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Predicting Bank Failure Using Regulatory Accounting Data

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This is to certify that the doctoral study by

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Abstract

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by

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MBA, Amberton University, 1993

BBA, University of Texas at Arlington, 1986

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Abstract

A liquidity shortfall in the United States triggered the bankruptcy of several large commercial banks, and bank failures continue to occur, with 50 banks failing between 2013 and 2015. Therefore, it is critical banking regulators understand the correlates of financial performance measures and the potential for banks to fail. In this study, binary logistic regression was employed to assess the theoretical proposition that banks with higher nonperforming loans, lower Tier 1 leverage capital, and higher noncore funding dependence are more likely to fail. Archival data ranging from 2012–2015 were collected from 250 commercial banks listed on the Federal Deposit Insurance Corporation's website. The results of the logistic regression analyses indicated the model was able to predict bank failure, $X^2(3, N = 250) = 218.86$, $p < .001$. Nonperforming loans, Tier 1 leverage capital, and noncore funding were all statistically significant, with Tier 1 leverage capital (β = -1.485), $p < .001$) accounting for a higher contribution to the model than nonperforming loans (β = .354, $p < .001$) and noncore funding dependence (β = -.057, p = .015). The implication for positive social change of this study includes the potential for bank regulators to enhance job security, wealth creation, and lending within the community by working with bank managers to develop more timely corrective action plans to alleviate the risk of bank failure.

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Section 1: Foundation of the Study

The basis for this study was the need for banking regulators to understand whether certain banking performance measures could predict bank failure. Many stakeholders blame regulators and bank managers for bank failures (Massman, 2015). Banking regulators face criticism for not having adaptable systems that forewarn of bank distress, and bank managers face criticism for not escalating issues quickly enough to allow regulators to implement corrective action (Massman, 2015). Existing bank monitoring tools and systems do not provide sufficient early warning during a financial crisis (Pakravan, 2014). My objective with this study was to help bank regulators understand how performance measures, such as nonperforming loans, Tier 1 leverage capital, and noncore funding dependence, may help to indicate the potential for bank failure.

Banking regulators do not fully understand how certain banking performance measures relate to bank failure (Cox & Wang, 2014). Bank managers make more loans when the economy is favorable, based on borrower employment, income, and ability to make loan payments, but challenges arise during an unfavorable economy as borrowers lose their jobs or make less money to repay their loans (Cox & Wang, 2014). The borrowers stop paying on their loans, which leads to lower profits for the banks and possible bank failure (Lu & Whidbee, 2013). Bank regulators use different types of performance measures to assist them in identifying events that occur prior to a bank failing (Liu, 2015). Banking regulators should understand the relationship between different banking financial performance measures and the potential for banks to fail (Di, Chai, & Geok See, 2016). In this study, I examined how banking regulators might use financial performance measures as a tool to help prevent bank failure.

Background of the Problem

Banking regulators use a variety of supervisory tools to oversee the financial condition of individual banks (Samitas & Polyzos, 2016). The financial condition of a bank is important because bank managers serve as stewards for customer deposits and shareholder investments (Cherpack & Jones, 2013). Bank customers and shareholders could suffer losses when a bank fails (Alali & Romero, 2013). Bank regulators provide on-site examinations and off-site monitoring to monitor compliance with regulations and to prevent bank failure (Kerstein & Kozberg, 2013). Since the early 1980s, bank examiners have used on-site bank examination ratings as a way to monitor banks; however, these ratings can only indicate a static 12- to 18-month point in time (Cox & Wang, 2014). Banking regulators in the United States adopted a supervision-by-risk approach in 1996 by making continuous assessments of a bank's exposure related to credit, capital, liquidity, and other performance measures that could ultimately lead to bank failure (Agarwal, Lucca, Seru, & Trebbi, 2014). Notwithstanding existing supervisory protocol, opportunities exist for banking regulators to enhance their understanding of the likelihood of nonperforming loans, Tier 1 leverage capital, and noncore funding dependence leading to bank failure.

Problem Statement

A liquidity shortfall in the United States triggered the bankruptcy of several large commercial banks (Liu, 2015). Bank failures leading to closures increased from three in

2007 to 322 between 2008 and 2010 (Cox & Wang, 2014); the pace has slowed since 2010, but bank failures continue to occur, with 50 banks failing between 2013 and 2015 (Federal Deposit Insurance Corporation [FDIC], 2016). The general business problem was the difficulty banking regulators face trying to prevent bank failure. The specific business problem was that some U.S. banking regulators do not know if nonperforming loans, Tier 1 leverage capital, and noncore funding dependence predict the likelihood of bank failure.

Purpose Statement

The purpose of this quantitative correlational study was to examine if nonperforming loans, Tier 1 leverage capital, and noncore funding dependence predict the likelihood of bank failure. The targeted population was federally-insured depository institutions in the United States that failed or survived between 2012 and 2015. The implications for positive social change of this study include the potential to provide small business leaders with easier access to loans that could help those businesses thrive, and in turn, create more jobs within the community.

Nature of the Study

I chose a quantitative method for this study. Researchers use the quantitative methodology to perform numerical tests, analyze numerical data, provide explanations or predictions, and generalize to other populations (Hagan, 2014). The quantitative methodology was the most appropriate method for this study because the purpose of the study was to examine the relationship between multiple variables by analyzing numerical data and then inferring the results to a larger population. Quantitative researchers analyze numerical data and infer the results to a larger population (Fassinger & Morrow, 2013). A mixed-method study was not appropriate for this study. The attributes of both quantitative and qualitative methods must be present in mixed-method research (Maxwell (2016). A qualitative study was also not appropriate for this study as the purpose of this study was not to understand underlying reasons and motivations. The purpose of a qualitative study is to understand underlying reasons and motivations (McCusker & Gunaydin, 2015).

I chose a nonexperimental correlational design for this study. A correlation design involves examining the relationship between two or more variables (Bosco, Singh, Aguinis, Field, & Pierce, 2015). The correlation design was appropriate for this study because a key objective was to examine the relationship between variables. Other designs, such as experimental and quasi-experimental designs, are appropriate when researchers seek to assess a degree of cause and effect (Flannelly & Jankowski, 2014). In an experimental research design, the researcher controls certain variables and manipulates other variables to observe whether the results of the experiment reflect that the manipulations directly caused the outcome (Flannelly & Jankowski, 2014). An experimental research design was not appropriate for this study, as I was not controlling or manipulating the variables to determine the cause of bank failure. Therefore, a correlation design was the most suitable choice for this study.

Research Question

I developed the following research question to guide this quantitative correlation study:

Do nonperforming loans, Tier 1 leverage capital, and noncore funding dependence predict the likelihood of bank failure?

Hypotheses

H_0: Nonperforming loans, Tier 1 leverage capital, and noncore funding dependence do not predict the likelihood of bank failure.

H_1: Nonperforming loans, Tier 1 leverage capital, and noncore funding dependence predict the likelihood of bank failure.

Theoretical Framework

The purpose of a theory is to explain data and generate hypotheses that researchers can test through research (Judge, Ilies, & Colbert, 2004). I did not have a theory for this study. In the absence of a named theory, however, a theoretical proposition is sometimes appropriate (Judge et al., 2004). The theoretical proposition that guided this study was that banks with higher nonperforming loans, lower Tier 1 leverage capital, and higher noncore funding dependence are more likely to fail (see Cox & Wang, 2014). I found evidence for how each variable relates to bank failure in my review of the literature. Ultimately, the purpose of this study was to test this proposition.

My discussion of the independent variables and bank failure includes more synthesis and critical analysis of the theoretical proposition that was grounded on my findings in the literature review. Lu and Whidbee (2013) found a more significant relationship between higher performing loans and bank survival than between lower performing loans and bank survival. Banks failed when borrowers defaulted on their loans, which resulted in nonperforming loans (Lu & Whidbee, 2013). In contrast, Lu and

Whidbee noted that banks survived when borrowers repaid their loans, which resulted in higher performing loans. Cherpack and Jones (2013) found a significant relationship between Tier 1 leverage capital and bank survival. These researchers found that banks with lower Tier 1 leverage capital failed at higher rates than banks with higher Tier 1 leverage capital and that banks experience lower profits when borrowers do not repay their loans, which results in lower Tier 1 leverage capital and the potential for bank failure. Bologna (2015) found a positive correlation between banks with higher noncore funding dependence and bank failure. Bologna concluded that banks failed when sources that are more expensive, such as brokered deposits and other costly funds, funded operations. In contrast, banks survived when bank managers used core deposits and less expensive funds for their operations (Bologna, 2015). In this study, I expected that there was a significant likelihood that nonperforming loans, Tier 1 leverage capital, and noncore funding dependence contribute to bank failure.

Operational Definitions

Several terms appear throughout the study that are technical or relate to the banking and financial regulatory industry, so I have provided the following operational definitions:

FDIC: Regulators at the FDIC insure depositors at approximately 7,000 depository banks in the United States (Salameh, 2013).

FDIC Call Report (Call Report): The financial statements of FDIC-insured banks filed quarterly with various regulatory agencies (Huizinga & Laeven, 2012).

Loan charge-offs: The accounting treatment that triggers the recognition or write-off of loans against a bank's financial statements when a borrower defaults on the payment of a loan (Alali & Romero, 2013).

Noncore funding dependence: A measure of liquidity based on the difference between noncore liabilities and short-term investments relative to a bank's long-term assets (Horn, 2005).

Nonperforming loans: In the context of banking, these loans represent a deteriorating credit relationship involving nonperformance and results in becoming a generator of losses or in temporary blockages of credit resources for creditor banks (Filip, 2014).

Regulatory bank examination rating: A longstanding confidential quantitative regulatory measurement scale used to assess a bank's financial health, including capital adequacy, asset quality, management, earnings, liquidity, and sensitivity to interest rate risk(CAMELS; Kerstein & Kozberg, 2013).

Tier 1 leverage capital: A risk-management tool banking regulators use to measure bank capital levels to support asset growth and absorb losses, which includes stockholders' or common equity and the allowance for loan loss (Abreu & Gulamhussen, 2015).

Assumptions, Limitations, and Delimitations

Assumptions

Assumptions are facts considered true but are not actually verifiable by the researcher (Foss & Hallberg, 2014). My assumptions within the scope of this study pertained to the accuracy and validation of published financial data for the FDIC's Call Report. My first assumption was that bank managers review the Call Reports for accuracy prior to publication. My second assumption was that the FDIC's analysts validate the published financial data. The availability of financial reporting instructions to bank managers mitigates the assumptions related to the accuracy of the published financial data to prepare the FDIC's Call Report (FDIC, 2016). The FDIC analysts' use of advanced technological tools mitigates data validation risks for the preparation of the Call Report.

Limitations

Limitations are study weaknesses that the researcher cannot address because they are out of the researcher's control (Denscombe, 2013). A limitation of this study was that the independent variables included proxies for only three of the six components of the confidential regulatory rating used to assess commercial banks' financial condition. A researcher could yield different results if the six confidential regulatory examination components were part of a study (see Denscombe, 2013). Another limitation of this study was the lack of access to confidential regulatory examination data. The availability of this confidential regulatory examination data would have assisted me in determining which financial indicators relate to bank closings.

Delimitations

Delimitations are the factors that limit the scope and define the boundaries of a study (Medrano, López-Perea, & Herrera, 2014). The data I used in this study were historical and archival data for federally-insured banks in the United States. International banks and uninsured banks did not fit within the scope of this study. Regulators at the FDIC established guidelines to ensure the accuracy of the data on its public website. Obtaining current market data was not feasible for me in this study given the limited availability of the data. The confidential nature of the regulatory examination reports and the proprietary FDIC ratings preclude the public from knowing which financial indicators are for bank closings. Thus, my use of historical data instead of current market data was acceptable, as historical data were readily available from the FDIC website.

Significance of the Study

Contribution to Business Practice

The results of this study may contribute to the understanding and effective practice of business in several ways. Banking regulators could use the results to identify distressed banks in a timely manner and to avoid taking on risks that lead to bank failure. Banking regulators could also use the financial performance measures to improve their efficiency during regulatory examinations.

