1981), they find no significant value in orthogonalizing the data series. In addition, they examine the effect of anticipated changes in interest rates by replacing the raw bond returns with

the residuals from an AR(3) autoregressive model. They find that the returns on bank stocks are highly correlated with interest rate changes, supporting Stone's 2-factor model, and that using unanticipated interest rate changes, as opposed to raw interest rate data, does not produce superior results. Like Flannery and James (1984), Kane and Unal (1988) find that using unorthogonalized, unadjusted (ie not estimated) holding-period returns for long-term government bonds provides the greatest explanatory power when used in Stone's 2-factor model. They also find that the betas for both the market and bond indexes change over time, suggesting the need to re-estimate them over time.

Subsequent researchers either try to improve on Stone's basic 2-factor model or to identify the underlying factors that make the return on bank stocks dependant on interest rates. Kwan (1991) tests the hypothesis that bank stocks are sensitive to interest rate changes due to the mismatch between the duration of their assets and liabilities. He finds that this is so for a bond index using short term government bonds, but when a long-term government bond index is used, bank stock returns are affected only by the stock market index and the bond index, not the gap between asset and liability duration. Kwan finds no advantage to orthorgonalizing the indexes, but does use an AR(3) model to estimate the impact of unanticipated changes in interest rates. Dinenis and Staikouras (1998) find that the choice of bond duration does not matter, but that the affect is greater during periods of high interest rate volatility. They do orthogonalize their indexes and use the change in rates, but do not check to see if this affects their results. Fraser, Madura and Weigand (2002) orthogonalize the market index and estimate the unexpected component of the change in interest rates. They find that the magnitude of a bank stocks' reaction to interest rate changes is stable and independent of the size of the bank. In summarizing the research in this area, Staikouras (2003, 2006) finds that four factors seem to explain the

sensitivity of bank stock returns to changes in interest rates: “(a) the intermediary’s balance sheet mix, (b) the direction of interest rates, (c) the volatility of interest rates, and (d) inappropriate/non-existent off-balance sheet hedging platforms.”

2.4 The Contribution of this Dissertation to the Literature

This research adds to the literature in six important ways. First, statistical models that attempt to identify problematic banks span the range of statistical methods from simple factor analysis to complex, nonparametric techniques requiring intricate programming and sophisticated data manipulation. Each model claims the power to identify problematic banks, and a few of the studies attempt to demonstrate that their new method is an improvement over some previous methods. However, none of the researchers compare their models to a universal objective standard, such as the power of markets to discern which banks are most likely to fail. This dissertation is the first research comparing archetypical bank failure models to a universal objective standard: the power of markets to discern which banks are most likely to fail.

Second, using this universal objective standard allows us to determine which models work best and if newer, more complex models perform better than their simpler predecessors. I examine model performance using two measures: their ability to correctly predict the three publicly traded commercial banks that failed during the study period as well as their ability to form portfolios that can outperform a naïve all bank strategy, both adjusted and unadjusted for risk.

Third, this study is the first long term study (24 years, from 1986 through 2009) of these models using a modern dataset. This is especially instructive during the financial crisis of 2008 as this is the first study to examine the use of many of these models during such a chaotic and potentially unpredictable time.

Fourth, it is necessary to construct a unique dataset for matching failed banks to nonfailed banks for those models that require a priori identification of failed banks and matching them to nonfailed banks because the period under study includes a long period of time when relatively few bank failures occurred. This is done by accumulating data over the entire period (see section 4.2 for more on the matching method used). For this method to work, the parameters used in the studies must be stable over time, that is, if a ratio of 1:5 for net income to total assets is associated with a nonfailed bank while a ratio of 1:10 is associated with a failed bank, this ratio must be relatively stable over time for this accumulation method to work. Thus, in the later years of this study, the predictive power of the models is a joint test of the model and this method of applying the model during times of limited numbers of bank failures, as well as a test of the stability of key factors that may predict bank failure, which is the fifth contribution of this research to the literature.

And finally, by testing the power of these models to create trading rules which might be able to beat the market on a risk adjusted basis, this research lends significant support to the efficient market hypothesis after 1994.

3. Methodology

3.1 Portfolio Formation

Given the purpose of this research, I decided that the models studied should be mature, that is, they should be regularly used by researchers as tools to study banks rather than the model itself being the focus of research, which would imply that the model is still under development. The models studied include logit analysis as typified by Martin (1977), MDA as typified by Pettway and Sinkey (1980), Cox PHM as typified by Lane et al (1986), trait recognition as typified by Kolari et al (2002), and robust regression as typified by the LOESS regression used by Kimmel et al (2010).

I use these five statistical models as trading rules to form zero cost portfolios, long winners and short losers, accounting for the effect of dividends on short sales. Portfolio formation lags the end of the quarter by 2 months to allow dissemination of the quarterly reports to investors. The portfolios are adjusted for risk using the CAPM, and as a robustness check, by using Stone's (1974) two-factor model using unorthogonalized, unadjusted holding-period returns for an index of long-term government bonds. Betas are estimated using a rolling 24 month estimation period to avoid parameter shifts. Portfolios are equally weighted so that the focus is on the model's ability to predict poor performance rather than on the market capitalizations of the stocks in each portfolio. Returns are calculated on portfolios that are rebalanced each quarter which eliminates survivor bias. The risk adjusted returns on the arbitrage portfolio and its long and short components are compared to risk adjusted returns on a long portfolio of all banks in the sample. If the models allow investors to "consistently make better

evaluations of available information than are implicit in market prices” (Fama 1970) we will have shown that markets are inefficient.

3.1.A Portfolio Formation: logit analysis based on the work of Martin (1977)

Martin (1977) uses an ex-post empirical model in which banks are grouped into failed and non-failed categories which are used as the dependent variable in a logit regression. Failure is defined as the occurrence of failure, supervisory merger or other emergency measure to resolve an imminent failure situation within two years of the statement year to which the financial ratio data apply. Characteristics (the independent variables of the logit regression) of the failed group one or more years before the failure are compared to the same characteristics of the non-failed group and used to predict future failure by examining these characteristics in future periods. The independent variables are drawn from a set of 25 financial ratios found by earlier studies to be useful as early warning indicators.

The population, N , is defined as all banks which are members of the Federal Reserve (FED) System and the number of failed banks in the estimation period is denoted n . A bank is assigned to the failed bank group if its estimated probability is higher than n/N , that is if it has a greater than equal probability of failure. The likelihood ratio index (LRI) and Akaike Information Criterion (AIC) are used to select the combination of variables that best fit the given data set. The model works best when using estimates from periods of the business cycle when bank failures are more common. This will tend to overestimate failure during times of low rates of bank failure, but “the relative weights of different characteristics will be based on their objective contribution to risk rather than the subjective weights currently used in rating banks.”

Using 1974 data, Martin (1977) finds that a constant, net income/total assets, gross charge-offs/net operating income, commercial loans/total loans, and gross capital/risk assets provide the best fit (see Table: 1 Martin (1977)).

3.1.B Portfolio Formation: discriminant analysis based on the work of Pettway and Sinkey (1980)

Pettway and Sinkey (1980) use a two-variable MDA classification model (the model is described more completely in Sinkey (1979)). A sample of distressed banks (33 large banks that failed between 1970 and 1975) is compared to a paired sample (based on deposit size, number of branches, and location) of healthy banks (note that in his 1979 paper Sinkey recommended using a random sample to match with the failed banks rather than the paired sample he used in the 1980 paper. He offers no reason for this in the 1980 paper). The two variables used are given in Table 2: Pettway & Sinkey (1980), as are the variables used to match failed banks to healthy banks.

Coefficients are calculated during a classification period and then applied in the test period to calculate the probability that a bank belongs to each group (failed and non-failed). While MDA would theoretically work with banks of any size, Pettway and Sinkey (1980) focus on “giant” banks which they define as having total assets greater than \$1 billion and “large” banks with assets greater than \$100 million and only validate their model using 6 of the largest banks ever to have failed as of the date of their research.

3.1.C Portfolio Formation: Cox proportional hazard model based on the work of Lane et al (1986)

The PHM used by Lane et al (1986) is a semiparametric model that does not require distributional assumptions for the estimation of the baseline hazard function or probability that an average bank will fail⁵. The model is designed to predict the probability that a bank that was “alive” at time t will fail in the next instant. In this way, the model can not only predict which banks are likely to fail, but it can provide an estimate of the probable time to failure.

The probability that a bank will fail an instant after time t given the state of certain explanatory variables is called the hazard function and is denoted by

$$h(t|z) = \exp(\beta'z)h_0(t), \quad \text{Equation 1}$$

where z are the explanatory variables, β is a vector of their regression coefficients, and $h_0(t)$ is the hazard of an average bank at time t .

Like MDA, PHM requires matching samples of failed banks to nonfailed banks, but unlike Pettway and Sinkey (1980) who match one failed bank to one nonfailed bank, Lane et al (1986) match each failed banks with one to ten nonfailed banks resulting in a sample of 130 failed banks and 334 nonfailed banks. The matching is based on geographic location, charter status (state or national), size (total assets, the match must not be more than twice its size), holding company affiliation, and age. A set of 21 ratios are used in the classification phase (see Table 3: Lane et al (1986) for a listing of the variables). Data for each variable is gathered for each bank as of December 31 for one and two years before the sample banks failed, resulting in two data sets. For a nonfailed bank, the censored survival time is defined as the number of

⁵ The Cox PHM does require a multiplicative relationship between the underlying hazard function and the log-linear function of the covariates (the proportionality assumption). This assumption does not hold for ratio 11 (log total capital/total assets) in our dataset. Lane et al (1986) acknowledge the problem but dismiss it saying, “even if the assumption of constant ratios is not valid for these data, the Cox model based on this assumption still provides useful results.”

months from the data reporting date to the end of the year in which its matched bank failed. A stepwise procedure combining forward and backward elimination is used to determine which combination of explanatory variables provides the best fit with the data.

In the test phase, the betas from the classification phase are used to calculate the probability that a particular bank will survive for longer than t months. Betas from the one year before data set are used to predict the likelihood of failure ($1 - \text{probability of survival}$) within 12 months and betas from the two year data set are used to predict the likelihood of failure between 12 and 24 months. If the likelihood of failure is greater than some cutoff value, C , then the bank is classified as likely to fail and “healthy” otherwise. As in the logit procedure of Martin (1977), this value is set as the percentage of failed banks in the sample during the classification phase. The model is validated using a holdout sample of 137 banks.

3.1.D Portfolio Formation: trait recognition⁶ based on the work of Kolari et al (2002)

Trait recognition is a nonparametric model and so does not rely on statistical or distributional assumptions about the predictor variables. “Building a trait recognition model is a multistep procedure that involves: (1) selecting cutpoints for each of the variables, (2) binary coding of the variables, (3) constructing a trait matrix for each observation, (4) identifying good and bad traits (or distinctive features), and (5) implementing voting matrix classification rules.”