Implications for Social Change

The implications for positive social change of this study include the potential to provide organizations with easier access to loans, which could help those organizations thrive (see Babajide, Olokoyo, & Adegboye, 2015). In turn, the leaders of those organizations could use those loans to create jobs within the community. This process of reinvesting in the community could also lead to overall economic growth.

A Review of the Professional and Academic Literature

This literature review will include my synthesis and critical analysis of the research on predicting bank failure. The literature I found underscored the importance of three bank performance measures commonly used in bank failure prediction models: nonperforming loans, Tier 1 leverage capital, and noncore funding dependence (see Alali & Romero, 2013). The large majority of the studies reviewed appeared in scholarly journals between 2013 and 2017; however, the review will also include a smaller number of older, seminal studies. The review will include a discussion of the roles and responsibilities of banking regulators as well as the purpose of U.S. depository institutions.

The references for this study came from targeted searches within a variety of databases. The primary keywords I searched included *bank failure prediction, distressed banks*, *early warning systems*, *nonperforming loans*, *Tier 1 leverage capital*, and *liquidity*. My search parameters expanded from the results of the initial search and key words from relevant articles.

My search included scholarly works that reference banks' asset quality characteristics or attributes, such as nonperforming loans and delinquent loans. The search strategy involved reviewing articles pertaining to bank solvency measures, such as Tier 1 leverage capital, and to bank liquidity measures, such as noncore funding dependence. My search strategy also included locating scholarly works pertaining to the FDIC regulatory framework to assess the health of banks, regulatory bank measurements such as the CAMELS rating, data collection, and statistical techniques for analyzing bank failure. I identified 140 sources relevant to this study. My primary focus was peer-reviewed articles published between 2013 and 2017, but the review contains some articles outside this range based on their relevance to the study topic. Eighty-seven percent of the references were peer reviewed and had publication dates between 2013 and 2017.

The purpose of this quantitative correlational study was to examine if nonperforming loans, Tier 1 leverage capital, and noncore funding dependence predict the likelihood of bank failure. The study included three independent variables: nonperforming loans, Tier 1 leverage capital, and noncore funding dependence.

Theoretical Proposition

Grounding this study in a larger theoretical model of financial vulnerability would have been ideal, but no such model emerged in my review of the literature. However, in the absence of a named theory, a theoretical proposition may be appropriate (see Judge et al., 2004). The theoretical proposition that served to guide this study was that banks with higher nonperforming loans, lower Tier 1 leverage capital, and higher noncore funding dependence are more likely to fail (see Cox & Wang, 2014). Evidence for the importance of these variables appeared other places in the literature as well. The purpose of this study was to test this proposition.

The first independent variable of the theoretical proposition was nonperforming loans. Lu and Whidbee (2013) found a significant relationship between higher performing loans and bank survival than between lower performing loans and bank survival. Nonperforming loans influence a bank’s credit quality and performance. The phenomenon of nonperforming loans includes past-due loans, bankrupt and quasibankrupt assets, and doubtful assets (Hajialiakbari, Gholami, Roshandel, & Hatami-Shirkouhi, 2013). Loans are nonperforming when bank managers determine they have exhausted all sources for collecting repayment under the terms of the loan agreement (Neţoiu, Neţoiu, & Meiţă, 2013). The interest earned on loans is a significant source of bank revenue and diminishes with the preponderance of nonperforming loans. Nonperforming loans are one of the eight most important elements that adversely affect bank performance (Bexley & Breazeale, 2012). The other elements are return on average assets, return on average equity, net charge-offs to average loans, reserves to nonperforming assets, loan loss provision to net charge-offs, loan loss reserves to gross loans, and equity to assets. Nonperforming loans are loans that are delinquent in principal or interest for 90 or more days, whereas a low number depicts better asset quality with respect to nonperforming loans (Bexley & Breazeale, 2012). Nonperforming loans are a component of credit risk and have the potential of leading to bank failure.

Nonperforming loans relate to bank failure. Nikolaidou and Vogiazas (2014) found that nonperforming loans weakened the asset quality of banks in Bulgaria, despite other economic challenges the country was undergoing. Nonperforming loans are on the radar screen of banking regulators, who require banking managers to implement corrective action plans when nonperforming loans increase. The number of nonperforming loans a bank has is a concern for banking regulators. High credit risk facilitates an unsustainable level of nonperforming loans as well as further deterioration in a bank that could result in bank failure (Canicio & Blessing, 2014). Weak European banks exhibited signs of failure when a significant concentration of nonperforming loans existed (Apergis & Payne, 2013). Declining asset values increase a bank's credit risk resulting from nonperforming loans.

The second independent variable of the theoretical proposition was that banks with lower Tier 1 leverage capital are likely to fail. Cherpack and Jones (2013) found a significant relationship between Tier 1 leverage capital and bank success, as banks with lower Tier 1 leverage capital failed at higher rates than banks with higher Tier 1 leverage capital. Bank regulators require banks to maintain capital levels to support asset growth and absorb losses, which includes stockholders' or common equity and the allowance for loan loss (Abreu & Gulamhussen, 2015). Capital adequacy is one of the leading metrics that regulators use to assess the health of a bank, and low capital levels can potentially lead to bank failure. The lack of sufficient capital to absorb and sustain losses arising from risky loans and other assets contributes to bank failure (Handorf, 2014). The minimum requirements can vary, but the Tier 1 leverage capital ratio typically ranges from 4% to 6% (Camara, Lepetit, & Tarazi, 2013). Capital standards are important in banking because of the ability to predict default risk (Merle, 2013).

The third and final independent variable of the theoretical proposition was banks with higher noncore funding dependence are likely to fail. Bologna (2015) found banks with higher noncore funding dependence positively correlated with bank failure. Noncore funding dependence is a measure of a bank's liquidity. Net noncore funding dependence pertains to the difference between noncore liabilities and short-term investments relative to a bank's long-term assets (Horn, 2005). The basis of this concept is the premise that noncore liabilities are more suitable for funding short-term investments rather than long-term assets. Liquidity is another important component to assess the performance of a bank, as it shows the ability of bank management to fund loans and deposits.

Bank managers and regulators can use the behavioral characteristics of a bank's deposit base to determine its liquidity position as well as use a local customer base consisting of demand and savings deposits for sufficient funding sources. In contrast, more expensive or temporary large brokered or government deposits could strain a bank's liquidity position because of the potential of immediate runoff (Li, Escalante, Epperson, & Gunter, 2013). When a bank's loan-to-deposit ratio is significant, bank regulators seek corrective action to alleviate further bank distress (Handorf, 2014). The ratio of noncore deposits to total deposits is another measure of a bank's liquidity position that bank managers could use to obtain insights into high funding costs.

Liquidity for surviving a financial crisis is essential for preventing bank failure. Bank managers can survive a bank failure when they maintain sufficient liquidity levels (Batavia, Parameswar, Murthy, & Wague, 2013). Bank managers encounter liquidity risks when the owners of these short-term and high-cost deposits are likely to leave the bank in search of higher interest rates (Li et al., 2013). As a result, the bank managers may have to sell other assets to accommodate the funding source.

Seminal works on bank failure prediction. The scholarly literature I found on this topic included a number of seminal works in which authors used publicly available financial data to predict the failure of banks or other businesses (Meyer & Pifer, 1970; Sinkey, 1975; West, 1985). The aforementioned authors discovered that the same fundamentals used for predicting business failures were pertinent to the prediction of bank failure. As the years progressed, researchers (Beaver, 1968; Pawlak, 1982; Sinkey, 1975; West, 1985) began to validate most of the prediction models with statistical analyses. Multiple discriminant analysis and logistic regression emerged as the most frequently used method for these analyses.

Approaches to predict bank failure. The approaches used to predict business or bank failure gradually evolved to provide improved clarity and rigor (Altman, 1968; Beaver, 1968; Martin, 1977; Sinkey, 1975). Failure-prediction approaches initially included multivariate discriminant analysis; subsequently, the approaches included ratios to differentiate between failed and nonfailed companies in the United States (Altman, 1968). The apparent limitations of the business failure-prediction approach became evident from subsequent research that assessed the validity of just using ratios to predict business failure. The rigor of the earlier business failure-prediction approaches improved substantially with the addition of a multivariate framework. If analyzed within a multivariate framework, the ratios would take on greater statistical significance than the common technique of sequential ratio comparisons. An assessment showed that the discriminant-ratio model accurately predicted 94% of all firms in the bankrupt and nonbankrupt groups (Altman, 1968). Business failure prediction became clearer with the use of ratios.

Most effective ratios to predict bank failure. Beaver (1968) determined that ratios were most effective in predicting bank failure. Commonly-used financial ratios, including liquid asset and current asset ratios, have longstanding power and credibility with regard to ascertaining solvency (Beaver, 1968). Beaver's goal was to determine whether banking regulators could have better success using liquid asset measures versus nonliquid assets measures for predicting bank failure. Furthermore, if liquid asset measures were the better selection, then which of the liquid assets measures should the banking regulators use to improve their effectiveness in predicting bank failure (Beaver, 1968). To that end, Beaver identified several liquid asset measures that could help managers improve their effectiveness in the prediction of business failure.

Beaver (1968) examined 11 liquid asset measures: current assets to total assets, quick assets to total assets, net working capital to total assets, cash to total assets, current ratio, quick ratio, cash to current debt, current assets to sales, quick assets to sales, net working capital to sales, and cash to sales. The three nonliquid asset measures included cash flow to total debt, net income to total assets, and total debt to total assets (Beaver, 1968). The results of Beaver's examination indicated that liquid asset measures were most effective as short-term predictors, as they fared better than the nonliquid asset measures at predicting bank failure an average of 1 to 2 years before failure. In contrast, the nonliquid measures were most effective as long-term predictors; they were more effective than liquid measures at helping managers predict bank failure 4 to 5 years before failure (Beaver, 1968). Liquid asset measures were the most effective for helping managers predict business failure.

Sinkey (1975) discovered other attributes that distinguish distressed banks, and these attributes, in the form of financial ratios, can be derived from year-end balance sheets, income statements, and tracking of trends. Regulators can use these ratios to measure a bank's operation and performance in such areas as liquidity, loan operations, asset and deposit compositions, efficiency, profitability, capital adequacy, and sources and uses of revenue (Sinkey, 1975). Analysis of such data indicates that a bank's deterioration to failure is not an overnight transition as distressed banks are less efficient, are less liquid, and have inadequate capital compared to nondistressed banks (Sinkey, 1975). Early recognition of these financial characteristics is effective in predicting bank failure.

Ruzgar, Unsal, and Ruzgar (2008) used financial ratios with the rough-set approach to determine whether many of the bank failures that occurred in Turkey between 1995 and 2007 were predictable using publicly available financial data. The rough-set approach uses information available to regulators to discriminate between failed and successful banks. The data for Ruzgar et al.'s study were from the Turkish banking regulators' public website. The key ratios provided proxies for confidential regulatory bank ratings of capital, asset quality, liquidity, and profitability (Pawlak, 1982). Their study analyzed the financial ratios over a 3-year period. The study showed decision attributes, where 1 indicated a healthy bank and 0 indicated a failed bank. Ruzgar et al. did not provide any statistical analysis, such as a logistic regression, to test the model's predictive power, which weakened the credibility of their study.

West (1985) used the conventional logistic regression approach and financial ratios to predict bank failure. However, West's study is an outlier among other bank failure-prediction studies because the predictors included both publicly available data and confidential bank examination data. Therefore, despite its high predictive power, West did not provide an appropriate model for this study because the data contained in confidential regulatory examination reports were not readily accessible to me.

In this chronological review of the literature, I have shown how researchers have combined statistical techniques and probabilistic functions to improve the prediction of bank failures. A bank failure-prediction or early warning model should show the probability of future failure using variables from a bank's financial statements or past financial data (Martin, 1977). The common thread to predict failure in statistical techniques, such as logit regression, is to apply the real-world classification into failure and nonfailure groups as a dependent variable and attempt to explain the classification as a function of several independent variables (Martin, 1977). The independent variables are mostly, but not exclusively, ratios computed from the bank's financial statements.

Developing a predictive approach that will help banking regulators identify, in a timely manner, banks that are at risk of failing is of continuing significance given the role of banks in global financial crises (Apergis & Payne, 2013). Bank failures increase exponentially during periods of economic crisis. The aforementioned is one reason it is so important for bank regulators to develop bank failure prediction approaches to supplement on-site bank examinations.

Bank examiners conduct on-site bank examinations on a 12- to 18-month basis (Kerstein & Kozberg, 2013). The infrequency of such examinations inhibits banking regulators' ability to detect distressed financial conditions and implement corrective action. The ineffectiveness of the existing financial indicators underscores the criticality of early warning systems for predicting bank failure (Kerstein & Kozberg, 2013). The national prominence of banks with respect to economics and financial markets heightens the importance of improving the approach for predicting bank failure.

Given the urgency of preventing bank failures, significant discussions persist regarding what additional elements banking regulators could include to enhance the existing approaches for predicting bank failure. For instance, bank credit risk is one of the priorities for regulators, governmental agencies, insurance companies, financial institutions, corporate lenders, small businesses, and private investors (Ilk, Pekkurnaz, & Cinko, 2014). The approach to assessing bank failure encompasses a close examination of the immediate probabilities of the risk-adjusted model assets that may cause a fundamental failure within a bank portfolio (Ilk et al., 2014). Regulators indicated that probabilistic measures such as logit regression are likely the solution for improving bank failure prediction.

The literature review showed that all the seminal works used publicly available financial ratios to predict bank failure in the absence of more precise information. Precise information is lacking because bank examination ratings and findings are not available to the public; the nondisclosure of confidential examination reports limited the predictive power of the seminal works. This study also included only publicly available indicators of bank performance, including nonperforming loans, Tier 1 leverage capital, and noncore funding dependence. The aim of the study was to determine the impact of these three independent variables on the likelihood of bank failure.

Measurement. Statistical analysis techniques are prevalent measurement methods in bank failure-prediction studies. A bank failure-prediction or early-warning model should show the probability of future failure using variables from a bank’s financial statements or past financial data (Martin, 1977). The common thread in studies of this sort is applying a real-world classification into failure and nonfailure groups as a dependent variable and attempting to explain whether a bank has failed as a function of several independent variables (Altman, 1968). This classification method typically involves using a logistic regression model, which is a form of multiple regression with a dichotomous outcome variable: either the bank failed or it did not (Calabrese & Giudici, 2015). The independent variables are mostly but not exclusively ratios computed from the bank’s financial statements (Kerstein & Kozberg, 2013). For the purpose of this study, the independent variables were nonperforming loans, Tier 1 leverage capital, and noncore funding dependence.

Logistic regression produces likelihood ratios, also known as odds ratios, that depict the likelihood of being in one of the categories of the dependent variable (fail or survive), with a larger odds ratio indicating a higher likelihood of survival (Mendes & Fard, 2016). Logistic regression is more effective than alternative methods of analysis, such as discriminant analysis (Sinkey, 1975). Multiple discriminant analysis could not produce likelihood ratios. Therefore, the logistic regression analysis model was the appropriate method for this study.

Data for all the variables of interest to this study were publicly available from the banking regulator’s website; researchers have shown these variables are effective for predicting bank failures (Ruzgar et al., 2008). There is no ambiguity about how to measure these variables. This study included a single universally accepted measure for each of the variables, as published on the FDIC's website, which contrasts with the situation in many social science investigations, where multiple ways of measuring the construct may be of interest to a researcher.

Indicators of bank performance. This section includes a discussion of the indicators of bank performance, nonperforming loans, Tier 1 leverage capital, and noncore funding dependence. Nonperforming loans influence a bank's credit quality and performance. The phenomenon of nonperforming loans includes past-due loans, bankrupt and quasibankrupt assets, and doubtful assets (Hajialiakbari et al., 2013). Loans are nonperforming when bank managers determine they exhaust all sources for collecting repayment under the terms of the loan agreement (Neţoiu et al., 2013). Banking regulators consider nonperforming loans a key indicator of bank performance.

Tier 1 leverage capital is significant, as it is a risk management tool. Bank regulators require banks to maintain capital levels to support asset growth and absorb losses, which includes stockholders' or common equity and the allowance for loan loss (Abreu & Gulamhussen, 2015). The intent of the Tier 1 leverage capital ratio is to capture both a bank's on-balance sheet and off-balance sheet risk exposure (Federal Reserve Board of Governors, 2013). The Tier 1 leverage capital ratio comprises Tier 1 capital to average total consolidated assets as reported on a bank's regulatory report minus amounts deducted from Tier 1 capital (Federal Reserve Board of Governors, 2013). Banking regulators use the Tier 1 leverage capital ratio to monitor and measure bank performance.

Noncore funding dependence is a measure of a bank's liquidity. Net noncore funding dependence pertains to the difference between noncore liabilities and short-term investments relative to a bank’s long-term assets (Horn, 2005). The basis of this concept is the premise that noncore liabilities are more suitable for funding short-term investments than long-term assets. Liquidity is another important component to assess the performance of a bank. Bank liquidity is important, as it shows the ability of bank management to fund loans and deposits (Davies, 2013). Banking regulators review liquidity measures, including noncore funding dependence, to measure bank performance.

Nonperforming loans. Nonperforming loans influence a bank’s credit quality and performance. The phenomenon of nonperforming loans includes past-due loans, bankrupt and quasi-bankrupt assets, and doubtful assets (Hajialiakbari et al., 2013). Loans are nonperforming when bank managers determine they have exhausted all sources for collecting repayment under the terms of the loan agreement (Neţoiu et al., 2013). Nonperforming loans are indicators of a bank’s financial health.

Nonperforming loans have the potential of leading to bank failure. Nonperforming loans weakened the asset quality of banks in Bulgaria, despite other economic challenges the country was undergoing (Nikolaidou & Vogiazas, 2014). Banking regulators implement corrective action plans when nonperforming loans increase. Such plans could restrict the availability of loans to the public. Stakeholders link nonperforming loans to macroeconomic conditions and industry-specific factors. The Bulgarian economy experienced adverse effects from nonperforming loans, despite growth contraction in other countries in southeastern Europe (Nikolaidou & Vogiazas, 2014). The International Monetary Fund members’ stress test conducted in 2010 showed that nonperforming loans would continue to increase in light of the Greek public debt issues (Nikolaidou & Vogiazas, 2014). Understanding the implications of nonperforming loans is fundamental for assessing the financial health of a bank. Nonperforming loans do not provide any revenue source such as interest income to banks.

The interest earned on loans is a significant source of bank revenue and diminishes with the preponderance of nonperforming loans. Nonperforming loans are one of the eight most important elements that adversely affect bank performance (Bexley & Breazeale, 2012). The other elements are return on average assets, return on average equity, net charge-offs to average loans, reserves to nonperforming assets, loan loss provision to net charge-offs, loan loss reserves to gross loans, and equity to assets. Nonperforming loans are loans that are delinquent in principal or interest for 90 or more days. A low number depicts better asset quality with respect to nonperforming loans (Bexley & Breazeale, 2012). Nonperforming loans are a component of credit risk.

A relationship exists between weak credit policy with a high level of nonperforming loans and bank failure. Credit risk is a distinguishing factor between surviving banks and failed banks (Adeyeye & Migiro, 2015). The increase in nonperforming loans triggered bank failures during the 2007 financial crisis (Chen, 2014). Bank managers who operate banks with high levels of nonperforming loans were unable to repay dividends under the government's bailout program for banks under the Troubled Asset Relief Program (Wilson, 2013). The accounting treatment for nonperforming loans consists of entries that result in reducing both loan amount and revenue.

Bank managers measure nonperforming loans against the underlying value of the collateral, with any excess of the loan amount over the value resulting in a loss of revenue to the bank. Asset loss is a direct cause of bank failure (Kandrac, 2014). Bad loans or nonperforming loans include past-due loans, bankrupt and quasibankrupt assets, and doubtful assets (Hajialiakbari et al., 2013). Nonperforming loans are assets that cease to produce income for financial institutions. Nonperforming loans did not become an acute problem until the 2007 financial crisis, as worldwide credit quality was relatively benign. Nonperforming loans were complicating bank activities and soundness, and they signaled economic problems to investors and declining share prices (Poposka, 2015). Although a deficiency in interest revenue is the main characteristic of nonperforming loans, a number of other measures capture the severity of nonperforming loans, including rate, trend, and impact. The rate of nonperforming loans can provide comparative analysis for trends and patterns within the banking industry (Poposka, 2015). An impact analysis can also indicate the adverse effects of nonperforming loans on profitability, loan loss provisions, and capital augmentation. The increasing trend of nonperforming loans is not likely to change as leaders in the banking industry extend diversification efforts by reaching out to both domestic and foreign customers (Polodoo, Seetanah, Sannassee, Seetah, & Padachi, 2015). Higher capital levels are necessary to absorb the losses stemming from default because of the risk from nonperforming loans (Polodoo et al., 2015). Nonperforming loans are a primary indicator of a bank’s credit risk, and the findings from the aforementioned studies support the choice of using nonperforming loans as an independent variable for this study.

Nonperforming loans and several other factors are measures of credit risk. Credit risk is significant for a bank, as a bank's assets are mostly loans (Makri & Papadatos, 2014). Credit risk exists because of the possibility of lost income when borrowers do not meet their financial obligations (Benazić & Radin, 2015). Through the probit model, the best way to measure credit risk is to select a variety of ratios, including net charge-offs to loans, credit loss provision to net charge-off, allowance to loan losses, loss allowance to nonperforming loans, and nonperforming loans to total loans. Nonperforming loans as a percentage of total loans was a significant variable for predicting bank failure during the U.S. financial crisis (Makri & Papadatos, 2014). Credit risk associated with nonperforming loans can increase the instability of a bank.

Credit risk is one of the main risks in commercial banks, and the ability to manage credit risk affects banks' stability. The nonperforming loan ratio is a traditional measure of risk in a bank's loan portfolio (Knapp & Gart, 2014). Credit risk is germane to a bank's operating performance and stability (Benazić & Radin, 2015). As part of the selection of risk, bank managers use credit assessment models to derive the probability that a borrower will default or not repay the loan. Despite the influence of macroeconomic factors, a credit assessment model can serve as an early warning indicator for nonperforming loans. A credit assessment model has a predictive accuracy of 98.06% at least 2 years prior to default. Nonperforming loans are bank loans granted to clients whose financial situation worsens for different reasons during the credit process (Makri, Tsagkanos & Bellas, 2014). In India, nonperforming loans affect the earnings capacity of banks and are indicators of a banking crisis (Reddy, 2015). These findings cause banking regulators concern about nonperforming loans and the potential risk associated with them.

The amount of nonperforming loans a bank has is a concern for banking regulators. High credit risk facilitates an unsustainable level of nonperforming loans, as well as further deterioration in a bank that could result in bank failure (Canicio & Blessing, 2014). Weak European banks exhibited signs of failure when a significant concentration of nonperforming loans existed (Apergis & Payne, 2013). Declining asset values increase a bank's credit risk resulting from nonperforming loans.

Bank managers secure loans using assets such as a residence, equipment, or furniture and fixtures well before the loan enters a nonperforming status. Bank managers begin to charge off many nonperforming loans after determining that many borrowers cannot meet the contractual terms of their agreements (Filip, 2014). The term *loan loss charge-off* refers to an accounting mechanism that bank managers use to recognize the financial impact on bank performance by charging off or recognizing the portion of a loan that has declined in value. Nonperforming loans and their subsequent charge-offs peaked during the downturn of the housing market. The increase in nonperforming loans that bank managers subsequently charged off occurred in the acquisition and development category and was the main catalyst that drove the decline in regulatory capital and failures of small and medium-size banks in 10 states between 2008 and 2011 (Dodaro, 2013). In December 2001, only 2% of acquisition and development loans at small failing banks were nonperforming (Dodaro, 2013). During the beginning of the 2008 financial crisis, the level of nonperforming acquisition and development loans increased rapidly to 11% by June 2008 and to 46% by June 2011 (Dodaro, 2013). Distressed economic conditions affect the ability of borrowers to repay their loans. An uptick in nonperforming loans is evident during an economic crisis, as some borrowers lose their jobs and have insufficient resources to repay obligations such as debt owed to banks.