Cutpoints are set for each independent variable to divide the range of values into thirds based on variance. The middle range or segment is defined by ± 1 standard deviation from the

⁶ Software was provided by Dr. Kolari: TRAITS V7.0

Written by: Matthew B. Butler, modified by: Rajneesh Khanna, modified by: Hwan Shin (classification for original run)

Original programs by: Dr. James W. Kolari, Drew L. Wagner

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Documentation: User's Manual to Traits V2.0, Written By: Rajneesh Khanna, Modified By: Hwan Shin

Fortran used provided by the Free Software Foundation GNU project with help from Dr. Roumani of York University.

mean with the lower and upper ranges defined accordingly. These segments are coded 00, 01, and 11 respectively for the lower, middle, and upper segments. To capture the interaction between variables, traits are composed of groupings of three variables. Each trait is coded as a vector of 6 digits, two for each variable, that represent the variable and the range (lower, middle, or upper). A search routine is used to cull traits that do not help to discriminate between failed and nonfailed banks. The remaining traits that do help are called features. Features are grouped depending on whether they are associated with failed (unsafe) or nonfailed (safe) banks. The number of safe and unsafe features for each bank is tallied and this tally is used to place it into a voting matrix. Finally, rules for determining which cells in the voting matrix are safe and unsafe, determined by whether each cell is dominated by failed or nonfailed banks, are developed during the classification period and applied during the prediction period.

Kolari et al (2002) validate their model using large banks which they define as having total assets greater than \$250 million providing a sample of just over 1,000 banks each year during the prediction phase.

3.1.E Portfolio Formation: robust regression based on the work of Kimmel et al (2010)

Unlike the other models in this study, the robust regression model used by Kimmel et al (2010) does not require the a priori identification of failed banks and so does not require a classification phase to determine which levels of the predictor variables are associated with failure or nonfailure.

In this nonparametric model, the 46 largest (in terms of total assets) banks are ordered by total assets under the assumption that banks of a similar size should be similar in other respects, specifically in terms of total loans (TL), net income (NOI), net loan losses (NLL), and loan loss provision (LLP). Four models are evaluated using LOESS (Locally Weighted Scatter Plot

Smooth, a type of Local Regression Smoothing):

$$\text{Model 1 : } YX^{-1/2} = \beta_0 X^{-1/2} + \beta_1 X^{1/2} \quad \text{Equation 2}$$

$$\text{Models 2, 3, \& 4: } YX^{-1} = \beta_0 \text{Case} \quad \text{Equation 3}$$

where *Case* is the observation number identifying each bank in the original dataset and the variables are as defined in Table 5: .

Kimmel et al (2010) find that a smoothing parameter of 50% and a first degree polynomial works well in the LOESS regressions. The residuals from the regressions are inspected to determine if the bank is a potential problem. “Bad” is determined in the following manner. For models 1 and 2, problem banks are expected to have negative residuals, indicating they are not utilizing their total assets to earn net income as efficiently as other banks. For models 3 and 4, problem banks are expected to have positive residuals indicating they have high net loan losses (or high loan loss provisions) as a percentage of total loans and high net loan losses (or high loan loss provisions) compared to total assets respectively. In validating their model, Kimmel et al (2010) conclude that the model is successful if the problematic bank is one of the 5 banks with the largest (absolute value) “bad” residuals. Model 1 is the most adept at detecting the problematic banks and is the one used in this study.

3.2 Model Evaluation

Three statistics are used to judge the effectiveness of the models. The first is to determine whether the model is able to predict the failure of each of the 3 publicly traded commercial banks that failed during the period, and if so, by how many years before failure the model is able to flag the bank.

The second method used to evaluate the effectiveness of the models is the risk adjusted Cumulative Abnormal Return using both the CAPM and Stone 2-factor models. The normal

return is defined as the expected return without conditioning on the events taking place. For firm i and date t the abnormal return is

$$AR_{it} = R_{it} - E(R_{it}|X_{it}) \quad \text{Equation 4}$$

where AR_{it} , R_{it} , and $E(R_{it}|X_{it})$ are the abnormal, actual, and expected returns respectively for time period t .

The CAPM and Stone 2-factor models are econometric models which relate the return of any given security to the return of the market portfolio, and for the Stone 2-factor model, to an index of bond returns. The model's linear specification follows from the assumed joint normality of asset returns. For any security i the market model is

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \quad \text{Equation 5}$$

where $E(\varepsilon_{it}) = 0$ and $var(\varepsilon_{it}) = \sigma_{\varepsilon_i}^2$ for the CAPM and

$$R_{it} = \alpha_i + \beta_{mi} R_{mt} + \beta_{bi} R_{bt} + \varepsilon_{it} \quad \text{Equation 6}$$

for the Stone 2-factor model where R_{it} and R_{mt} and R_{bt} are period t returns for security i , the market portfolio, and a bond index respectively, and ε_{it} is the zero mean disturbance term. The Center for Research in Securities Prices (CRSP) NYSE/AMEX/NASDAQ equally-weighted stock index is used for the market portfolio.

To avoid problems with cross correlations due to clustering, the abnormal return observations are aggregated into equally weighted portfolios in order to draw overall inferences for the event of interest (Bernard 1987). The aggregation is along two dimensions – through time and across securities. The return for the portfolio will be

$$R_{pt} = \frac{1}{N} \sum_{i=1}^N R_{it} \quad \text{Equation 7}$$

The expected return on the portfolio is determined by regressing the portfolio return on the return for the market and estimating the parameters:

$$R_{pt} = \hat{\alpha} + \hat{\beta}(R_{mt}) + \varepsilon_t \quad \text{Equation 8}$$

for CAPM and

$$R_{pt} = \hat{\alpha} + \widehat{\beta}_m(R_{mt}) + \widehat{\beta}_b(R_{bt}) + \varepsilon_t \quad \text{Equation 9}$$

for the Stone 2-factor model during the estimation period. The abnormal return compares the return on the portfolio with the expected return given these parameters:

$$AR_{pt} = R_{pt} - \hat{\alpha} - \hat{\beta}(R_{mt}) \quad \text{Equation 10}$$

for the CAPM and by

$$AR_{pt} = R_{pt} - \hat{\alpha} - \widehat{\beta}_m(R_{mt}) - \widehat{\beta}_b(R_{bt}) \quad \text{Equation 11}$$

for the Stone 2-factor model. The Cumulative Abnormal Return for the portfolio is then

$$CAR = \sum_{t=1}^T AR_{pt}. \quad \text{Equation 12}$$

To test the hypothesis that the $CAR=0$ we use the test statistic

$$\Phi = CAR / [\sigma^2(AR_t)/T]^{1/2} \quad \text{Equation 13}$$

where T is the number of months in the period of study. Rejecting the null hypothesis in favor of positive cumulative abnormal returns indicates the model is able to beat the market. In addition, if the portfolios created using the models are able to outperform a naïve strategy of going long all publicly traded commercial bank stocks, it demonstrates that the models have predictive power and can inform markets. The ability of the models to beat the naïve strategy is given by $Perf_{CAPM}$ and $Perf_{STONE}$ which stands for “performance of the model adjusted for risk using the CAPM and Stone 2-factor model” respectively. Performance is defined as the cumulative abnormal return on the portfolio formed using the model minus the cumulative abnormal return on the naïve all bank

portfolio. The test statistic used here is

$$t = \frac{CAR_p - CAR_n}{\sqrt{\frac{\sigma_p^2}{N_p} + \frac{\sigma_n^2}{N_n}}} \quad \text{Equation 14}$$

where CAR_n and CAR_p are the cumulative abnormal returns on the naïve and model determined portfolios respectively and σ^2 is the variance of the returns.

The third method used to evaluate the effectiveness of the models is to compare the total return on a portfolio of all publicly traded commercial banks (the naïve strategy) to the return on winner, loser, and long-short portfolios formed by the models in question. Performance is defined as the total return on the portfolio formed using the model minus the total return on the naïve all bank portfolio. If the returns on the portfolios formed by the models are significantly different (greater than) from the naïve strategy, the models must be able to inform markets. The test statistic used here is

$$t = \frac{R_p - R_n}{\sqrt{\frac{\sigma_p^2}{N_p} + \frac{\sigma_n^2}{N_n}}} \quad \text{Equation 15}$$

where R_n and R_p are the returns on the naïve and model determined portfolios respectively and σ^2 is the variance of the returns.

4. Data

4.1 Data Description

The Chicago branch of the FED maintains two databases of bank related information, one for commercial banks and the other for bank holding companies. Bank holding companies may own one or more commercial banks as well as nonbank affiliates. The commercial bank database has data from 1976 while holding company data is available beginning with 1986 and does not contain as many variables as the commercial bank database. In order to facilitate research using these databases, the New York branch of the FED maintains a database matching the FED's identification number for each bank or bank holding company to the PERMCO number used by CRSP. The commercial bank database contains information on 86 publicly traded banks, while the holding company database contains information on 800 publicly traded institutions. Unfortunately, not every institution reports on each variable each quarter, so some data is missing, reducing the effective sample size for some of the models. The data used from these databases are specified for each model in Tables 1 through 5. Basic summary statistics for this data is presented in Table 8: Commercial Banks, FED database and Table 9: Bank Holding Companies, FED database.

Only the commercial bank database is used in this research. One of the main goals of this research is the development of a market-based test of the effectiveness of the bank EWS's, and this requires that the accounting data used as inputs into the models reflect the performance of the bank's stock. The publicly traded banks in the commercial database are pureplay banks, while multibank holding companies commonly engage in nonbank activities and “‘cross-subsidy’ policies whereby [they] provide credit support for other members” (Curry et al 2007).

In addition, since commercial banks are smaller than some of the largest bank holding companies, “Too Big To Fail” policies will not affect the outcome. Finally, the number of BHC that fail between 1986 and 2008 average less than three per year, while for commercial banks, the average is 54 per year during the same period.

Data on bank failures come from the Federal Deposit Insurance Corporation (FDIC) and are summarized in Table 7: FDIC Bank Failures 1986 Through June 2010. Most failures of commercial banks occurred between 1986 and 1992, averaging over 100 per year. The rate of failure then fell off, averaging less than three a year until 2009 when 19 commercial banks failed with another 10 failing in the first half of 2010. For commercial banks affiliated with a BHC, the number of failures remained fairly steady up until 2008, averaging less than three per year between 1986 and 2008, then rising to 18 in 2008, 111 in 2009, and 63 in the first half of 2010. Of special interest are the three publicly traded commercial banks that fail during the study period: the Bank of San Pedro which failed July 15, 1994, the Fairfield Bank which failed July 12, 1996, and the City Bank of Lynnwood which failed April 16, 2010 (see Table 12).

Monthly stock prices and returns, both adjusted and un-adjusted for dividends, are obtained from CRSP. Summary statistics for this data is presented in Table 10: CRSP Data for Commercial Banks. The CRSP index of constant maturity Treasury bonds is used to obtain yields on 20 year government bonds and the CRSP Fama Risk Free database provides risk free rates based on the average prices of 3 month T-bills. Summary statistics for these variables are presented in Table 11: Yields.

4.2 Matching

All of the models used in this research, with the exception of the Kimmel et al (2010) LOESS model, require a priori identification of failed banks and matching (except the Martin

(1977) Logit model which does not require matching) these failed banks to non-failed banks to complete the training phase of the model. Since the goal of this paper is to use the stock market to measure the effectiveness of the models in predicting problematic or underperforming banks, and to ensure that failure is the result of bank related activity or conditions, only publicly traded pure play (not part of a larger holding company that may have non-bank components) commercial banks are used in the classification and prediction phases, however, because of the relatively small number of such banks, especially ones that fail during the study period (see Table 7), all failed commercial banks, whether publicly traded or not, are used in the training phase. Because this sample differs significantly from those used in the original model research, the matching method has to be modified, and is subsequently standardized across all models in this research.

Matching loosely follows Lane et al (1986). Matching is done utilizing fourth quarter, yearend results. Each failed bank is matched with up to 3 non-failed banks based on the highest point score from a formula that gives 70 percent weight to banks of similar total assets (with a maximum 2:1 ratio), 20 percent weight to banks of similar age, and 10 percent weight to banks headquartered in the same state. Banks from prior years are added to the current year for training purposes resulting in an increasing number of banks in the training sample each year, up to 978 failed and 392 non-failed banks. Training of the models is done each year. This aggregation is necessary due to the scarcity of failed banks during most of the period under study, especially during the mid 2000's (see Table 7). Without aggregation, training could not be done every year as there are several years without a single failure, and there are many more when the number of failures is in the single digits.

The result is a training sample that compares favorably with those used in much of the literature. The sample begins in 1986 with 102 failed banks matched to 34 nonfailed banks, and after aggregation, ends up with 978 failed and 392 non-failed banks in 2008. Meyer and Pifer (1970) use a sample of 30 matched banks, less than 2 failures per year of their study. Sinkey (1974, 1975) uses 110 matched banks or an average of 16 failures per year. Pettway and Sinkey (1980) use 66 matched banks for an average of 11 failures per year. Kolari et al (2002) use a sample with 55 bank failures or 14 per year on average. Curry et al (2007) use a database of commercial and savings banks with a combined average rate of 11 failures per year.

4.3 Merger activity

It is possible that some of the many mergers that occurred during the study period among non-failed publicly traded commercial banks were in fact on the verge of failure and the merger was forced by the bank's regulator as a less costly alternative to declaring the bank a failure. Such hidden failures would reduce the models' ability to differentiate between failed and non-failed banks. To see if such hidden failures explain some of the merger activity in the data set used, FDIC records are used to determine if the merger occurred "with assistance" of the regulator and if any enforcement actions had been taken against the bank. In addition, both local and national news articles are checked for stories about the merged banks for a period of 2 years prior and 1 year post merger and negative articles are tabulated. Table 6 shows that of the 89 publicly traded commercial banks that existed at some time during the study period, 61 merge and 28 do not. Only 3 merge with regulator assistance, all of which have FDIC enforcement orders and bad press in advance of the merger. Of the 57 that merge without assistance, only 18 (32%) have FDIC enforcement orders and 3 (5%) have bad press in advance of the merger. This compares with 8 (29%) banks with FDIC enforcement orders that do not merge. Most merged

banks have no FDIC enforcement orders or bad press reports before their merger, and since the percentage of banks with FDIC enforcement orders is about the same between banks that have and have not merged, it seems unlikely that the “unassisted” mergers were forced by the bank’s regulator. A more likely explanation for the high number of mergers is the consolidation going on in the banking industry during the period. For this research, only banks merged with overt FDIC assistance are considered to have failed.

5. Empirical Results

All of the models used in this research require some exercise of judgment on the part of the researcher to “tune” the model to produce acceptable results. This is sometimes a matter of using past experience to determine that the 5 banks with the most negative residuals will be deemed troubled instead of the worst 4 or 6 banks, as with the LOESS model of Kimmel et al (2010). At the other extreme, the trait recognition model of Kolari et al (2002) requires input at several stages of the analysis which can alter not just the number of banks deemed troubled, but also their relative ranking. In every case, I follow the original researchers as far as possible, making changes only when the model failed to produce reasonable results, ie flagging all banks as either troubled or non-troubled. When changes are made, they are made without back tracking. If changes are made using 2001 data to predict 2002 failures, no changes are made based on the success of the model in predicting actual failures in 2002 as an investor in 2001 would not be able to do this. As a result, different judgments on the part of the researcher might produce different results than those obtained here, but these results reasonably reflect what an investor might have done using these models to select a portfolio of bank stocks. In addition, because sample selection for both training and prediction is driven by the scarcity of publicly traded commercial banks, especially of failed publicly traded commercial banks, the sample used here differs significantly from that used by any of the original researchers in developing their models.

Three statistics are used to judge the effectiveness of the models. The first, given in Table 12: Prediction Success by 1 Year and 2 Year Ahead Models, shows whether the model is able to predict the failure of each of the 3 publicly traded commercial banks that failed during the period, and if so, by how many years before failure it is able to flag the bank. The second is the

risk adjusted Cumulative Abnormal Return using both the CAPM and Stone 2-factor models. This is compared to both the market as a whole and a naïve strategy of buying all publicly traded commercial bank stocks. The third is to compare the total return (unadjusted for risk) on a portfolio of all publicly traded commercial banks (the naïve strategy) to the return on winner, loser, and long-short portfolios formed by the models in question.

5.1.A Empirical Results: logit analysis based on the work of Martin (1977)

Table 12 shows that the Martin (1977) Logit model is able to predict the failure of the Bank of San Pedro as early as 1991 using both 1 and 2 year prediction data. The failure of Fairfield Bank is predicted as early as 1990 using both 1 and 2 year prediction data. The failure of the City Bank of Lynnwood is predicted in 2008 by the 2 year model, but missed by the one year model.

Table 13 shows that all of the portfolios, for both the 1 and 2 year prediction models, significantly underperform the market on a risk adjusted basis over the entire period from 1989 through 2009. In addition, the naïve strategy beats every model based portfolio on a risk adjusted basis using both the CAPM ($\text{Perf}_{\text{CAPM}}$) and Stone 2-factor ($\text{Perf}_{\text{STONE}}$) models for both 1 and 2 year predictions. However, Figure 1 clearly shows that from 1991 through 1994 the short portfolio does beat both the market and all other portfolios on a risk adjusted basis. Note that while only the figure for the 1 year prediction model using CAPM is shown, the figures of the 2 year model and the models using the Stone 2-factor model are similar.

Table 13 also shows that over the entire period the returns on all of the model based portfolios are significantly different from the naïve all bank portfolio for both the 1 year and 2 year prediction models. The return on the long portfolio is greater than the return on the all bank portfolio while the returns on the short and long-short portfolios (just labeled “portfolio” in the

table) are significantly lower. As can be seen from Figure 2, most of this difference comes from the post 1994 period. Note that while only the figure for the 1 year prediction model is shown, the figure of the 2 year model is similar.

Table 19 shows that all of the portfolios beat the market during the financial crisis period (2006 through 2009) on a risk adjusted basis (only CAPM results are shown, but results using the Stone 2-factor model are similar), and that the long portfolio is able to outperform the naïve all bank strategy, though the short and long-short (labeled portfolio in the table) portfolios do not. Similar results are seen in unadjusted total returns.

5.1.B Empirical Results: discriminant analysis based on the work of Pettway and Sinkey (1980)

Table 12 shows that the MDA model used by Pettway and Sinkey (1980) is one of only 2 models that are able to predict every failure during the study period using both the 1 and 2 year prediction models, and it is able to predict their failure earlier than the other models in almost every case. It is able to predict the failure of the Bank of San Pedro as early as 1988 using 2 year prediction data. The failure of Fairfield Bank is predicted as early as 1990 using both 1 and 2 year prediction data. The failure of the City Bank of Lynnwood is predicted as early as 1994 by the 1 year model and in 2007 by the 2 year model.

Table 14 shows that all of the portfolios, for both the 1 and 2 year prediction models, significantly underperform the market on a risk adjusted basis over the entire period from 1989 through 2009. However, unlike with the Martin (1977) Logit model, figures of the cumulative abnormal return, represented here by Figure 3, the 1 year ahead CAPM CAR, fails to show any period of time where the model is able to beat the market on a risk adjusted basis. In addition, the

naïve strategy beat every model based portfolio on a risk adjusted basis using both the CAPM ($\text{Perf}_{\text{CAPM}}$) and Stone 2-factor ($\text{Perf}_{\text{STONE}}$) models for both 1 and 2 year predictions.

Table 14 also shows that over the entire period the returns on all of the model based portfolios are significantly different from the naïve all bank portfolio for both the 1 year and 2 year prediction models. The return on the long portfolio is greater than the return on the all bank portfolio while the returns on the short and long-short portfolios (just labeled “portfolio” in the table) are significantly lower. As can be seen from Figure 4, most of this difference comes from the post 1994 period. Note that while only the figure for the 1 year prediction model is shown, the figure of the 2 year model is similar

Table 19 shows that all of the portfolios, except the Short portfolio, beat the market during the financial crisis period (2006 through 2009) on a risk adjusted basis (only CAPM results are shown, but results using the Stone 2-factor model are similar), though none of the portfolios are able to outperform the naïve all bank strategy. Similar results are seen in unadjusted total returns.

5.1.C Empirical Results: Cox Proportional Hazard Model based on the work of Lane et al (1986)

Table 12 shows that the Cox PHM used by Lane et al (1986) is one of only 2 models that completely fail to predict the failure of the City Bank of Lynnwood using both the 1 and 2 year models. It is able to predict the failure of the Bank of San Pedro as early as 1991 using 2 year prediction data. The failure of Fairfield Bank is predicted as early as 1991 using both 1 and 2 year prediction data.

Table 15 shows that all of the portfolios, for both the 1 and 2 year prediction models, significantly underperform the market on a risk adjusted basis over the entire period from 1989

through 2009. Like the Pettway and Sinkey (1980) MDA model, figures of the cumulative abnormal return, represented here by Figure 5, the 1 year ahead CAPM CAR, fails to show any period of time where the model is able to beat the market on a risk adjusted basis. In addition, the naïve strategy beat every model based portfolio on a risk adjusted basis using both the CAPM ($\text{Perf}_{\text{CAPM}}$) and Stone 2-factor ($\text{Perf}_{\text{STONE}}$) models for both 1 and 2 year predictions.

Table 15 shows that over the entire period the returns on all of the model based portfolios are significantly different from the naïve all bank portfolio for both the 1 year prediction models while only the short and long-short portfolios (just labeled “portfolio” in the table) are significant in the 2 year prediction models. The returns on all of the model based portfolios are less than (or the difference is insignificant) that of the naïve all bank portfolio except for the short portfolio using the 2 year ahead prediction model, which earns a slightly higher return (when shorted it produces a negative return). As can be seen from Figure 6, most of this difference comes from the post 1994 period. Note that while only the figure for the 1 year prediction model is shown, the figure of the 2 year model is similar.

Table 19 shows that all of the portfolios, except the Short portfolio, beat the market during the financial crisis period (2006 through 2009) on a risk adjusted basis (only CAPM results are shown, but results using the Stone 2-factor model are similar), and that the long portfolio is able to outperform the naïve all bank strategy, though the short and long-short (labeled portfolio in the table) portfolios do not. Similar results are seen in unadjusted total returns.

5.1.D Empirical Results: Trait Analysis based on the work of Kolari et al (2000)

Table 12 shows that the Kolari et al (2000) Trait Analysis is one of only 2 models that completely fail to predict the failure of the City Bank of Lynnwood using both the 1 and 2 year

prediction models. It is able to predict the failure of the Bank of San Pedro as early as 1991 using 1 year prediction data and 1990 using 2 year prediction data. The failure of Fairfield Bank is predicted as early as 1987 and 1986 using 1 and 2 year prediction data respectively.