Regulators and bank managers need more accurate and efficient early warning systems to predict bank failure. When testing for early warning signs of failure, the CAMELS proxies were less prominent than portfolio variables (Samitas & Polyzos, 2016). Portfolio variables such as real-estate loans are instrumental factors for determining the survival and failure of banks. A positive relationship exists between real-estate construction and development loans, commercial mortgages, and multifamily mortgages and bank failure (Samitas & Polyzos, 2016). Bank failures are likely to occur during an economic crisis, and absorption of capital is an additional concern during an economic crisis.

Loan losses contribute to the rapid absorption of capital. Rising levels of credit loss relate to nonperforming loans held by banks, and the subsequent charge-offs of these loans led to declines in regulatory capital at failing banks (Dodaro, 2013). For failed commercial banks and thrifts of all sizes nationwide, the credit losses that resulted from nonperforming loans were the largest contributors to the institutions' losses compared to any other asset class. The losses had a greater negative effect on institutions' net interest income and regulatory capital levels than those recorded at fair value.

Significant loan growth during stable economic conditions can mask the likelihood of nonperforming loans and other problem indicators. One study involved assessing the relationship between excessive loan growth and bank performance, including solvency, nonperforming loans, and profitability, in Colombian financial institutions between 1990 and 2011, and the findings indicated that nonperforming loans contributed to bank stress (Amador, Gómez-González, & Pabón, 2013). Amador et al. (2013) included a duration or hazard function model to determine the time to failure of financial institutions and an understanding of the relationship between abnormal credit growth and the probability of bank failure subsequent to a financial shock.

Nonperforming loans are a significant driver of a bank's financial health. Deteriorating asset quality, as measured by nonperforming loans to assets, contributes to bank failure (Samitas & Polyzos, 2016). In contrast, operational measures such as earnings and profitability were the most effective indicators of bank failure in the Philippines (de Claro, 2013). Asset quality is an indicator of bank distress, as increased loan originations did not improve earnings prospects (Kerstein & Kozberg, 2013). The volume of nonperforming loans hinders bank profitability.

The adverse effect of nonperforming loans is a national phenomenon. During the Colombian financial crisis in 1990, loan quality, measured by comparing nonperforming loans to total loans, declined at Colombian financial institutions (Amador et al., 2013). The crisis led to reduced capital and ultimately failure or absorption by another financial institution (Gomez-Gonzalez, 2012). Nonperforming loans adversely affected the profitability and liquidity funding needs of Nigerian banks during stressed economic conditions occurring between 1999 and 2001 (Toby, 2014). Nonperforming loans were a significant determinant of bank failure for Zimbabwe banks (Gumbo & Zoromedza, 2016). Nonperforming assets are a reliable indicator of a bank's asset quality (Growe, Debruine, Lee, & Maldonado, 2014; Rajeev & Subramoniam, 2016). These findings indicate that bank managers need to understand the probability of bank failure due to nonperforming loans.

Tier 1 leverage capital. Tier 1 leverage capital may be significant, as it is a risk management tool. Bank regulators require bank management to maintain capital levels to support asset growth and absorb losses, which includes stockholders' or common equity and the allowance for loan loss (Abreu & Gulamhussen, 2015). The intent of the Tier 1 leverage capital ratio is to capture both a bank's on-balance sheet and off-balance sheet risk exposure (Federal Reserve Board of Governors, 2013). The Tier 1 leverage capital ratio comprises Tier 1 capital to average total consolidated assets as reported on a bank's regulatory report minus amounts deducted from Tier 1 capital.

Cherpack and Jones (2013) found a significant relationship between Tier 1 leverage capital and bank survival. Banks with lower Tier 1 leverage capital failed at higher rates than banks with higher Tier 1 leverage capital. Tier 1 leverage capital could be significant, as it is a risk management tool. Bank regulators require bank managers to maintain capital levels to support asset growth and absorb losses, which includes stockholders or common equity and the allowance for loan loss (Abreu & Gulamhussen, 2015). The allowance for loan loss account is a contra account against the loan account on the balance sheet to fund bad debts such as nonperforming loans. The intent of the

Tier 1 leverage capital ratio is to capture a bank's on-balance sheet and off-balance sheet risk exposure (Federal Reserve Board of Governors, 2013). The Tier 1 leverage capital ratio comprises Tier 1 capital to average total consolidated assets as reported on the bank's regulatory report minus amounts deducted from Tier 1 capital.

Banking regulators assess and track capital positions continuously. Capital adequacy is one of the leading metrics that regulators use to assess the health of a bank. Low capital levels aligned directly to bank failures during the 2008 economic downturn (Cherpack & Jones, 2013). This finding concerning capital levels indicates that significant personal and corporate losses contribute to broader macroeconomic setbacks, and capital levels support a bank's ability to grow. Acquiring banks lack the resources necessary to originate new loans. Risky lending practices facilitate significant implications for the broader economy (Ilk et al., 2014). Acquiring banks must have sufficient capital to absorb failed banks' assets and liabilities without jeopardizing capital adequacy guidelines. Lack of capital can affect the stability of a bank.

Low capital levels can potentially lead to bank failure. The lack of sufficient capital to absorb and sustain losses arising from risky loans and other assets contributes to bank failure (Handorf, 2014). When losses occur on a bank's loans, profits and regulatory capital initially absorb the amount lost; however, if profits and capital are not sustainable, bank failure and loss of bank deposits can occur. The banking supervisory framework centers on regulating the capital reserve requirements of banks on a risk-weighted basis to prevent bank failure, and bank managers endure a capital charge relative to the riskiness of their activities, including loans and other assets (Huang &

Thomas, 2015). A relationship exists between lower capital as measured by equity to assets and a higher probability of failure (Samitas & Polyzos, 2016). Equity to assets is another metric researchers investigated to identify potential indicators of bank failures.

Banking regulators require banks to maintain a capital level that coincides with the risk profile. While the composition of assets is a component of a bank's risk profile, asset growth is the basis for regulatory capital standards (Amador et al., 2013). Bank managers must gauge, plan, and seek sources that could augment and sustain growth so that asset growth does not affect capital levels. A bank's capital ratios decline when exorbitant growth comes with funding that is costly or higher interest earning deposits. Unlike in other business organizations, bank managers serve as agents on behalf of depositors and ensure those funds are readily available at the request of the customers. Customer deposits facilitate bank growth that enables bank management to lend and invest funds in the absence of undue risk, and bank managers face challenges with capital management, particularly when reinvesting high-cost deposits or other borrowed funds into high-quality assets (Handorf, 2014). Assets growing at an unsustainable pace relative to capital could result in bank failure (Liu, 2015). Banking regulators require bank managers to increase equity capital, as many banks in the United States and Europe during the global economic crisis were on a path that could have led to bank failure (Cox & Wang, 2014). Maintaining correct capital levels is a concern for bank managers.

One method to ensure capital levels are at adequate levels is capital adequacy management. Capital adequacy management indicates the amount of capital that bank managers should maintain and the level available for supporting bank activities (Muller

& Witbooi, 2014). Bank managers must also manage capital for shareholders and regulators. Shareholders ascertain that using more capital will enhance the earning capacity of assets, which in turn facilitates maximum returns on equity. Consistent with safety and soundness expectations, regulators expect bank managers to augment capital to sustain losses and growth.

Capital measures are one of the primary tools banking regulators use to monitor a bank's financial health. The regulatory capital framework encompasses risk-based capital measures, including Tier 1 and total capital (Muller & Witbooi, 2014). The capital definitions for the risk-based measures influence both the quality and the quantity of capital (Camara et al., 2013). Banking regulators consistently update the capital standards with continuing emphasis on quantity and composition. The various measures of capital, including Tier 1 and Tier 2 capital, comprise several components; however, bank managers ensure the consistency of capital levels with the criteria for regulatory purposes (Muller & Witbooi, 2014). Certain items included in Tier 1 capital are not permissible for inclusion in Tier 2 capital and vice versa. Bank managers have the responsibility for ensuring capital measures are consistent with U.S. federal banking regulations.

Bank managers must comply with banking regulations and guidelines. U.S. federal banking regulators require bank managers to have well-capitalized institutions to avoid scrutiny (Khouaja & Boumediene, 2014). A well-capitalized bank has regulatory capital holdings that comprise at least 10% of its risk-adjusted loans, and the risk adjustment is applicable to the type of loan. Mortgages have a risk-adjustment weighting of 50%, so bank managers can lend twice as much in proportion to their regulatory capital holdings for mortgages than for other types of loans (Pakravan, 2014). Bank regulators classify assets held by banks into types and have different percentage capital requirements, which results in regulatory capital requirements that fit into two tiers of capital with different provisions and risk categorizations applying to the instruments held in them (Dodaro, 2013). An adequately capitalized bank under the national regulatory framework standards must have a ratio of at least 8% between its Tier 1 and Tier 2 capital reserves and its loans (Camara et al., 2013). Maintaining a specific ratio is important to a bank's stability. Without appropriate ratios, there is a potential for failure.

As discussed earlier, if bank managers maintain low capital levels, there is a possibility of bank failure. A bank fails when bank managers are unable to service outstanding debt or are incapable of sustaining risk-based capital adequacy minimum ratios, at which time the FDIC intervenes as the receiver (Ilk et al., 2014). FDIC officials frequently track a bank's capital adequacy by reviewing several risk factors. The risk factors include past and current financial condition, managerial resources, earnings prospects, the nature and size of off-balance sheet and funding risks that encompass derivatives and foreign exchange contracts, and unsafe and unsound banking activities (Federal Reserve Board of Governors, 2013). Additional monitoring methods are appropriate when evaluating capital levels.

Banking regulators have various monitoring mechanisms to track a bank's capital level. With respect to reporting requirements, bank managers regularly report the risk-based capital ratios on the FDIC's Call Report. The Board of Governors of the Federal Reserve System established the risk-based capital standards as the lower thresholds for the risk-based capital adequacy ratios (Federal Reserve Board of Governors, 2013). The minimum requirements can vary, but the Tier 1 leverage capital ratio typically ranges from 4% to 6% (Camara et al., 2013). The total capital ratio ranges from 8% to 10%, and the Tier 1 leverage ratio fluctuates from 4% to 5% (Ilk et al., 2014). Capital standards are important in banking because of the ability to predict default risk (Merle, 2013). In addition to capital standards, bank managers must consider capital reserves.

A bank's owners and shareholders provide equity capital reserves when creating the bank, and the reserves serve as a buffer to protect the bank's depositors against loan defaults (Huang & Thomas, 2015). Determining solvency involves using the ratios that measure Tier 1 and Tier 2 risk-based capital to risk-weighted assets (Amador et al., 2013). Bank regulators indicate that capital maintenance requirements are instrumental in regulating the risk-taking behavior of bank leaders to minimize bank failure, particularly during an economic crisis. Periods of sustained economic growth, at which time bank leaders engage in risky lending behavior, precede an economic crisis (Amador et al., 2013). Tier 1 leverage capital is a significant attribute in determining bank failure (Lu & Whidbee, 2013). This raises the question regarding the robustness of established regulatory capital guidelines given that the bulk of failures encompasses banks that did not have sufficient capital.

Banking regulators continuously focused and reassessed banking capital standards following the financial crisis in 2008. Since 2008, bank regulators have determined that more robust risk management practices were necessary to comply with capital regulations (Federal Reserve Board of Governors, 2013). Bank managers need to examine whether their banks have sufficient equity value or whether they need to start enhancing the equity-to-asset ratio by raising more capital or selling assets (Egami & Yamazaki, 2013). To satisfy the capital adequacy requirements, bank managers should monitor how much asset values deteriorated.

From the unexpected sharp declines in asset values during the 2008 financial crisis, determining when to undertake an action is an important but difficult problem. A bank's capital base is critical, as it is the last line of defense against uninsured depositor losses and general creditors. Capital adequacy is a measure of the level and quality of a capital base (Kandrac, 2014). Banking regulators pursued raising the capital standards following periods of economic distress.