Table 16 shows that all of the portfolios, for both the 1 and 2 year prediction models, significantly underperform the market on a risk adjusted basis over the entire period from 1989 through 2009. Like the MDA and PHM models, figures of the cumulative abnormal return, represented here by Figure 7, the 1 year ahead CAPM CAR, fails to show any period of time where the model is able to beat the market on a risk adjusted basis. However, the long only portfolio is able to outperform the naïve strategy in the 1 year prediction using both the CAPM ($\text{Perf}_{\text{CAPM}}$) and Stone 2-factor ($\text{Perf}_{\text{STONE}}$) models.

Table 16 shows that over the entire period the returns on all of the model based portfolios are significantly different from the naïve all bank portfolio for both the 1 year and 2 year prediction models. The return on the long portfolio is greater than the return on the all bank portfolio while the returns on the short and long-short portfolios (just labeled “portfolio” in the table) are significantly lower. As can be seen from Figure 8, most of this difference comes from the post 1994 period. Note that while only the figure for the 1 year prediction model is shown, the figure of the 2 year model is similar.

Table 19 shows that all of the portfolios, except the Short portfolio, beat the market during the financial crisis period (2006 through 2009) on a risk adjusted basis (only CAPM results are shown, but results using the Stone 2-factor model are similar), and that the long portfolio is able to outperform the naïve all bank strategy, though the short and long-short (labeled portfolio in the table) portfolios do not. Similar results are seen in unadjusted total returns.

5.1.E Empirical Results: LOESS based on the work of Kimmel et al (2010)

Table 12 shows that the LOESS as used by Kimmel et al (2010) is one of only 2 models that are able to predict every failure during the study period using both the 1 and 2 year ahead prediction models. It is able to predict the failure of the Bank of San Pedro as early as 1991 using 1 year prediction data and 1990 using 2 year prediction data. The failure of Fairfield Bank is predicted as early as 1990 and 1989 using 1 and 2 year prediction data respectively, while the failure of the City Bank of Lynnwood is predicted in 2008 and 2007 respectively.

Table 17 shows that all of the portfolios, for both the 1 and 2 year prediction models, significantly underperform the market on a risk adjusted basis over the entire period from 1989 through 2009. Like the logit model, figures of the cumulative abnormal return, represented here by Figure 9, the 1 year ahead CAPM CAR, clearly shows that from 1991 through 1994 the short portfolio beats both the market and all other portfolios on a risk adjusted basis. In addition, the long-short portfolio (labeled just “Portfolio” in the tables) beats the naïve strategy on a risk adjusted basis using both the CAPM ($\text{Perf}_{\text{CAPM}}$) and Stone 2-factor models ($\text{Perf}_{\text{STONE}}$) for the 1 year ahead prediction (the long portfolio does as well for the CAPM model, but not for the Stone 2-factor model).

Table 17 shows that over the entire period the returns on all of the model based portfolios are significantly different from the naïve all bank portfolio for both the 1 year and 2 year prediction models. The return on the long portfolio (and the long-short portfolio, just labeled “portfolio” in the table, for the 1 year prediction) is greater than the return on the all bank portfolio while the returns on the short and long-short portfolios (for the 2 year prediction) are significantly lower. As can be seen from Figure 10, most of this difference comes from the post

1994 period. Note that while only the figure for the 1 year prediction model is shown, the figure of the 2 year model is similar.

Table 19 shows that all of the portfolios beat the market during the financial crisis period (2006 through 2009) on a risk adjusted basis (only CAPM results are shown, but results using the Stone 2-factor model are similar), but that none of the portfolios are able to outperform the naïve all bank strategy. Similar results are seen in unadjusted total returns, except the long portfolio is able to beat the naïve all bank strategy.

5.2 Robustness

I conduct two robustness checks to ensure that my results are not an artifact of the methodology employed in this research. In the first analysis, I check to ensure that the matching method does not affect the results by rerunning the analysis for the 1996 1 year ahead prediction using data for all nonfailed publicly traded commercial banks instead of a matched sample.

Table 20 compares the predictions of problematic banks made by each model in the primary research with the prediction made using the “No Matching” sample and the results are summarized in Table 21. The additional data provided by the “No Matching” sample reduces the number of banks flagged as potential problems, but in every case, every bank flagged by the “No Matching” sample is also flagged by the models using a matched sample. In addition, all of the models were able to flag Fairfield Bank, PERMCO 7807, the bank that actually failed in 1996.

In the second robustness check, I seek to determine if the variables originally specified for the models drive the results or if it is the statistical method utilized. I examine the models to find a set of common significant variables. Results from the logit and Cox PHM are examined to determine which variables are consistently statistically significant in the models as originally specified and the results summarized in Table 22. Since MDA and LOESS, as originally

specified, only use two and one variable respectively, all three variables are utilized in this analysis. It is difficult to isolate significant variables in Trait Analysis because of the complex interaction between variables, so no variables unique to the Kolari et al (2002) specification of Trait Analysis were included in this analysis. The five numbered variables in Table 22 are used in place of the original variables in each model and the analysis for the 1996 1 year ahead prediction rerun.

The results are shown in Table 20, Table 22, and Table 23. Table 22, in the column labeled “Common”, shows which variables, from among the five common ones discussed in the paragraph above, are statistically significant in the Logit and Cox PHM using these five common variables. Surprising, none of the variables used by Lane et al (1986) in their specification of the Cox PHM were significant when combined with the other three common variables, while both significant variables from the Martin (1077) logit model remained significant when combined with the other three common variables.

Table 23 shows that all of the statistical methods, except LOESS, are able to predict the failure of Fairfield Bank. LOESS also has the lowest overlap between the banks predicted to fail using the original specification used by Kimmel et al (2010) and those predicted to fail when all five common variables are used. This is not surprising as earlier research by this researcher has shown the model works best when examining variables one at a time. The other statistical methods were all able to predict the fail of Fairfield Bank and all, except MDA, had a high degree of overlap. Table 20 shows that the relatively poor overlap between the results using original Pettway and Sinkey (1980) specification and the common variables is due to a significant decrease in the number of banks predicted to fail when the five common variables are

used, but over half of the problematic banks flagged using the common variables are also flagged using the original specification.

Table 20 also shows that there is a high degree of agreement among the statistical methods about which banks are most likely to fail. Using the original specifications, nine banks are flagged as likely to fail by at least three of the models, five banks by four of the models, and three by all five of the models. Using the common variables, ten banks are flagged by at least three of the statistical methods, five banks by four of the methods, and only one bank by all five methods. Results without matching, but using the original variable specifications, produces results similar to the original models with matching.

Table 20 shows that all of the models/statistical techniques using original specifications, common variables, and no matching are able to agree that certain banks are very unlikely to fail with five, five, and 12 banks not receiving a single flag from any of the models/statistical techniques respectively. In between are the majority of banks which are flagged by a model/statistical technique or two. This is most probably noise or type I errors which might be filtered out by using multiple models/statistical techniques.

6. Summary

All of the models do a good job predicting bank failure even though the models are not “back-tuned” and the sampling procedures used in this study differ significantly from those of the original researchers (see sections 4.2 Matching and 5: Empirical Results). Three of the 5 models predict 2 of the 3 failures among the publicly traded commercial banks in the study, while 2 of the models are able to predict all 3 (see Table 12.)

On a risk adjusted basis, the short portfolio is able to outperform the market and all other portfolios during the period from 1991 through 1994 when formed using the Martin (1977) Logit and Kimmel et al (2010) LOESS models for both 1 and 2 year predictions. Over the entire study period, the Kolari et al (2002) Trait Analysis model is able to form a long portfolio that beat the all bank naïve strategy using the 1 year ahead prediction, while the Kimmel et al (2010) LOESS model is able to form a long-short strategy (labeled “Portfolio” in the tables) that beats the naïve strategy using 1 year ahead predictions.

All of the models, with the exception of the Lane et al (1986) Cox PHM, are able to form long portfolios that beat the naïve strategy in terms of absolute total returns for both the 1 and 2 year predictions. In addition, the Kimmel et al (2010) LOESS model is able to form a short portfolio that beats the naïve strategy in terms of absolute total returns using the 1 year prediction.

Table 19 makes it clear that all of the models are able to continue performing during the financial crisis of 2008. The fact that all of the portfolios of all of the models (except the short portfolios of three of the models) are able to beat the market on a risk adjusted basis is probably more a reflection of changes in beta lagging the market because of its rolling 24 month estimation period than a demonstration of predictive power of the models themselves. More

significant is the ability of the Martin (1977), Lane et al (1986), and Kolari et al (2002) models to beat the naïve all bank strategy with their long portfolios, demonstrating their power to filter out underperforming bank stocks even during this volatile period. The long portfolios of the Martin (1977), Lane et al (1986), Kolari et al (2002) and Kimmel et al (2010) models are also able to beat the naïve all bank strategy on an absolute return basis during the period. This strong showing is somewhat tempered by the failure of the Lane et al (1986) and Kolari et al (2002) models to forecast the failure of the City Bank of Lynwood in 2010. It is interesting to note that during this period, marked by the financial crisis, the stocks of publicly traded commercial banks are able to outperform the market and return 51.8 percent over the period versus a loss of 22 percent for the market (as measured by the CRSP equally weighted index).

From this research, it is clear that all of the models do a good job of predicting bank failure. It is also clear that all of the models, except the Lane et al (1986) Cox PHM, are able to improve the performance of the long portfolio by identifying and filtering out some underperforming stocks (see Figure 12). The returns on the problematic banks, which are formed into the short portfolios, clearly underperform the long and all bank naïve strategy portfolios, though they do not lose value over the study period and so following a strategy of shorting these stocks fails. After adjusting for increases in risk, results are not as favorable (see Figure 11). Only the Kolari et al (2002) Trait Analysis and Kimmel et al (2010) LOESS models are able to produce portfolios that performed better than the naïve strategy over the study period, though the Martin (1977) Logit and Kimmel et al (2010) LOESS models are able to produce short portfolios that beat the market and the naïve strategy on a risk adjusted basis for a 3 year period from 1991 to 1994.

These results seem to indicate that the market for publicly traded commercial bank stocks became more efficient after 1994, though even after, the market is not perfectly efficient. This conclusion cannot be explained by the sampling method used in this research as the pattern of returns, both unadjusted and adjusted for risk, is virtually the same for all of the models, even the Kimmel et al (2010) LOESS model, which does not use a training cycle or require matching failed and nonfailed banks and does not depend on the a priori identification of failed banks, and so uses data only from 1 or 2 years prior to the year of prediction.

There is no evidence, under the sampling method used in this research, that more complex or newer models outperform the simpler and/or older models in terms of failure prediction. In terms of identifying underperforming bank stocks, the performance of the Kolari et al (2002) and Kimmel et al (2010) models provide some evidence that newer models outperform older models, but not that more complex models outperform simpler models. Despite significant differences in the composition of the portfolios formed by the various models, the pattern of returns for all of them are remarkably consistent, as shown by Figure 11 and Figure 12. The failure of some of the models to predict the failure of the City Bank of Lynnwood in April 2010 could be due to changes in the relative importance of some of the variables used by those models over the period of the study as these are kept constant throughout the study, or it could be caused by the lack of failures among commercial banks during the later years of the study which diminished the sample size for training the models. However, the fact that some of the models are able to predict this failure using the same sampling method and using unchanged variables suggests that these are not significant factors, or that some models are more sensitive to these factors than others. Models which were best able to predict bank failure were not always the best

able to discern which bank stocks will underperform the market (whether defined as the stock market as a whole or the market for commercial bank stocks).