Banking regulators determined that the composition of a bank's capital level and a bank's activities are important during distressed economic periods. Although the capital adequacy ratio in banking regulation is important for absorbing losses, some imperfections exist with the ratio during a subprime crisis (Khouaja & Boumediene, 2014). The ratio is easy to calculate and understand, but the events associated with the 2007 financial crisis cast doubts pertaining to the rigor of the measure (Abreu & Gulamhussen, 2015). Considering the doubts concerning the measures, banking regulators' sole reliance on this measure did little to alleviate bank failure. Developing and implementing stress test scenarios could supplement and improve the identification and accuracy of bank failure prediction models (Apergis & Payne, 2013). Banking regulators could gain further knowledge by focusing on the nature of bank activities and the implications for capital management.

Some regulatory measures reduce bank stability as a means to bolster bank vulnerability. A highly significant relationship exists between subordinated debts and the risk of failure, in that debt in the Tier 2 capital structure includes the increased risk of bank failure (Khouaja & Boumediene, 2014). Restrictions on bank activities increase bank distress by introducing subordinated debt in the Tier 2 capital and do not improve the stability of banks. Furthermore, subordinated debts are sensitive to market risk and an indicator of market discipline.

Bank managers are able to circumvent capital restrictions by taking excessive risks, especially as banks benefit from explicit and implicit guarantees, which encourages the managers to take excessive risks. A sole capital requirement cannot ensure banking stability (Camara et al., 2013). Strengthening the power of supervision and transparency requirements can act as a counterweight against excessive risk taking in banks (Khouaja & Boumediene, 2014). Systemic risk throughout a bank is also a concern for bank managers.

Banking managers engage in global banking activities that could make other banks connected to the financial system susceptible to losses. A link exists between large bank failure and systemic risk (Laeven, Ratnovski, & Tong, 2014). Bank managers essentially spread their risk to other banks by doing business with each other, which results in a contagion effect of losses or potentially bank failure. Bank capital influences systemic risk, as measured by the Tier 1 capital ratio (Alali & Romero, 2013). A higher capital ratio was important for reducing the systemic risk for large banks such as Countrywide Financial Corporation, Northern Rock, and Lehman Brothers (Laeven et al., 2014). In addition to systemic risk, capital adequacy is a topic of discussion among researchers.

Capital adequacy is a ratio that measures the weighted risk of credit exposure and is a major distinguishing factor of banks that survive versus those that fail (Adeyeye & Migiro, 2015). Banks absorb losses initially from profits on loans and secondarily from regulatory capital (Huang & Thomas, 2015). When profits and capital adequacy are insufficient to absorb losses on loans, banks could fail. Regulators deploy guidelines to ensure banks maintain adequate capital reserve requirements. Banks with high-leverage positions were likely to fail during the Netherlands financial crisis in the 1920s, as those banks did not have sufficient capital to sustain losses from risky assets (Colvin, Jong, & Fliers, 2015). Banks that maintain high equity-to-asset ratios are less likely to undergo financial distress (Rahman & Masngut, 2014). In contrast, one other researcher contended that regulatory capital measures such as the Tier 1 leverage capital ratio are not a significant predictor of distress for large financial institutions because of their subjective nature (Schenck, 2014). Nonperforming loans and operating efficiency are stronger determinants of default risk because they can show a portion of the variation in market-risk default measures.

The Tier 1 leverage capital ratio, along with both the risk-weighted and gross revenue ratios, strongly influences bank failure (Li, Chen, Chien, Lee, & Hsu, 2016). Furthermore, Li et al. (2016) showed that that the risk-weighted ratio was the most effective predictor of bank failure over long time horizons. Bank managers are less likely to engage in risky behavior with lower capital levels, as banking regulators restrict activities until such time that capital levels can be restored to healthier levels. The Tier 1 leverage capital ratio appears to be a better predictor of bank failure over a time horizon of less than two years.

Noncore funding dependence. Noncore funding dependence is a measure of a bank's liquidity. Net noncore funding dependence pertains to the difference between noncore liabilities and short-term investments relative to a bank's long-term assets (Horn, 2005). The basis of this concept is the premise that noncore liabilities are more suitable for funding short-term investments rather than long-term assets. Liquidity is another important component of assessing the performance of a bank. Bank liquidity is important, as it shows the ability of bank management to fund loans and deposits.

Noncore funding dependence is a reliable measure of liquidity. Bologna (2015) found banks with higher noncore funding dependence positively correlated with bank failure. Noncore funding dependence is a measure of a bank's liquidity. Net noncore funding dependence pertains to the difference between noncore liabilities and short-term investments relative to a bank's long-term assets (Horn, 2005). The underlying premise is that noncore liabilities are more suitable for funding short-term investments rather than long-term assets. The higher the reliance on less stable funding sources, the more likely a bank is to encounter financial distress (Bologna, 2015). Essentially, when a bank has more liquid assets on its balance sheet, its lending is minimally unlikely affected by other stressed market conditions (Bussière, Camara, Castellani, Potier, & Schmidt, 2015). Liquidity is another important component for assessing the performance of a bank. Bank liquidity is important, as it shows the ability of bank management to fund loans and deposits.

When measuring bank liquidity, bank managers and supervisors consider the level of loans, marketable assets, and deposits. Managers use the liquidity measure with the volume of loans relative to deposits to gain insights regarding concentration and default risk (Kerstein & Kozberg, 2013). When a bank's loan-to-deposit ratio is significant, bank regulators seek corrective action to alleviate further bank distress. The instability of funding sources signals financial vulnerability (Hahm, Shin, & Shin, 2013). The ratio of noncore deposits to total deposits is another measure of a bank's liquidity position that bank managers could use to obtain insights into high funding costs.

The literature review included a study in which researchers compared and contrasted two liquidity measurements, noncore funding dependence and the loan-to-deposit ratio, relevant for predicting bank failure. Li et al. (2013) assessed a bank's vulnerability in a bank failure prediction study using two measures of liquidity. The first measure of liquidity showed how liquidity resulted from costlier sources of funds, including nondeposit liabilities, as opposed to cheaper deposit sources. Li et al. noted that although this funding source comprising nondeposit liabilities was a favorable option for improving liquidity, such funding option negatively affected a bank's profitability, which improved the likelihood of bank failure. The liquidity funding structure comprising nondeposit liabilities parallels the noncore funding dependence variable presented in this study.

The second measurement of liquidity appeared more favorable for bank survival. The other liquidity measurement, calculated as the loan-to-deposit ratio, captures the bank's financing strategy where the funding for bank loans occurs through deposits, which is a less risky funding structure for bank managers to assume (Li et al., 2013). Li et al. (2013) noted that a sudden upward movement in the loan-to-deposit ratio could also signal trouble related to growth and unexpected funding needs, which would improve the likelihood of the bank's failure. Banking regulators' understanding of liquidity measures is essential for preventing bank failure.

Liquidity for surviving an economic crisis is essential for preventing bank failure. Bank managers can survive a bank failure when they maintain sufficient liquidity levels (Batavia et al., 2013). Liquidity is essential for surviving an economic crisis and for preventing bank failure. Bank managers encounter liquidity risks when the owners of these short-term and high-cost deposits are likely to leave the bank in search of higher interest rates. As a result, the bank managers may have to sell other assets to accommodate the funding source. Banks are intermediaries in which managers borrow in order to lend, and they must raise funding to lend to their borrowers (Hahm et al., 2013). When credit expands rapidly and exceeds the pool of available retail deposits, bank managers will turn to other generally more expensive sources of funding to support their bank's credit growth.

A bank's liquidity or level of cash and marketable assets could become strained or unavailable for operations when customers sense financial issues with a bank. This sense of distress by customers may cause those customers to withdraw their deposits, which will result in a liquidity crisis for the bank (de Claro, 2013). Determining the liquidity structure is a leading indicator for predicting bank failure (Davies, 2013). The alleviation of bank failure can occur when bank managers and regulators identify the appropriate funding structure.

A bank's liquidity position is predictable from both the asset and the liability components of the balance sheet (Bozh'ya-Volya & Maksimenko, 2015). Managers and regulators can use the behavioral characteristics of a bank's deposit base to determine its liquidity position, as well as a local customer base consisting of demand and savings deposits for sufficient funding sources. In contrast, more expensive or temporary large brokered or government deposits could strain a bank's liquidity position because of the potential of immediate runoff.

Researchers use statistical tests to understand the relationship between liquidity and bank failure. One empirical study involved logit regression analysis and showed that the liquidity ratio was a significant indicator of bankruptcy for firms in Jordan (Almansour, 2015). The study included a definition of liquidity as the net current assets of a company expressed as a percentage of its total assets or the difference between current assets and current liabilities. Almansour (2015) justified the liquidity ratio as a strong indicator of bankruptcy because managers reduce the current assets relative to total assets when businesses incur consistent operating losses. Banks are unique because of the various federal and state regulations. Part of a bank's function is to make loans and accept customers' funds in the form of deposits. The funding for loans comes from customer deposits. Credit risk belies banks when customers do not repay loans according to the terms of the agreement. Customers' deposits could be at risk if a bank loses significant funds because of bad loans. The result is that banks are subject to significant regulatory scrutiny. In the United States, the regulatory scheme includes a dual banking system whereby bank managers have the option of operating a bank using a charter by the federal government or by the state government (Jizi, Salama, Dixon, & Stratling, 2014). Federal banking regulators include the FDIC, the Federal Reserve Board of Governors (Federal Reserve), and the Office of the Comptroller of the Currency. The leaders of these organizations are in charge of overseeing banks chartered within their respective states (Dodaro, 2013). Banking regulators collectively establish rules and regulations and conduct periodic examinations to ensure compliance and operations take place in a safe manner (Jizi et al., 2014). The relative size of noncore deposits is an early warning indicator (Chung, Lee, Loukoianova, Park, & Shin, 2015). As described in a later section of this study, a bank's operations are subject to single and dual regulatory oversight to ensure the protection of customer deposits.

Bank Failures

The bank failure process is complex and overseen by banking regulators. The bank failure process involves the chartering authority or the FDIC regulators closing a bank's operations by redistributing its assets and liabilities and reimbursing its depositors (Ng & Roychowdhury, 2014). The leading indicators of bank distress and failures are in the form of both microeconomic and macroeconomic data. The data fit into three categories: ratios, market prices, and measures of bank risk and financial strength (Arabi, 2013). Authorities close a bank when its capital levels are critically below regulatory guidelines.

Indicators of bank failures. This section includes information on the dependent variable bank failure. First discussed are financial ratios as indicators of bank failure. The ratios used in this study served as proxies for three of the six CAMELS ratings used by FDIC regulators to identify distressed banks. The three ratings were capital adequacy, asset quality, and liquidity. Also discussed was the FDIC's bank closure process. The bank failure process involved the chartering authority or the FDIC regulators closing a bank's operations by redistributing its assets and liabilities and reimbursing its depositors (Ng & Roychowdhury, 2014). Authorities close a bank when its capital levels are critically below regulatory guidelines (Lu & Whidbee, 2013). The final topic included in this section is solving and preventing bank failures. Despite the confidential nature of bank examination ratings, regulators can use numerous proxies for the ratings to determine bank distress. A consensus exists that the CAMELS rating system is essential for predicting bank failure. The components in the CAMELS rating system are relevant proxies for predicting bank failure (Messai & Jouini, 2013). Such proxies include ratios that are specific to the banking industry from the balance sheet and income statement. For example, certain ratios are relevant to capturing capital adequacy, credit risk, risk management, liquidity, and income (Kerstein & Kozberg, 2013). These variables collectively influence the solvency of a banking organization, and understanding and assessing these measures provide insight into the economic climate of a bank's operating environment.

Use of financial ratios as indicators of bank failures. The financial performance indicators used to predict bank failures for this study were the nonperforming loans ratio, Tier 1 leverage capital ratio, and noncore funding dependence ratio. Managers of FDIC-regulated financial institutions must provide quarterly financial statements to various regulatory agencies in the format of a Call Report (Kerstein & Kozberg, 2013). The published Call Report was the primary source for the financial performance indicators used in this study.