7. Conclusions and Implications

Using markets as a universal standard to evaluate bank EWS shows that all of the models evaluated in this study produce similar results despite their varying statistical models and wide range of financial variables. It would seem that the use of financial variables influences the results more than the model used. The complexity of the model and the data requirements don't seem to produce consistently better results. The financial indicators used by these models seem to be quite stable over long time periods, allowing the models to work even when there are long periods of time when few bank failures occur. The market for publicly traded commercial banks is quite efficient, though the use of these models can be used to improve an investor's return by filtering out problematic banks, but at the cost of adding risk to the portfolio.

The change in apparent market efficiency identified by the Martin (1977) Logit and Kimmel et al (2010) LOESS models which occurs in 1994 is problematic with several possible explanations. It is possible that some exogenous change in bank regulation or the widespread adoption of bank EWS by analysts' or regulators actually improved the efficiency of the market. It is possible that the risk adjusted abnormal returns detected by these two models are just a random occurrence of the method and variables used by the models, a kind of data snooping, and not a repeatable finding. Finally, it is possible that the efficiency of these models is tied to the number of bank failures during a given period. When the number of bank failures is high, as they are prior to 1994, they can identify both the extreme outliers which fail and the less extreme outliers which underperform in the stock market but ultimately do not fail. When the number of bank failures is low, the models can only identify the extreme outliers, the ones that actually fail, with any degree of precision.

Investors should not rely on any of these models as the sole means of picking stocks, but may wish to use any of them as a means to identify potentially underperforming stocks for further investigation. Sophisticated investors with access to computational resources and data may wish to utilize more than one model, but less sophisticated investors should be assured that the simplest of them can improve the performance of their portfolios.

Regulators, whose primary concern is the identification of banks likely to fail, should consider using a combination of parametric (MDA, for example) and non-parametric models, especially one like the Kimmel et al (2010) LOESS model that does not require the a priori identification of failed banks. Regulators should also recognize the limitations of these models and the similarity of their results. Models that use factors other than the financial variables utilized by these models should be incorporated into their screening process.

Researchers can be assured that any of these models can be used to predict bank failure, so the choice of model should rest on the number and type of variables being studied. They can be assured that the predictive powers of these financial variables are stable over relatively long periods of time, which allows for the aggregation of data over long periods of time, allowing the study of the properties of banks during times when few failures are occurring.

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Table: 1 Martin (1977)

Original NY FED database		Chicago FED Database	
		Commercial Bank File	Bank Holding Company File
Field name	ratio no.	item no	item no
NRWAT007	3	RCFD3210/RCFD2170	BHCK3210/ BHCK2170
NRWAT009	5	RIAD4340/(RCFD2170 -RCFD0020)	BHCK4340/(BHCK2170-NA)
NRWAT011	7	RIAD4635/RIAD4340 +RIAD4230	BHCK4635/ BHCK4340 + BHCK4230
NRWAT015	11	RCFD1600*/RCON1400	NA/BHCK2122
* RCFD1600 is not reported after 2000 and is estimated thereafter by RCFD2122 – RCFD1410 (Total loans minus real estate loans)			
		Ratio description	
		Equity Capital/Total Assets	
		Net Income/Total Assets-Cash Items In Process	
		Gross Charge Offs/Net Operating Income + Loss Provision	
		Commercial And Industrial Loans/Total Loans (Domestic Only)	

Table 2: Pettway & Sinkey (1980)

Original	Chicago FED Database		Ratio description
	Commercial Bank File	Bank Holding Company File	
Field name	item no	item no	
OEOI	RIAD4130 /RIAD4000	NA/NA	Total operating expenses as a percentage of total operating income
IA	RCFD0390 /RCFD2170	BHCK0390 /BHCK2170	Investments as a percentage of total assets, where investments include all securities plus federal funds sold.
Matching variables	RCFD2200	NA	deposit size
	RSSD9380	NA	number of branches
	RSSD9180	NA	location (SMSA)
	RSSD9150	RSSD9150	location (county)

OEOI is a measure of a bank's operating efficiency and IA is a measure of safety (or risk).

Table 3: Lane et al (1986)

Chicago FED Database			Variable definition
Original Variables	Commercial Bank File	Bank Holding Company File	
Dimension	Ratio	item no	
Capital (leverage)	11	RCFD3210/RCFD2170	log total capital/total assets
	12	RCFD2122/RCFD3210	log total loans/total capital
	3	(RCFD1350+RCFD2800)/RCFD2170	log fed. funds sold +securities purchased/total assets
Asset (loan) quality	15	RIAD4605/RCFD2122	net loan recoveries/total loans
	9	RIAD4230/RIAD4130	log provision for loan losses/total operating expense
	10	RIAD4635/(RIAD4340+RIAD4230)	log gross loan charge-offs/net income +provision for loan losses
Loan composition	6	RCFD1600*/RCFD2122	log commercial and industrial loans/total loans
	7	RCFD1410/RCFD2122	real estate loans/total loan
	16	RIAD4010/RCFD2125	loan revenue/net loans
Efficiency (pricing)	14	RIAD4000/RCFD2170	total operating income/total assets
	17	RIAD4170/RCFD2350	interest on deposits/total time and savings deposits
	20	RIAD4302/RIAD4301	income taxes/earnings before taxes and security transactions
Earnings	13	RIAD4130/RIAD4000	log total operating expense/total operating income
	18	RIAD4340/RCFD2170	net income/total assets
	19	RIAD4340/RCFD3210	net income/total capital
	21	RIAD4340/RIAD4000	net income/gross operating income
	8	RCFD2122/RCFD2200	total loans/total deposits
Liquidity	5	RCFD2122/RCFD2170	total loans/total assets
	1	(RCFD0080 + CFD0400)/RCFD2170	log cash and U.S. securities/total assets
	4	(RCFD2800+RCFD1350)/RCFD2170	log fed. funds purchased + securities sold/total assets
Matching Variables		RSSD9180	(a) geographic location (SMSA)
		RSSD9150	(a) geographic location (county)
		RSSD9421	(b) charter status (state)
		RSSD9340	(b) charter status (national)
		RCFD2170	(c) size
		RSSD9950	(d) age

*RCFD1600 is not reported after 2000 and is estimated thereafter by RCFD2122 – RCFD1410 (Total loans minus real estate loans)

Table 4: Kolari et al (2000)

Chicago FED Database			
Xj	Commercial Bank File	Bank Holding Company File	variable description
1	RCFD2170	NA	Total assets (millions)
2	NA	BHCK2170	Bank holding co. (BHC) total assets (millions)
3			Maximum change in X1/mean X1
4			Maximum change in X1/mean change X1
5	RIAD4074/RCFD2170	BHCK4074/BHCK2170	Net interest income/total assets
6			Max change in X5/mean X5
7	RIAD4340/RCFD2170	BHCK4340/BHCK2170	Net income after taxes/total assets
8			Maximum change in X7/mean X7
9	RCFD3210/RCFD2170	BHCK3210/BHCK2170	Total equity/total assets
10			Maximum change in X9/mean X9
11	RCFD3123/ RCFD2170	BHCK3123/ BHCK2170	Allowance for loan losses/total assets
12			Max change in X11/mean X11
13	RIAD4230/RCFD2170	BHCK4230/BHCK2170	Provision for loan losses/total assets
14			Maximum change in X13/mean X13
15	(RIAD4635-RIAD4605)/RCFD2170	(BHCK4635-BHCK4605)/BHCK2170	Net loan charge-offs/total assets
16			Maximum change in X15/mean X15
17	RCFD1407	BHCK1407	Maximum change in loans past due at least 90 days/mean of numerator
18	RCFD0390*/RCFD2170	BHCK0390/BHCK2170	Total securities/total assets
19			Maximum change in X18/mean X18
20	(RCFD2948 - RCFD2200)/RCFD2948	(BHCK2948 - NA)/BHCK2948	Nondeposit liabilities/total liabilities
21			Maximum change in X20/mean X20
22	RCFD2215/RCFD2200	NA/NA	Certificates of deposit/total deposits
23			Maximum change in X22/mean X22
24	RCFD1400/RCFD2170	BHCK2122/BHCK2170	Total loans and leases/total assets
25			Maximum change in X24/mean X24
*RCFD0390 is replaced by RCFD1350 whenever it is missing. Division by zero errors and missing data are replaced by zero because the Fortran program does not handle missing data.			

Table 5: Kimmel et al (2010)		
Model	Y	X
1 & 2	Net Income (NI)	Total Assets (TA)
3	Net Loan Losses (NLL) or Loan Loss Provision (LLP)	Total Loans (TL)
4	Net Loan Losses (NLL) or Loan Loss Provision (LLP)	Total Assets (TA)
Chicago FED Database		
variable	Commercial Bank File	Bank Holding Company File
Net Income	RIAD4340	BHCK4340
Total Assets	RCFD2170	BHCK2170

Table 6: Analysis of Merger Activity						
Date Of Merger	With Assistance	Without Assistance				
		Number	Bad Press		FDIC Enforcement Orders	
			Number	Percent	Number	Percent
1988		1				
1992		1				
1994	1	0				
1995		1				
1996	1	7				
1997		2				
1998		9			4	44%
1999		6			1	17%
2000		6	1	17%	2	33%
2001		6	1	17%	2	33%
2002		2			1	50%
2003		0				
2004		5	1	20%	4	80%
2005		2			1	50%
2006		3			1	33%
2007		3			1	33%
2008		1				0%
2009		0				
2010	1	2			1	50%
total merged	3	57	3	5%	18	32%
did not merge		28			8	29%
		89				

note: I do not look for bad press among firms that do not merge

Table 7: FDIC Bank Failures 1986 Through June 2010

Year	Commercial Banks not Affiliated w/ BHC	Commercial Banks Affiliated w/ BHC	Publicly Traded Commercial Bank	Publicly Traded BHC	Publicly Traded Commercial Bank Affiliated w/BHC
1986	105	1		1	
1987	198	3			
1988	269	11		5	
1989	207				
1990	166	1			
1991	121	3			
1992	118	1			
1993	23	20			
1994	7	6	1	1	
1995	5	1		1	
1996	3	2	1		
1997	1				
1998	1	2			
1999	5	2			
2000	1	5			
2001	3				
2002	5	5		1	
2003	2	1			
2004		3			
2007	2				
2008	8	18		5	
2009	19	110		20	1
2010	10	63	1	10	
Grand Total	1279	258	3	44	1