The ratios used in this study served as a proxy for three of the six CAMELS ratings used by FDIC regulators to identify distressed banks. The three ratings were capital adequacy, asset quality, and liquidity. Banking regulators rate banks on a scale between 1 and 5 in each of the six CAMELS categories as well as by a composite ranking of all six (Alali & Romero, 2013). These ratings are confidential. The proxy for asset quality in this study was nonperforming loans. Nonperforming loans include past-due loans, bankrupt and quasi-bankrupt assets, and doubtful assets (Hajialiakbari et al., 2013). Loans are nonperforming when bank managers determine they have exhausted all sources for collecting repayment under the terms of the loan agreement (Neţoiu et al., 2013). The nonperforming asset ratio is total reported nonperforming loans to total loans. The higher the nonperforming loans ratio, the lower the perceived asset quality and the higher the probability of failure.

The proxy for capital adequacy in this study was Tier 1 leverage capital. The Tier 1 leverage capital ratio comprises Tier 1 capital to average total consolidated assets as reported on a bank's regulatory report minus amounts deducted from Tier 1 capital

(Federal Reserve Board of Governors, 2013). The lower the Tier 1 leverage capital ratio, the higher the probability of failure.

The proxy for liquidity in this study was noncore funding dependence. Noncore funding dependence is a measure of a bank's liquidity. Net noncore funding dependence pertains to the difference between noncore liabilities and short-term investments relative to a bank's long-term assets (Horn, 2005). The basis of this concept is the premise that noncore liabilities are more suitable for funding short-term investments rather than long-term assets. A higher noncore funding dependence ratio translates into a higher probability of bank failure.

Bank regulators can use financial ratios to provide the foundation for bank failure models. The extensive use of financial ratios to measure profitability, liquidity, and solvency raises concern because of the absence of guidelines that include the significance of their importance (Lin, Liang, Yeh, & Huang, 2014). The predictive quality of ratios can apply when examining the causes of bank failures.

Bank regulators can use financial ratios to enable the predictive power of bank failure models. A high nonperforming-loans ratio positively correlates with bank failure (Liu, 2015). Furthermore, individual bank performance ratios can apply during various economic stages. Bank regulators can use liquidity, profitability, and asset quality measures to predict bank failure during both precrisis and postcrisis periods (Batavia et al., 2013). Focusing on financial factors has limitations, and nonfinancial features add additional information.

Financial factors are mostly point-in-time measures. Thus, prediction models are inherently inefficient when the focus involves examining only financial features (Lin et al., 2014), although one instance exists of nonfinancial features, such as regulatory enforcement actions as a variable in a bank failure prediction model (Kerstein & Kozberg, 2013). Bank lobbying is also appropriate in a bank failure prediction model (Gregory & Hambusch, 2015). In some cases, profitability and earnings ratios are the most effective predictors of bank failures (de Claro, 2013). Regulatory enforcement features and ratios work well in models, and other financial indicators receive consideration. The major financial features for financial distress prediction include financial leverage, long-term and short-term capital intensiveness, return on investment, earnings per share, and debt coverage stability (Lin et al., 2014). These features were suitable because of their frequent use in previous studies on bankruptcy prediction and business-failure prediction, as well as their availability in the data set.

Purpose and function of U.S. depository institutions. Bank managers serve as stewards for bank stakeholders. Bank officials serve as mediators between savers and investors to stimulate the economy (Arabi, 2013). Bank managers have a dual role that involves acquiring and lending funds and regulatory scrutiny, which is necessary to prevent misuse or abuse (Arabi, 2013). Lending is relevant to the risks undertaken by commercial bank managers, and bank managers attempt to offset the risk through pricing decisions. The pricing decisions are the interest rates charged to customers that generally reflect the costs that arise from defaulting on the obligation. Defaulting adversely affects a bank’s credit quality and results in nonperforming loans (Dhal & Ansari, 2013). Default of the obligation results in borrowers' inability or unwillingness to comply with the contractual terms of the loan agreement, including both interest and principal. The interest charged on loans adds to a bank's economic prospects, including generating capital to meet regulatory guidelines, as well as providing investors and shareholders with a return on their investment. The source of funding for loans is customer deposits, and the repayment of loans aligns with the contractual terms of the loan agreement, which is essential to a bank's economic stability.

The concentration of bank lending in one industry or market sector could result in bank distress or failure. Many bank managers made loans to borrowers for purchasing residential home loans when the housing market was appreciating. However, when the U.S. housing market began to experience a significant decline in 2006, many banks became distressed because of excessive holdings of incorrectly priced loans concentrated in the mortgage industry for risk undertaken by the banks (Ng & Roychowdhury, 2014). The pricing or interest rates charged on mortgage loans during the housing sector boom did not adequately reflect risk or borrowers' ability to repay according to the contractual terms. Instead, bank lenders linked the pricing of loans to the underlying value of the residence, which at that time was experiencing significant appreciation. When borrowers stopped paying according to the terms of the contractual arrangement, the economic prospects for banks were nonexistent, as bank managers were unable to augment capital because of foregone income resulting from nonperforming loans (Dodaro, 2013). Nonperforming loans are prevalent during a financial crisis.

The pace of the 2008 financial crisis in the United States did not appear to be slowing down and could narrow even further because of the interconnectedness of banking activities among financial institutions. The United States had banking crises in the 20th and 21st centuries, commencing with the savings and loans in 1980 and the banking institutions in 2008 (Kerstein & Kozberg, 2013). The 2008 financial crisis led to a global recession in the United States and Europe.

Bank closure process. The complexities in identifying the factors for bank closing are minimal. The bank failure process involves the chartering authority or the FDIC regulators closing a bank's operations by redistributing its assets and liabilities and reimbursing its depositors (Ng & Roychowdhury, 2014). The leading indicators of bank distress and failures are in the form of both microeconomic and macroeconomic data. The data fit into three categories: ratios, market prices, and measures of bank risk and financial strength (Arabi, 2013). Authorities close a bank when its capital levels are critically below regulatory guidelines.

As mentioned in the previous section, banking regulators rely on the level of capital for triggering the closure of a bank. Banking regulators consider a bank's health, such as the level of capital, when closing a bank, and the bank regulators look at a bank's condition with respect to the level of regulatory capital (Abreu & Gulamhussen, 2015). Federal regulations stipulate that federal banking regulators close a critically undercapitalized bank within a 90-day period (Dodaro, 2013). Regulators view the level of regulatory capital as a bank's protection for sustaining losses on nonperforming loans and other assets. As such, regulators require banks to maintain certain capital thresholds commensurate with their risks to facilitate the safety and soundness of the banking system.

The preponderance of bank failures between 2008 and 2011 occurred within 10 states. Arizona, California, Florida, Georgia, Illinois, Michigan, Minnesota, Missouri, Nevada, and Washington experienced 10 or more bank failures between 2008 and 2011. Bank failures in the aforementioned 10 states collectively totaled 298 of the 414 bank failures in the United States between 2008 and 2011 (Dodaro, 2013). The most failures occurred in California, Florida, Georgia, and Illinois. The size of a bank as measured by assets is a factor that bank regulators also investigate.

Smaller banks have difficulty remaining solvent. The findings from one study indicated that 86% of the bank failures were smaller banks with assets of less than $1 billion (Dodaro, 2013). The cause of bank failures reflected on bank management's focus on achieving an aggressive growth strategy by way of risky residential mortgages (Dodaro, 2013). Although the size of a bank is a factor to consider, an economic impact exists when banks fail. Bank failures contribute to economic distress, and among the bank failures that took place between 2008 and 2010, insolvency aligned with the leading cause. Insolvency occurs when a bank's liabilities exceed its assets. Determinants of measures that predict credit risk are essential to preempt a future global financial crisis (Buncic & Melecky, 2013). Regulators need reliable measures to predict bank failure.

Statistical tests are relevant for studying bank failure. Cox and Wang (2014) included a discriminant analysis on the U.S. bank failures during the financial crisis of 2008–2010. Discriminant analysis (linear discriminant analysis and quadratic discriminant analysis) and a univariate *t* test show the mean differences for financial variables between failed and surviving banks. Cox and Wang showed evaluated models for accuracy in the classification of banks that survived and failed. Deploying such tests could assist regulators with enhancing existing early warning systems of financial distress.

Bank failure prediction models include proxies for the regulatory ratings, including capital, asset quality, liquidity, and profitability ratios. Although examination ratings remain unpublished, banking regulators publish data that depict risky or unhealthy bank conditions, and researchers evaluate the data using statistical models for predicting bank failure (Kandrac, 2014). The most appropriate model for regulators to predict failure and survival includes the following variables: real estate loans, growth rate of loans, equity capital to assets, size of bank, return on assets, loan loss allowance, nonperforming loans, net charge-offs, and foreclosures (Cox & Wang, 2014). In addition to the quantitative measures, qualitative measures apply in bank failure prediction models.

An association exists between bank failure and lobbying efforts. Bank managers engage in riskier activities when lobbying efforts result in favorable regulations (Gregory & Hambusch, 2015). Favorable regulations could result in lax lending standards, thereby causing bank managers to make riskier loans. Using a survival analysis theory, Alali and Romero (2013) found that banks with high nonperforming loans to assets, a high loan-to-deposit ratio, and a high equity-to-asset ratio are likely to fail (Alali & Romero, 2013). Statistical analysis is still mandatory for assessing the relationship between bank performance measures and bank failure.

Statistical regression models are suitable for assessing the relationship between bank failure and financial measures. The country-specific models are appropriate for establishing the relationship between variables (Buncic & Melecky, 2013). The model includes a diverse scenario for conducting stress tests using nonperforming loans of commercial banks. The researchers looked at various underwriting practices and probability of default scenarios during stress periods and measured the bank's resilience against nonperforming assets relative to capital adequacy (Buncic & Melecky, 2013). In contrast, the findings in another study indicated that the asset quality variables, such as nonperforming loans, lose predictive power when other variables are present in the bank failure prediction model (Kerstein & Kozberg, 2013). The nonperforming loan rate can reasonably represent the default risk of commercial banks (Buncic & Melecky, 2013). The nonperforming loan factor is an important indicator to evaluate the status of portfolios in commercial banks. As the nonperforming loan rate increases, bank managers take higher risks to call in loans.

Outbreaks of corporate financial crises worldwide intensified the need to reform the existing financial architecture. Business crisis prediction is a challenging problem that stimulated numerous studies over the past few decades (Lin et al., 2014). A general belief exists that symptoms and alarms occur prior to a business encountering financial difficulty or crisis, which is why a need remains for additional research on the topic of bank failures.

Roles and Responsibilities of U.S. Banking Regulators

This section includes information on the role and responsibilities of banking regulators. Essentially, this portion of the literature review shows the need for continuous improvement to the banking supervision framework. This section concludes with information on the prevention of bank failures.

Bank regulations and monitoring. Global banking regulators are instrumental in implementing regulations to ensure depository institutions operate safely. U.S. federal banking regulators coordinate with global financial institution supervisors to manage systemic risk (DeYoung et al., 2013). Bank capital regulation is fundamental to ensuring financial stability. Capital formation includes the agents necessary for absorbing operational losses. The basis of the global regulatory frameworks known as Basel II, implemented in Europe in 2008, and Basel III are appropriate for strengthening capital at banks (Huang & Thomas, 2015). Capital levels were insufficient to sustain bank losses during the 2007 financial crisis. The lack of capital triggered a need for regulators and signaled the need for a rigorous capital framework to sustain the challenges associated with significant economic events (Camara et al., 2013). Banking regulators continuously monitor a bank's capital position for signs of distress.

Banking regulators have a dual role in protecting depositors and the FDIC insurance fund. FDIC regulators provide insurance for the deposits of all federally insured banks up to $250,000 per depositor. The FDIC incurs significant expenses when a bank fails, ultimately borne by taxpayers. Despite the charter selection, federal oversight is prominent. As described in the next section, questions have arisen regarding the competency and ability of banking regulators to oversee the health of banks effectively.

Banking regulators faced intense scrutiny when several banks weakened or failed during the 2007 economic crisis. The prominence of regulators could influence their role in a bank's governance practices (John, De Masi, & Paci, 2016). Banking regulators' credibility was in question with respect to the intensity or scrutiny of the banking institutions supervised in light of the distressed conditions during the 2007 economic crisis and prior economic events.