Table 8: Commercial Banks, FED database

Variable	max	min	mean	median	std dev	skewness	kurtosis	count	missing
PERMCO	43,694	841	14,310	11,698				4675	0
RCFD0020	1,706,108	0	41880	4782	197,734.61	6.34	40.43	2892	1783
RCFD0080	842,571	0	11835	1195	61,571.72	7.91	69.22	4171	504
RCFD0390	1,353,717	0	68377	15365	157,764.88	4.80	27.63	1783	2892
RCFD0400	1,244,528	0	27238	2478	83,938.51	6.74	63.03	1696	2979
RCFD1000	31,988	0	3372	0	7,546.88	2.74	7.15	48	4627
RCFD1350	1,614,012	0	24970	6439	83,554.27	9.66	125.20	3604	1071
RCFD1400	49,161,663	0	745015	136026	3,296,869.74	8.49	82.37	4675	0
RCFD1407	174,720	0	1900	136	8,881.79	11.22	158.59	4675	0
RCFD1410	30,439,399	0	431335	85788	1,817,843.10	9.96	119.98	4675	0
RCFD1600	13,203,055	0	158126	23113	924,645.94	10.14	114.15	3408	1267
RCFD2122	49,161,663	0	742251	135015	3,289,062.62	8.52	82.89	4675	0
RCFD2125	25,427,098	0	466623	103040	2,079,733.01	8.64	82.57	3408	1267
RCFD2170	69,736,605	3,752	1106725	207462	4,773,564.43	8.31	77.81	4675	0
RCFD2200	47,391,300	6	900012	180038	3,898,771.61	8.39	77.54	4675	0
RCFD2350	6,776,480	371	261282	84081	718,547.69	6.03	43.03	770	3905
RCFD2800	1,709,686	0	22980	0	128,272.99	8.66	84.51	3604	1071
RCFD2948	62,348,899	8	1005087	189676	4,337,777.53	8.34	78.44	4675	0
RCFD3123	724,654	0	12838	1862	58,595.31	7.51	60.16	4675	0
RCFD3210	7,387,706	(375)	101384	17214	447,318.93	8.10	73.07	4675	0
RCFD8639	6,325,775	0	144131	8613	637,313.26	7.08	53.91	2892	1783
RCFD8641	12,227,614	0	277376	44847	1,070,328.79	7.10	56.51	2892	1783
RCFDA223	62,025,971	2,062	1345373	241155	5,686,357.66	6.94	51.76	2366	2309
RCFDB558	5,759,567	0	129413	17462	535,073.01	6.73	49.58	1267	3408
RCON1400	48,307,292	0	728912	134700	3,193,981.11	8.52	83.75	4675	0
RCON1430	19,373,838	0	181726	25822	1,085,555.38	11.63	154.87	4675	0
RCON2215	10,261,675	0	192445	45828	852,021.97	7.91	65.87	4675	0
RIAD3123	724,654	0	15765	2700	63,676.60	6.79	49.57	3237	1438
RIAD4000	3,787,694	0	51306	9774	232,053.35	9.51	105.32	4675	0
RIAD4010	2,534,870	0	34384	6783	150,715.93	9.41	104.83	4675	0
RIAD4074	2,045,651	0	26462	5003	122,646.38	9.68	108.37	4675	0
RIAD4130	2,894,600	0	38514	8021	165,409.82	9.42	106.00	4675	0
RIAD4170	1,078,212	0	13748	3024	52,380.20	9.50	115.86	4675	0
RIAD4230	511,190	(60,776)	2447	270	16,508.76	16.45	371.27	4675	0
RIAD4301	1,108,275	(212,006)	10509	1213	61,305.02	10.69	133.55	4675	0
RIAD4302	406,528	(73,087)	3654	379	20,680.37	10.56	132.71	4675	0
RIAD4340	842,217	(138,919)	6890	852	41,162.25	11.15	148.58	4675	0
RIAD4605	58,370	0	628	32	3,665.20	9.82	109.07	4675	0
RIAD4635	322,469	0	2610	152	15,542.19	11.64	164.19	4675	0
RIADA220	63,984	(24,418)	632	0	4,765.39	7.88	74.62	1709	2966
RSSD9001	3,153,288	31,303	1033512	775214	823,006.20	1.12	0.34	4675	0
RSSD9010	0	0						4675	0
RSSD9017	0	0						889	3786
RSSD9047	6	1						4675	0
RSSD9048	300	200						4675	0
RSSD9050	57,487	114						4675	0
RSSD9052	20010409	0						889	3786
RSSD9053	99991231	20050422	99541687	99991231				889	3786
RSSD9130	0	0						4675	0
RSSD9150	810	1						4675	0
RSSD9180	9,200	240						3488	1187
RSSD9181	97	0						3488	1187
RSSD9200	0	0						4675	0
RSSD9210	53	6						4675	0
RSSD9220	97204-2012	00000-0000						4675	0
RSSD9331	10	1						4675	0
RSSD9348	3,811,467	0	566,441	0				4663	12
RSSD9421	2	1						4675	0
RSSD9424	7	1						4675	0
RSSD9950	20030127	18760415	19757948	19830307				4675	0
RSSD9999	20081231	19860331	19962132	19960331				4675	0

Table 9: Bank Holding Companies, FED database

Variable	max	min	mean	median	std dev	skewness	kurtosis	count	missing
BHCK0390	29,053,918	932	852,753	134,655	2,251,641	5.64	40.68	13,097	29,391
BHCK0400	23,584,911	-	240,297	37,468	783,412	14.73	345.69	13,096	29,392
BHCK1350	138,668,000	-	542,141	10,461	5,534,442	17.04	328.35	12,400	30,088
BHCK1407	971,000	-	11,582	1,702	49,208	11.69	174.19	6,521	35,967
BHCK1410	547,830,645	-	3,007,371	340,670	16,612,180	15.72	328.16	39,889	2,599
BHCK2122	967,736,912	9,509	6,394,106	543,238	35,636,146	14.00	248.45	39,889	2,599
BHCK2125	400,522,000	9,403	4,050,829	381,596	16,907,745	10.85	165.29	26,803	15,685
BHCK2170	2,358,266,000	31,150	11,848,444	843,504	77,225,723	16.40	335.34	39,890	2,598
BHCK2800	181,775,000	-	908,892	16,441	6,554,957	15.25	283.18	12,391	30,097
BHCK2948	2,225,254,000	26,583	10,881,457	770,381	71,171,423	16.52	342.17	39,890	2,598
BHCK3123	29,616,000	-	120,213	7,510	714,262	15.52	349.12	39,890	2,598
BHCK3210	177,051,777	(254,123)	940,396	71,520	6,003,911	15.85	304.95	39,890	2,598
BHCK4074	54,086,000	142	224,315	18,742	1,422,355	17.51	403.58	39,890	2,598
BHCK4230	33,674,000	(175,136)	38,402	975	426,468	37.61	2,048.23	39,879	2,609
BHCK4301	32,007,503	(53,055,000)	113,130	6,488	919,892	7.23	676.59	39,890	2,598
BHCK4302	10,839,974	(20,612,000)	37,473	1,900	301,276	4.13	869.47	39,882	2,606
BHCK4340	24,589,000	(33,277,000)	75,694	4,550	625,744	9.01	664.31	39,890	2,598
BHCK4605	2,555,000	-	7,811	235	61,116	19.85	526.11	39,873	2,615
BHCK4635	20,770,000	-	40,625	923	363,888	24.08	815.45	39,872	2,616
BHCK9802	3	-	1	1	0	3.13	22.28	34,413	8,075
BHCKA220	8,986,000	(26,158,000)	18,122	-	353,406	(20.12)	1,722.54	22,815	19,673
BHCKA223	1,377,059,500	-	12,271,506	743,942	68,430,354	11.26	153.66	22,655	19,833
PERMCO	45,567	25	14,726	12,139	11,504	1.30	0.91	42,488	-
RSSD9001	3347292	1020331						42,488	-
RSSD9010	0	0						19,641	22,847
RSSD9017	0	0						42,488	-
RSSD9047	11	1						19,641	22,847
RSSD9048	720	500						19,641	22,847
RSSD9050	0	0						19,641	22,847
RSSD9052	20040826	0						42,488	-
RSSD9053	99991231	19881230						42,488	-
RSSD9130	0	0						42,488	-
RSSD9150	840	1						42,488	-
RSSD9200	0	0						42,488	-
RSSD9210	72	1						42,488	-
RSSD9220	995100000	680						42,488	-
RSSD9331	28	28						19,641	22,847
RSSD9347	13903	0						22,847	19,641
RSSD9348	3811467	0						42,488	-
RSSD9350	13905	0						22,847	19,641
RSSD9421	0	0						19,641	22,847
RSSD9955	0	0						19,641	22,847
RSSD9999	20081231	19860630	19969275	19970331				42,488	-

Table 10: CRSP Data for Commercial Banks

Variable	max	min	mean	median	std dev	skewness	kurtosis	count	missing
DATE	20091231	19830131	19980140.7	19980731				7806	0
COMNAM								7729	77
CUSIP	98,431,410	1,268,410	52,456,703	54,266,910				7806	0
DCLRDT	20091124	19821228	19973278.8	19971170.5				1330	6476
DLAMT	74	0	18	17	16.53	0.77	0.33	91	7715
DLSTCD	585	100	223	231	108.36	1.82	4.56	91	7715
NEXTDT	20091218	19940117	19995606.8	19955527.5				6	7800
PAYDT	20100115	19830201	19974899.6	19980218.5				1420	6386
RCRDDT	20091231	19830113	19974101.8	19980166.5				1420	6386
TICKER								7729	77
PERMNO	93,060	10,037	67,335	80,808				7806	0
NAMEENDT	20091231	19851103	20008513.3	20020919				218	7588
SICCD	6,710	0	6,022	6,020				7729	77
NAICS	551,111	522,110	526,218	522,110				1822	5984
PRIMEXCH	0	0						7729	77
TRDSTAT	0	0						7729	77
SECSTAT	0	0						7729	77
PERMCO	45,996	841	17,028	12,203	13,772.73	1.22	(0.01)	7806	0
DISTCD	6,581	1,212	1,875	1,232	1,501.30	1.98	2.07	1420	6386
DIVAMT	73.50	0.00	0.78	0.10	4.56	8.65	89.90	1420	6386
FACPR	3	-1	0.00453346	0	0.25	2.24	40.50	1420	6386
FACSHR	20.806	-1	0.0249159	0	0.62	26.82	885.02	1420	6386
ACPERM	90,490	10,932	59,469	65,939				26	7780
ACCOMP	44,891	582	10,291	10,694				34	7772
NWPERM	92,555	0	29,754	0				91	7715
DLRETX	0.30	(0.85)	0.00	0.02	0.14	(4.05)	23.61	91	7715
DLPRC	5.10	(0.81)	0.05	0.00	0.55	8.74	81.39	91	7715
DLRET	0.30	(0.85)	0.01	0.02	0.14	(4.05)	23.57	91	7715
SHROUT	175,260	273	7,620	3,005	19,400.21	6.56	45.82	7729	77
PRC	125							7645	161
VOL	1,024,325	0	3,803	477	20,238.85	25.94	1,087.46	7694	112
RET	3	-0.8125	0.01092925	0.0019685	0.12	3.67	71.11	7645	161
CFACPR	16	0	1.58234478	1	1.84	5.43	35.22	7729	77
CFACSHR	16	0	1.58208321	1	1.84	5.43	35.21	7729	77
RETX	3	-0.8125	0.00973408	0	0.12	3.69	71.53	7645	161
vwretd	0.128496	-0.225363	0.00907616	0.01452	0.04	(0.97)	2.67	7806	0
vwretx	0.126924	-0.227344	0.00719152	0.012441	0.04	(0.97)	2.68	7806	0
ewretd	0.225012	-0.272248	0.01111127	0.015778	0.05	(0.46)	3.30	7806	0
ewretx	0.224061	-0.273085	0.00966383	0.014571	0.05	(0.46)	3.30	7806	0

Table 12: Prediction Success by 1 Year and 2 Year Ahead Models

				Model				
Bank	Date of failure	RSSD9001	PERMCO	Martin (1977): Logit	Pettway & Sinkey (1980): MDA	Lane et al (1986): Cox PHM	Kolari et al (2002): Trait	Kimmel et al (2010): LOESS
Bank of San Pedro	7/15/1994	813563	10784					
		1 Year Prediction:		92-94	92, 94	92-94	92-94	92
		2 Year Prediction:		93-94	90-95	92-94	92-94	92-94
Fairfield Bank	7/12/1996	699002	7807					
		1 Year Prediction:		91-96	89-96X92	92-96	88-96X89	91,92,94,96
		2 Year Prediction:		92-96	90-97	93-96	88-96X89,90	91-97
City Bank Lynnwood	4/16/2010	456474	16572					
		1 Year Prediction:		missed	95-08X03	missed	missed	09, 10
		2 Year Prediction:		10	09-10	missed	missed	09, 10

88-96X89,90 for 1 YEAR predictions means that the model predicted the bank would fail in 1988 based on data from 1987 and predicted its failure each year during the given period except for 1989 and 1990. For 2 YEAR prediction it would mean that the bank is predicted to fail in 1988 based on data from 1986.

Table 13: Martin (1977) Total Cumulative Returns Over the Period

1 year prediction									
	AR CAPM	Perf _{CAPM}	AR Stone	Perf _{STONE}	RET	Perf _{RET}	EWRET _D	-RET _X	
all banks	-0.60197		-0.56418		2.58167		2.77265		
long no shorts	-0.63056	-0.02859	-0.64431	-0.08013	2.76730	0.18563	2.77265		
shorts	-3.61097	-3.00900	-3.19651	-2.63233	1.67667	-0.90500	2.77265	-1.49024	
portfolio	-0.87935	-0.27738	-0.84156	-0.27738	2.30429	-0.27738	2.77265		
RET for shorted stocks is the return they would have earned if we had gone long.									
2 year prediction									
total cumulative returns over the period									
	AR CAPM	Perf _{CAPM}	AR Stone	Perf _{STONE}	RET	Perf _{RET}	EWRET _D	-RET _X	
all banks	-0.53537		-0.50882		2.52310		2.75210		
long no shorts	-0.71369	-0.17832	-0.74388	-0.23506	2.72944	0.20634	2.75210		
shorts	-2.58400	-2.04863	-2.34040	-1.83158	1.40218	-1.12092	2.75210	-1.21489	
portfolio	-0.97416	-0.43879	-1.20956	-0.70074	2.08431	-0.43879	2.75210		
RET for shorted stocks is the return they would have earned if we had gone long.									
Statistical Significance, p-values									
	AR CAPM	Perf _{CAPM}	AR Stone	Perf _{STONE}	Perf _{RET}				
all banks	0.00000		0.00000						
long no shorts	0.00000	0.00000	0.00000	0.00000	0.00000				
shorts	0.00000	0.00000	0.00000	0.00000	0.00000				
portfolio	0.00000	0.00000	0.00000	0.00000	0.00000

Figure 1

Figure 2

Table 14: Pettway & Sinkey (1980) Total Cumulative Returns Over the Period

1 year prediction							
	AR CAPM	Perf _{CAPM}	AR Stone	Perf _{STONE}	RET	Perf _{RET}	-RET _X
all banks	-0.60197		-0.56418		2.58167		2.77265
long no shorts	-0.59795	0.00402	-0.64497	-0.08079	3.06716	0.48549	2.77265
shorts	-4.07736	-3.47539	-4.00614	-3.44196	1.92635	-0.65532	-1.63443
portfolio	-2.05260	-1.45063	-2.01481	-1.45063	1.13103	-1.45063	2.77265
RET for shorted stocks is the return they would have earned if we had gone long.							
2 year prediction							
	AR CAPM	Perf _{CAPM}	AR Stone	Perf _{STONE}	RET	Perf _{RET}	-RET _X
all banks	-0.60197		-0.56418		2.58167		2.77265
long no shorts	-0.88038	-0.27841	-0.84243	-0.27825	2.62578	0.04411	2.77265
shorts	-5.48133	-4.87936	-5.44963	-4.88545	2.54785	-0.03382	-2.22794
portfolio	-4.21430	-3.61234	-4.17651	-3.61234	-1.03067	-3.61234	2.77265
RET for shorted stocks is the return they would have earned if we had gone long.							
Statistical Significance, p-values							
	AR CAPM	Perf _{CAPM}	AR Stone	Perf _{STONE}	Perf _{RET}		
all banks	0.00000		0.00000				
long no shorts	0.00000	0.00000	0.00000	0.00000	0.00000		
shorts	0.00000	0.00000	0.00000	0.00000	0.00000		
portfolio	0.00000	0.00000	0.00000	0.00000	0.00000

Figure 3

Figure 4

Table 15: Lane et al (1986) Total Cumulative Returns Over the Period

1 year prediction								
	AR CAPM	Perf _{CAPM}	AR Stone	Perf _{STONE}	RET	Perf _{RET}	EWRETD	-RETX
all banks	-0.61867		-0.57536		2.71972		2.88062	
long no shorts	-0.75427	-0.13559	-0.72981	-0.15444	2.69928	-0.02044	2.88062	
shorts	-5.13570	-4.51703	-5.00952	-4.43416	2.67294	-0.04678	2.88062	-2.33599
portfolio	-1.69153	-1.07285	-1.64822	-1.07285	1.64686	-1.07285	2.88062	
RET for shorted stocks is the return they would have earned if we had gone long.								
Statistical Significance, p-values								
	AR CAPM	Perf _{CAPM}	AR Stone	Perf _{STONE}	Perf _{RET}			
all banks	0.00000		0.00000					
long no shorts	0.00000	0.00000	0.00000	0.00000	0.00001			
shorts	0.00000	0.00000	0.00000	0.00000	0.00000			
portfolio	0.00000	0.00000	0.00000	0.00000	0.00000			
2 year prediction								
	AR CAPM	Perf _{CAPM}	AR Stone	Perf _{STONE}	RET	Perf _{RET}	EWRETD	-RETX
all banks	-0.60197		-0.56418		2.58167		2.77265	
long no shorts	-0.71623	-0.11426	-0.70775	-0.14357	2.58900	0.00733	2.77265	
shorts	-5.10635	-4.50438	-4.94733	-4.38315	2.61933	0.03766	2.77265	-2.38900
portfolio	-1.59130	-0.98933	-1.55351	-0.98933	1.59234	-0.98933	2.77265	
RET for shorted stocks is the return they would have earned if we had gone long.								
Statistical Significance, p-values								
	AR CAPM	Perf _{CAPM}	AR Stone	Perf _{STONE}	Perf _{RET}			
all banks	0.00000		0.00000					
long no shorts	0.00000	0.00000	0.00000	0.00000	0.11498			
shorts	0.00000	0.00000	0.00000	0.00000	0.00000			
portfolio	0.00000	0.00000	0.00000	0.00000	0.00000

Figure 5

Figure 6

Table 16: Kolari et al (2002) Total Cumulative Returns Over the Period

1 year prediction									
	AR CAPM	Perf _{CAPM}	AR Stone	Perf _{STONE}	RET	Perf _{RET}	EWRET _D	-RET _X	
all banks	-0.61867		-0.57536		2.71972		2.88062		
long no shorts	-0.15155	0.46713	-0.34474	0.23063	2.95642	0.23671	2.57227		
shorts	-5.36871	-4.75004	-5.33411	-4.75874	2.66094	-0.05877	2.88062	-2.35932	
portfolio	-3.53174	-2.91306	-3.48843	-2.91306	-0.19335	-2.91306	2.88062		
Note that the long portfolio had an 8 month gap									
RET for shorted stocks is the return they would have earned if we had gone long.									
2 year prediction									
	AR CAPM	Perf _{CAPM}	AR Stone	Perf _{STONE}	RET	Perf _{RET}	EWRET _D	-RET _X	
all banks	-0.60197		-0.56418		2.58167		2.77265		
long no shorts	-1.08376	-0.48179	-1.12452	-0.56034	2.74298	0.16131	2.77265		
shorts	-4.69494	-4.09297	-4.54217	-3.97800	2.46495	-0.11671	2.77265	-2.22924	
portfolio	-1.98490	-1.38293	-1.94711	-1.38293	1.19874	-1.38293	2.77265		
RET for shorted stocks is the return they would have earned if we had gone long.									
Statistical Significance, p-values									
	AR CAPM	Perf _{CAPM}	AR Stone	Perf _{STONE}	Perf _{RET}				
all banks	0.00000		0.00000						
long no shorts	0.00000	0.00000	0.00000	0.00000	0.00000				
shorts	0.00000	0.00000	0.00000	0.00000	0.00000				
portfolio	0.00000	0.00000	0.00000	0.00000	0.00000

Figure 7

Figure 8

Table 17: Kimmel et al (2010) Total Cumulative Returns Over the Period

1 year prediction									
	AR CAPM	Perf _{CAPM}	AR Stone	Perf _{STONE}	RET	Perf _{RET}	EWRET _D	-RET _X	
all banks	-0.53537		-0.50882		2.52310		2.75210		
long no shorts	-0.47133	0.06404	-0.51838	-0.00956	2.75907	0.23597	2.75210		
shorts	-2.78344	-2.24807	-2.29097	-1.78215	0.94478	-1.57833	2.75210	-0.79860	
portfolio	-0.41089	0.12448	-0.40691	0.10191	2.56927	0.04617	2.75210		
RET for shorted stocks is the return they would have earned if we had gone long.									
2 year prediction									
Statistical Significance, p-values									
	AR CAPM	Perf _{CAPM}	AR Stone	Perf _{STONE}	Perf _{RET}				
all banks	0.00000		0.00000						
long no shorts	0.00000	0.00000	0.00000	0.02609	0.00000				
shorts	0.00000	0.00000	0.00000	0.00000	0.00000				
portfolio	0.00000	0.00000	0.00000	0.00000	0.00000				
Statistical Significance, p-values									
	AR CAPM	Perf _{CAPM}	AR Stone	Perf _{STONE}	RET	Perf _{RET}	EWRET _D	-RET _X	
all banks	-0.53537		-0.50882		2.52310		2.75210		
long no shorts	-0.57812	-0.04275	-0.64446	-0.13564	2.79759	0.27448	2.75210		
shorts	-2.57502	-2.03966	-2.24017	-1.73135	0.97650	-1.54660	2.75210	-0.78456	
portfolio	-0.74386	-0.20849	-0.71731	-0.20849	2.31461	-0.20849	2.75210		
RET for shorted stocks is the return they would have earned if we had gone long.									
Statistical Significance, p-values									
	AR CAPM	Perf _{CAPM}	AR Stone	Perf _{STONE}	Perf _{RET}				
all banks	0.00000		0.00000						
long no shorts	0.00000	0.00000	0.00000	0.00000	0.00000				
shorts	0.00000	0.00000	0.00000	0.00000	0.00000				
portfolio	0.00000	0.00000	0.00000	0.00000	0.00000