The banking regulators use both on-site and offsite tools to supervise banks. The most common tool is an on-site bank examination that takes place at least annually in which bank examiners review banks' financial records (Alali & Romero, 2013). Federal banking regulators use on-site examinations as a tool to monitor bank performance. After the review is complete, the bank receives a rating. The examinations are a micro prudential supervisory tool that results in a CAMELS rating that reveals the condition of a bank on a scale of 1 through 5. The rating applies to the CAMELS categories (Agarwal et al., 2014). The assigned rating is confidential and not disclosed to the public.

Despite the confidentiality of the bank examination ratings, proxies or attributes of the CAMELS rating are available in the Call Report, the Uniform Bank Performance Report, and the U.S. Securities and Exchange Commission's Form 10K. The published reports contain the balance sheet, income statement, financial ratios, and financial footnotes and disclosures for each bank (FDIC, 2016). These reports include equity capital, nonperforming loans, regulatory enforcement actions, net income, investments, and interest rate risk financial footnotes and disclosures. The information could show users a bank's financial performance. Proxies for the CAMELS rating are historically important determinants of bank failure, as banks with higher capital ratios, low nonperforming assets, significant liquidity sources, and strong earnings performance are less likely to fail (Samitas & Polyzos, 2016). Federal banking regulators coordinate with global regulatory authorities to manage systemic risk given the interconnectedness of banking institutions. The results of the global financial crisis revealed the fragilities of the existing supervisory framework, thus necessitating coordinated regulatory efforts and robust monitoring tools.

Existing bank monitoring tools did not provide sufficient early warning during the economic crisis. Many stakeholders blamed the regulators as well as the bank managers for the bank failures (Massman, 2015). Regulators received criticism for not having adaptable systems that forewarn of bank distress and bank managers did not escalate issues quickly enough to allow the regulators to implement corrective action. Given the international competitiveness of banks, the sudden reduction in services, including funding loans, weakens economic prospects both domestically and abroad (Chennells & Wingfield, 2015). The interdependence of the United States and global economies during the 2007 economic crisis prompted financial institution regulators to implement processes and procedures to contain future shocks on the banking system (DeYoung, Kowalik, & Reidhill, 2013). The significant economic costs emanating from the 2007 financial crisis were the impetus that shifted the focus, purpose, and priorities of the financial regulators

(Pakravan, 2014). The infrastructure was both fragile and not able to absorb and overcome the effects of future financial catastrophes.

The financial regulators and the global regulators discerned that both an orderly resolution and the appropriate mix of regulations were essential for preventing bank failures (DeYoung et al., 2013). As a result, the bank regulators and other global financial services supervisors devised a robust and supervisory proactive framework, including the Wall Street Reform and Consumer Protection Act (the Dodd-Frank Act), adopted and implemented in 2010. Bank regulators also updated the Basel Accord global regulatory framework with guidelines that pertained to strengthening capital adequacy levels at banking organizations. The intent of the Dodd-Frank Act and the Basel Accord was to preserve the financial system through increased regulatory coordination and oversight, as well as managing systemic risk and developing contingency plans for liquidating large financial services institutions (Pakravan, 2014). Capital standards are integral for the bank regulatory framework.

Developing and enhancing a bank's capital standards became the focus following the economic crisis. The global financial crisis led the way for banking regulators to reform the regulatory framework to ensure banks had sufficient capital to withstand turbulent economic challenges (Camara et al., 2013). Banking regulators deployed a reactionary plan for crisis management and focused on deploying regulations and tools to keep banks from failing (Repullo & Suarez, 2013). The banking regulators' supervisory framework was not sustainable during an economic crisis, and the stakeholders contended that the existing framework was counterproductive during an economic cycle.

Developing and implementing proactive or holistic plans is appropriate to minimize adverse economic effects. Some of the recommendations include banks maintaining higher capital to absorb losses as well as curtailing lending during an economic crisis (Huang & Thomas, 2015). Stakeholders viewed bank regulators as contributing to the economic crisis and resulting bank failures because of their micro prudential supervisory framework (Repullo & Suarez, 2013). Banking regulators' existing regulatory framework limits bank managers from lending because of higher capital requirements, which in turn causes business owners to halt expansion, resulting in higher unemployment (Buncic & Melecky, 2013). The higher capital requirements translate into reducing a bank's profitability and limit the process to stimulate the economy during a recessionary period.

The supervisory framework should highlight capital adequacy. Achieving and maintaining certain capital benchmarks could help banking regulators improve existing early warning systems (Merle, 2013). Mandatory capital requirements are a reference point for an early warning system, as the indicators could facilitate the early detection and cure of bank distress in a timely manner (Camara et al., 2013). The framework includes banks having uniform capital requirements as a measure that could provide regulators with advance warning (Li et al., 2016). This supervisory approach could cause less disruption to the economy, as banks are able to continue normal business operations, such as making loans and accepting deposits. A comparative analysis of the mandatory capital levels with subsequent and self-imposed capital increases could serve as an early warning sign of bank distress.

Prevention of bank failures. Despite the confidential nature of bank examination ratings, regulators can use numerous proxies for the ratings to determine bank distress. A consensus exists that the CAMELS rating system is essential for predicting bank failure. The components in the CAMELS rating system are relevant proxies for predicting bank failure (Messai & Jouini, 2013). Such proxies include ratios that are specific to the banking industry from the balance sheet and income statement. For example, certain ratios are relevant to capturing capital adequacy, credit risk, risk management, liquidity, and income. These variables collectively influence the solvency of a banking organization, and understanding and assessing these measures provides insight into the economic climate of a bank's operating environment (Kandrac, 2014). By using logistic regression analysis, regulators may be able to predict the probability of bank failure years in advance.

Logistic regression aligned to weight the six financial indicators into a composite measure of failure from the bank failures that began in 2008 (Di et al., 2016). The analysis showed that failed banks maintained less Tier 1 leverage capital and less net income, with each measurement as a percentage of total assets and less cash and securities as a percentage of total deposits than banks that did not fail. The regression model results in a prediction of the likelihood of failure, which accurately predicts failure or survival at 98% (Di et al., 2016). The data showed that banks with more loans and leases as a percentage of total assets and a higher allowance for loan losses as a percentage of total loans than their counterparts survived. The allowance for loan loss, which is an indicator of asset quality, affects profitability because the funding derives from profitability.

A relationship exists between bank failure and the variability in profitability. Bank managers should increase their awareness of budgeting and cost-saving measures during an economic crisis and assess the impact of external market factors (Laeven et al., 2014). A downturn in the economy challenges the survivability of banks. More specifically, bank-specific variables, including interest rate risk, liquidity risk, capital risk, and credit risk, affect bank profitability (Buncic & Melecky, 2013). The logit regression applies to analyze other markets as well.

Ilk et al. (2014) applied logit regression to predicting bank failure in Turkey. The logit regression model was statistically significant at the 95% confidence level for revealing the probability of Turkish bank failures (Ilk et al., 2014). Financial ratios show that bank failure increases as income to average total assets, total income to total expenditure, and provisions for taxes to total income decrease (Luo, Zhang, & Zhu, 2016). By using logit regression models, bank regulators may predict and potentially avoid bank failures.

When regulators take preventive measures early in the process, they can either prevent the bank from failing or reduce the cost to taxpayers. Finding solutions to bank failure could transcend efficiency among regulators as well as reduce the cost to taxpayers when distinguishing between failing banks and surviving banks (Özel & Tutkun, 2014). However, stakeholders did not view the enhanced capital framework as a solution to fixing the early warning system given the complexities and continuous revisions involved.

The regulatory infrastructure could also surround specific and measurable objectives. Regulators could simplify the capital framework by using a less complex tangible common equity capital ratio (Pakravan, 2014). To achieve effectiveness, the regulatory framework must balance supervisory objectives and appear comprehensive. Focusing on systemic risk appears more appropriate for managers than bank failure, particularly when coordination occurs with other regulators. An effective supervisory approach could provide indicators that signal bank distress, which then permits sufficient time for resolution and intervention mechanisms (Petitjean, 2013). Banking supervisors have a measureable framework that can facilitate reviewing compliance with regulations (Khouaja & Boumediene, 2014). Banking regulators continue to make continuous refinements to the regulatory framework.

Methodology

The methodology used for this study was quantitative. A review of the literature showed that previous studies use a quantitative methodology to address bank failure (Alali & Romero, 2013: Cox & Wang, 2014; Kerstein & Kozberg, 2013; Lu & Whidbee, 2013). In a bank-failure prediction model, data come from published quarterly financial reports. Specific regulations require bank managers to submit quarterly financial statements of Call Reports to the FDIC, and the data are publicly available on the FDIC website. The data derive from the Call Report to capture or proxy the confidential bank examination (CAMELS) rating. To illustrate, the proxy for capital was equity as a percentage of assets. The proxy for asset quality was nonperforming loans. To capture earnings and liquidity, net income as a percentage of assets and loans as a percentage of deposits, respectively, emerged. Data were essentially taken from the Call Report to substitute for the components of the CAMELs rating (Kerstein & Kozberg, 2013). The statistical analysis included correlations among the independent variables (proxies) and the dependent variable bank failure.

Statistical analyses underpin bank failure prediction studies. Researchers commonly apply a series of logit regression techniques to identify and assess the cause of failure (Lu & Whidbee, 2013). The independent variables consist of publicly available financial ratios and a binary outcome or dependent variable. The binary outcome or dependent variable could assume only two possible values: 0, meaning no or failure, and 1, meaning yes or not failed. The result of the methodology shows the likelihood of failure over a 1-year time horizon. Consistent with the theoretical proposition for this study, bank failure is likely with higher nonperforming loans, lower Tier 1 leverage capital, and higher noncore funding dependence.

A review of the literature did not show complexities with using the quantitative methodology in bank failure prediction studies. What emerged was that the practical application and use of the quantitative methodology is relatively simple given that the data requirements are easily retrievable from publicly available sources (West, 1985). In the case of this study, the data came from published financial reports available on the FDIC's public website. The collection of data must have a clear definition of failure and specifications of the population from which a researcher selects the banks (Rankov &

Kotlica, 2013). The FDIC publishes a listing of failed banks. The next step was to collect the financial reports that contain the ratios.

Transition

Section 1 included the theoretical proposition, variables, and seminal works that bank regulators can use to predict bank failures. Included in the literature review was information on the three independent variables, nonperforming loans, Tier 1 leverage capital, and noncore funding dependence, and the dependent variable, bank failure. The review included information on the roles and responsibilities of banking regulators, as well as the purpose of U.S. depository institutions. The literature review included synthesis and information of the theoretical proposition and other seminal works on bank failure prediction. The literature review also included support for using the independent variables for inclusion and relevance in predicting bank failure.

Existing longstanding measures such as bank examinations and off-site monitoring are insufficient for predicting bank failure (Agarwal et al., 2014). Banking regulators could determine the probability of bank failure using the supervision-by-risk approach. The supervision-by-risk approach provides a greater risk monitoring frequency (Petitjean, 2013). Risk is a conditional probability of future loss (Ilk et al., 2014). The probability of bank failures becomes the logical metric for bank regulators to assess the financial condition of individual banks (Ilk et al., 2014). The deployment of off-site models has become increasingly appropriate to monitor the safety and soundness of banks between on-site examinations. The underlying theory is that banking regulators can use key financial performance measures immersed in the income and balance sheet statements for a direct estimate regarding the probability of failure (Rahman & Masngut, 2014). The next two sections will include a description of the project, the data analysis, and the results.

Section 2: The Project

Section 2 will begin with an overview of the project, including the role of the researcher, participants, research method, research design, population, and sample size. This section will also include information related to ethical research, instrumentation, data collection technique, and data analysis. I will conclude this section with a discussion of the study's validity and an overview of Section 3.

Purpose Statement

The purpose of this quantitative correlational study was to examine if nonperforming loans, Tier 1 leverage capital, and noncore funding dependence predict the likelihood of bank failure. The targeted populations were federally-insured depository institutions in the United States that failed or survived between 2012 and 2015. The implications for positive social change of this study include the potential to provide leaders of small businesses with easier access to loans, which could help those businesses thrive, and in turn, create more jobs within the community.