Figure 9

Figure 10

Table 18: Summary

Model	Prediction	Prediction Success (Table 12)	Risk Adjusted Returns (Table 13 – Table 17)	Total Returns (Table 13 – Table 17)
Martin (1977): Logit	1 Year Ahead	67%	$CAR_{SHORT} > CAR_{MKT}$ 91-94	LONG > NAÏVE
	2 Year Ahead	100%	$CAR_{SHORT} > CAR_{MKT}$ 91-94	LONG > NAÏVE
Pettway & Sinkey (1980): MDA	1 Year Ahead	100%		LONG > NAÏVE
	2 Year Ahead	100%		LONG > NAÏVE
Lane et al (1986): Cox PHM	1 Year Ahead	67%		
	2 Year Ahead	67%		
Kolari et al (2002): Trait Analysis	1 Year Ahead	67%	$CAR_{LONG} > CAR_{NAÏVE}$	LONG > NAÏVE
	2 Year Ahead	67%		LONG > NAÏVE
Kimmel et al (2010): LOESS	1 Year Ahead	100%	$CAR_{SHORT} > CAR_{MKT}$ 91-94, $CAR_{PORTFOLIO} > CAR_{NAÏVE}$	LONG, SHORT > NAÏVE
	2 Year Ahead	100%	$CAR_{SHORT} > CAR_{MKT}$ 91-94,	LONG > NAÏVE

Table 19: Summary Financial Crisis (2006 — 2009)					
statistically significant total cumulative returns over the period using 1 year ahead prediction models					
Model	Portfolio	CAPM Risk Adjusted return	$PERF_{CAPM}$	Total Return (Market return = -0.220)	$PERF_{RET}$
Martin (1977)	All (Naïve)	0.525		0.518	
	Long	0.575	0.050	0.613	0.094
	Short	0.369	-0.156	0.029	-0.490
	Portfolio	0.475	-0.050	0.468	-0.050
Pettway & Sinkey (1980)	All (Naïve)	0.525		0.518	
	Long	0.527		0.505	
	Short	-0.660	-1.184	-0.601	-1.120
	Portfolio	0.276	-0.249	0.270	-0.249
Lane et al (1986)	All (Naïve)	0.525		0.518	
	Long	0.685	0.160	0.647	0.128
	Short	-0.294	-0.819	-0.170	-0.689
	Portfolio	0.482	-0.043	0.476	-0.043
Kolari et al (2002)	All (Naïve)	0.525		0.518	
	Long	0.665	0.140	0.694	0.176
	Short	-0.279	-0.804	-0.286	-0.804
	Portfolio	0.048	-0.476	0.042	-0.476
Kimmel et al (2010)	All (Naïve)	0.525		0.518	
	Long	0.527		0.602	0.083
	Short	0.567		0.022	-0.497
	Portfolio	0.541		0.535

Figure 11

Figure 12

Table 20: Publicly Traded Banks (1996) Flagged as Potential Problems by Model and Data Set																		
PERM CO	Martin (1977): Logit			Pettway & Sinkey (1980): MDA			Lane et al (1986): Cox PHM			Kolari et al (2002): Trait			Kimmel et al (2010): LOESS			Total "Hits"		
	Origin al	Comm on	No Matchi ng	Origin al	Comm on	No Matchi ng	Origin al	Comm on	No Matchi ng	Origin al	Comm on	No Matchi ng	Origin al	Comm on	No Matchi ng	Origin al	Comm on	Combin ed
841										XXXX	XXXX	XXXX			1	1	1	3
3718				XXXX											1	0	0	1
3976										XXXX	XXXX	XXXX			1	1	1	3
4313				XXXX						XXXX	XXXX	XXXX	XXXX		2	2	1	5
4693				XXXX						XXXX	XXXX				2	1	0	3
5918					XXXX		XXXX	XXXX	XXXX	XXXX	XXXX	XXXX			2	3	2	7
7807	XXXX	XXXX	XXXX	XXXX	XXXX	XXXX	XXXX	XXXX	XXXX	XXXX	XXXX	XXXX	XXXX		5	4	4	13
7822										XXXX	XXXX	XXXX			1	1	1	3
7944										XXXX	XXXX	XXXX			1	1	1	3
7985				XXXX						XXXX	XXXX	XXXX			2	1	1	4
8759					XXXX		XXXX			XXXX	XXXX	XXXX			2	2	1	5
8999				XXXX						XXXX	XXXX	XXXX			2	1	1	4
9152				XXXX						XXXX	XXXX	XXXX			2	1	1	4
9348	XXXX		XXXX	XXXX	XXXX					XXXX	XXXX	XXXX	XXXX		4	2	2	8
9529	XXXX	XXXX	XXXX	XXXX	XXXX		XXXX	XXXX	XXXX	XXXX	XXXX	XXXX	XXXX		5	4	3	12
9796										XXXX	XXXX	XXXX			1	1	1	3
9877										XXXX					1	0	0	1
9974				XXXX						XXXX	XXXX	XXXX			2	1	1	4
10035										XXXX	XXXX	XXXX			1	1	1	3
10414											XXXX				0	1	0	1
10458				XXXX							XXXX				1	1	0	2
10487				XXXX						XXXX	XXXX	XXXX			2	1	1	4
10537				XXXX	XXXX		XXXX	XXXX	XXXX	XXXX	XXXX	XXXX			3	3	2	8
11350										XXXX	XXXX	XXXX			1	1	1	3
11395										XXXX	XXXX	XXXX			1	1	1	3

PERM CO	Martin (1977): Logit			Pettway & Sinkey (1980): MDA			Lane et al (1986): Cox PHM			Kolari et al (2002): Trait			Kimmel et al (2010): LOESS			Total "Hits"			
	Origin al	Comm on	No Matchi ng	Origin al	Comm on	No Matchi ng	Origina l	Comm on	No Matchi ng	Origin al	Comm on	No Matchi ng	Origin al	Comm on	No Matchi ng	Origin al	Comm on	No Matchi ng	Combin ed
11688					XXXX		XXXX			XXXX		XXXX				0	1	0	1
12203		XXXX					XXXX	XXXX	XXXX	XXXX	XXXX	XXXX				2	3	2	7
12732	XXXX	XXXX	XXXX	XXXX	XXXX		XXXX	XXXX	XXXX	XXXX	XXXX	XXXX	XXXX	XXXX		5	5	3	13
13032											XXXX					0	1	0	1
13291										XXXX	XXXX	XXXX				1	1	1	3
13347				XXXX						XXXX	XXXX	XXXX				2	1	1	4
13464				XXXX	XXXX	XXXX				XXXX						2	1	1	4
13664										XXXX	XXXX	XXXX				1	1	1	3
13953					XXXX					XXXX	XXXX	XXXX				1	2	1	4
14022										XXXX	XXXX	XXXX				1	1	1	3
14056											XXXX					0	1	0	1
14361					XXXX					XXXX	XXXX	XXXX				1	2	1	4
14526										XXXX	XXXX	XXXX				1	1	1	3
14660								XXXX		XXXX	XXXX	XXXX				1	2	1	4
14759				XXXX		XXXX				XXXX	XXXX	XXXX		XXXX		2	2	2	6
14820				XXXX	XXXX					XXXX	XXXX	XXXX				2	2	1	5
14853				XXXX	XXXX			XXXX		XXXX	XXXX	XXXX				2	3	1	6
15152										XXXX	XXXX	XXXX				1	1	1	3
15274										XXXX	XXXX	XXXX				1	1	1	3
15669										XXXX	XXXX	XXXX				1	1	1	3
15675				XXXX												1	0	0	1
15762										XXXX	XXXX	XXXX		XXXX		1	2	1	4
15772	XXXX	XXXX	XXXX	XXXX			XXXX	XXXX		XXXX	XXXX	XXXX				4	3	2	9
15904				XXXX						XXXX	XXXX	XXXX				2	1	1	4
15922	XXXX	XXXX	XXXX		XXXX		XXXX	XXXX	XXXX	XXXX	XXXX	XXXX				3	4	3	10
16116				XXXX	XXXX	XXXX	XXXX	XXXX	XXXX	XXXX	XXXX	XXXX				3	3	3	9
16298											XXXX					0	1	0	1
16318										XXXX	XXXX	XXXX				1	1	1	3

PERM CO	Martin (1977): Logit			Pettway & Sinkey (1980): MDA			Lane et al (1986): Cox PHM			Kolari et al (2002): Trait			Kimmel et al (2010): LOESS			Total "Hits"			
	Origin al	Comm on	No Matchi ng	Origin al	Comm on	No Matchi ng	Origina l	Comm on	No Matchin g	Origin al	Comm on	No Matchi ng	Origin al	Comm on	No Matchi ng	Origin al	Comm on	No Matchi ng	Combin ed
16321	XXXX	XXXX	XXXX	XXXX	XXXX					XXXX	XXXX	XXXX		XXXX		3	4	2	9
16427				XXXX						XXXX	XXXX					2	1	0	3
16572				XXXX												1	0	0	1
16578										XXXX	XXXX	XXXX				1	1	1	3
17669										XXXX	XXXX	XXXX				1	1	1	3
32170				XXXX						XXXX	XXXX	XXXX				2	1	1	4
37133				XXXX						XXXX	XXXX	XXXX				2	1	1	4
38453										XXXX		XXXX	XXXX			2	0	1	3
39178							XXXX		XXXX	XXXX	XXXX	XXXX				2	1	2	5
41268										XXXX	XXXX	XXXX				1	1	1	3
43502										XXXX	XXXX	XXXX				1	1	1	3
44291				XXXX	XXXX					XXXX	XXXX	XXXX				2	2	1	5
Total	7	7	7	29	17	4	11	11	9	56	58	52	5	5	108	98	72		278

**Table 21: Analysis of Matching Method
Original Matching VS no Matching**

Model	Percentage Overlap in Failure Predictions	Predicted Failure of Fairfield Bank
Martin (1977): Logit	100%	Yes
Pettway & Sinkey (1980): MDA	24%	Yes
Lane et al (1986): Cox PHM	90%	Yes
Kolari et al (2002): Trait Analysis	95%	Yes

Table 22: Significant Variables by Statistical Method

#	Original Variables	Common variables	Variable	FED ID
1	Logit	Logit	Equity Capital/Total Assets	RCFD3210/RCFD2170
*	Logit		Net Income/(Total Assets – Cash Items in Process)	RIAD4340/(RCFD2170 – RCFD00020)
2	MDA	COX PHM, Logit	Total Operating Expense/Total Operating Income	RIAD4130/RIAD4000
3	MDA	COX PHM	Investments/ Total Assets	RCFD0390/ RCFD2170
4	COX PHM		Total Loans/Total Deposits	RCFD2122/RCFD 2200
**	COX PHM		Log Total Capital/Total Assets	Log RCFD3210/RCFD2170
5	LOESS	COX PHM, Logit	Net Income/Total Assets	RIAD4340/RCFD2170
* similar to # 5				
** similar to # 1				

Table 23: Analysis of Statistical Methods using Common Variables VS Original Model Variables

Statistical Method	Percentage Overlap in Failure Predictions	Predicted Failure of Fairfield Bank
Logit	86%	Yes
MDA	48%	Yes
COX PHM	82%	Yes
Trait	93%	Yes
LOESS	20%	No