Role of the Researcher

The role of a researcher in a quantitative correlational study is to collect and analyze data using a series of steps that other researchers can replicate (Hamilton, 2016). In this quantitative study, my role was to collect secondary data from the FDIC's Call Report located within the Bank Data and Statistics section of the FDIC's public website. The scholarly literature related to predicting bank failure includes the FDIC website as a data collecting resource (see Alali & Romero, 2013). Kerstein and Kozberg (2013) downloaded the bank data for their bank failure prediction study from a public website.

Bank data obtained from the public website are expressed as ratios (Makri & Papadatos, 2014). Using existing data is appropriate and cost efficient, as long as the data can actually answer the research questions (Cheng & Phillips, 2014). The data examined in this study were publicly available and helped to predict which banks are at risk of failing.

Currently, I am a financial institution regulator with 30 years of experience; I understand financial institution risk metrics and regulatory examination protocol. Bank regulators perform periodic reviews of a bank's financial condition (Jenkins & Ong, 2014). In this study, I drew on my own experience, and that of others, to select variables that seemed most likely to predict which banks are at risk of failure.

The role in reflecting ethics is to access data that are available to the public instead of confidential or sensitive data. The *Belmont Report* protocol was not applicable, as my role in this study involved collecting archival data, which did not require human participants to understand and apply the data. Human participants are nonessential for understanding and applying data for bank failure prediction studies (Di et al., 2016). The financial ratios that I collected to conduct this study were publicly available and derived from nonconfidential or nonsensitive information. I did not have access to confidential bank examination reports and did not attempt to gain access in connection with my role as a researcher for this study.

Participants

I did not include human participants in this study; instead, I included data from the FDIC's website, which is a commonly-used repository for data on individual banks (see Kerstein & Kozberg, 2013). Researchers often use secondary data and information from government websites in research studies (Ellram & Tate, 2016). For example, Cox and Wang's (2014) study on the prediction of bank failure included data from the FDIC website. Financial performance measures for individual banks are accessible by downloading the data from the FDIC's public website (Lin & Yang, 2016). The strategy for obtaining the data is simple: The researcher navigates to the FDIC website and downloads the information (Kerstein & Kozberg, 2013).

The sample for this study consisted of 250 commercial banks, including 201 that survived and 49 that failed between 2012 and 2015. The data I downloaded from the FDIC's website included three independent variables, (a) nonperforming loans, (b) Tier 1 leverage capital, and (c) noncore funding dependence, and one dependent variable, whether the bank failed in 2009. In this study, my strategy followed the practice in previous bank failure prediction studies (Alali & Romero, 2013; Makri & Papadatos, 2014). The data were free of charge (see Lu & Whidbee, 2013) and no permission was necessary (see Petitjean, 2013). As the data consisted entirely of publicly available financial records, I did not need to identify strategies for establishing a working relationship with participants. Researchers conducting studies on bank failure use published financial data, rather than human participants (Cheng & Phillips, 2014; Kerstein & Kozberg, 2013; Samitas & Polyzos, 2016). Published financial data, rather than human participants, were appropriate because my aim was to examine the effects of financial factors on financial outcomes, not the opinions or behavior of human actors.

Research Method and Design

Research Method

The research method I chose for this study was quantitative. This method was appropriate because the research question was whether a combination of quantitative independent variables can predict a quantitatively measureable outcome: the likelihood of bank failure. Quantitative data include variables expressed as ratios (Hagan, 2014). Providing explanations or predictions, and generalizing from samples to populations, are among the principle aims of quantitative analysis (Barnham, 2015). Researchers using quantitative methods can use credible and objective sampling methods to validate the statistical significance of the data (Elo et al., 2014). In this study, I included a random, stratified sample drawn from the best publicly available database; consequently, the quantitative method was appropriate because the purpose of the study was to analyze numerical data and infer the results to a larger population.

In contrast to quantitative methods, qualitative methods are appropriate when the research intent is to explain the experiences and attitudes of people, answer a question about a phenomenon, and generate words rather than numbers as data for analysis (McCusker & Gunaydin, 2015). The mixed-method approach includes attributes of both quantitative and qualitative methods (Maxwell, 2016). Researchers only use the qualitative research method because of their inability to collect verifiable and objective data (Elo et al., 2014). A qualitative approach was not appropriate for this study because the research question I explored had nothing to do with people's experiences or attitudes; instead, the question under study was whether a set of quantitatively-defined financial conditions predict a quantitatively-defined financial outcome. Therefore, the qualitative method and the qualitative portion of a mixed-method approach were inappropriate for this study, and a quantitative method was the only logical choice.

Research Design

In this study, I used a correlation design. A correlation design involves examining the relationship between or two or more variables (Bosco et al., 2015). The correlation design was appropriate because my objective was to examine whether a statistically significant relationship exists between nonperforming loans, Tier 1 leverage capital, and noncore funding dependence (the independent variables) and bank failure (the dependent variable). A correlation design is a practice that researchers commonly use to identify associations among variables (Babajide, Olokoyo, & Adegboye, 2015). Furthermore, a correlation design is prominent in bank failure prediction studies (Kerstein & Kozberg, 2013). Therefore, a correlation design was the most suitable choice for this study.

A causal-comparative design might appear to have been an alternate option for this study but was not appropriate. In a causal-comparative research design, a researcher demonstrates that a statistically significant relationship exists among variables and makes the further claim that variations in scores among the independent variables are the cause of variations in scores for the dependent variable (Kozlowski, Chao, Grand, Braun, & Kuljanin, 2013). Furthermore, a causal-comparative research design is used when researchers want to study the direct, indirect, and mediating relationships between the variables (Türker, Duyar, & Çalik, 2012). I made no such claim in this study and did not include the aforementioned types of relationships. As predicted, bank failure correlates with nonperforming loans, Tier 1 leverage capital, and noncore funding dependence and the results of this study showed that these independent variables are predictors, not necessarily causes, of bank failure.

For the same reason, I did not use any sort of experimental design. Experimental and quasi-experimental designs are appropriate when a researcher seeks to assess a degree of cause and effect (Flannelly & Jankowski, 2014). A multiple methods design is appropriate when the researcher applies more than one method to answer the research question (Wahyuni, 2012). The objective of this study was to identify a predictive model, not a causal explanation; thus, the experimental and quasi-experimental designs and the multiple methods design were not appropriate.

Population and Sampling

The population for this study consisted of 5,338 federally-insured depository institutions in the United States listed on the FDIC's website in 2015. The website includes information on banks by year and by state. The FDIC's listing of commercial banks is available to the public (Cox & Wang, 2014). The FDIC's listing of commercial banks is the population commonly used by researchers conducting bank failure prediction studies (Samitas & Polyzos, 2016).

To use the website to conduct a bank failure prediction study, a researcher selects a sample of banks from the population using specific parameters (Lu & Yang, 2012). In the case of this study, the population aligned with my overarching research question concerned with identifying a correlation between the three independent variables nonperforming loans, Tier 1 leverage capital, and noncore funding dependence and the dependent variable bank failure. A correlation design involves examining the relationship between or two or more variables (Bosco et al., 2015). The variables underpin the financial statements of the banks (Kerstein & Kozberg, 2013). For this study, the independent variables for the banks appeared as ratios (see Arabi, 2013).

The sample for this study came from the FDIC's website that I created by using a combination of two approaches: a census of all banks that failed between 2013 and 2015 (a total of 49 banks) and a simple random sample of 201 banks, drawn from the same FDIC list, that did not fail in those years. In a census, the researcher collects complete information from all cases in the population (Pantoja, Rosa, Reinemann, & Ruegg, 2012). The strength of using a census is that it provides a true measure of the entire population (Asadollahi et al., 2015). There is no possibility of sampling error (that is, a disparity between the population of interest and the smaller sample of that population selected for the study; Asadollahi, et al., 2015), and therefore, no uncertainty about whether the findings in the sample are generalizable to the population because the entire population has been studied. There are no weaknesses to the census approach for the aforementioned reasons.

For the banks that did not fail, I used a simple, random sampling technique. I started with a numbered list taken from the FDIC website of the 5,338 banks that did not fail in 2015. I selected 201 banks from the list using a random number generator. The strengths of the random sampling procedure are that it is the best way of reducing the possibility for bias in the selection of cases for the sample and ensuring the sample is representative of the larger population (Gheondea-Eladi, 2014). This, in turn, allowed me to generalize from the sample to the population. The weakness with the random sampling procedure arises when the sample is not large enough to represent the entire population (Robinson, 2014). However, the sampling procedures that I used in this study gave every bank in the population an equal likelihood of appearing in the sample, which made the weaknesses unlikely. For both sampling procedures, the strengths outweighed the weaknesses. There was a single, complete list of FDIC-insured banks; for that reason, it was not necessary for me to construct the list from multiple sources. The list was publicly available, and I had no difficulty gaining access to it. There was no human population involved; consequently, there was no difficulty contacting participants on the list.

I used a sample of 250 banks, including 49 that failed, and 201 that did not fail, between 2013 and 2015. Logistic regression requires a minimum sample size of 200 data collection points (R. Taylor, personal communication, January 26, 2017). I used a random number generator to create the sample of 201 banks that did not fail. A random number generator is a statistical software package used by researchers to generate random numbers based on a defined set of criteria (Monroe, 2017). A review of similar studies showed researchers used a random sample generator to create the sample for banks that failed (Arabi, 2013; Babajide et al., 2015; Cox & Wang, 2014; Luo et al., 2016; Samitas & Polyzos, 2016). Researchers conducting a similar study on predicting bank failure also used a sample of failed banks obtained from the FDIC website (Alali & Romero, 2013). As described previously, the FDIC website is appropriate for selecting the sample size. Downloading publicly available financial data from the FDIC website is a common practice for researchers conducting studies on bank failure. The sampling method and approach was appropriate for this study.

Ethical Research

This section includes ethical considerations. Ethical considerations for research with human subjects typically include such issues as informed consent, voluntary participation, incentives for participation, procedures for withdrawal from the study, and confidentiality (Nunan & Yenicioglu, 2013); none of these were relevant for this study. The data needed for this study were historical records compiled for the Call Report that were already collected and publicly available on the FDIC website. The FDIC's website is the source for data regarding banks that failed during the financial crisis that began in 2008 and lasted through 2010. Researchers offer incentives to individuals for participating in research (Ardern, Nie, Perez, Radhu, & Ritvo, 2013). As the data were already collected and publicly available, safeguards for voluntary participation, incentives for participation, procedures for withdrawal from the study, confidentiality, and the potential for harm were not an issue. Researchers who previously conducted studies on predicting bank failure obtained data from the FDIC's website (Cox & Wang, 2014). Two hundred fifty banks, including 201 surviving banks and 49 banks that failed between 2012 in 2015, comprised the sample for the study for which the information was publicly available; therefore, the study did not include individual participants and a consent form was not necessary. Researchers conducting bank failure prediction studies did not use individual participants or obtain consent forms because the data were publicly available (Babajide et al., 2015). The data gathered and analyzed for this study will remain secured for 5 years using password protection for the electronic files and will not include any identifiable information of individuals or organizations. The protocol for securing research data includes storage on local hard drives, departmental servers, or equipment hard drives (Buys & Shaw, 2015). The Walden University Institutional Review Board approval number was 04-19-17-0291927.

Instrumentation

This study did not include instruments such as surveys, questionnaires, or other data collection mechanisms; instead, the approach used mirrored the common practice of obtaining data from public websites. I used the data from the FDIC's publicly available database that contained bank performance measures for the study (FDIC, 2016). The independent variables were nonperforming loans, Tier 1 leverage capital, and noncore funding dependence. Researchers commonly use these variables to conduct research for bank failure prediction (Samitas & Polyzos, 2016). The dichotomous dependent variable was bank failure or survival. The data that comprised the model came from the FDIC's website, downloaded for the Uniform Bank Performance Report via the Call Report.

The purpose of this study was to examine if nonperforming loans, Tier 1 leverage capital, and noncore funding dependence predict the likelihood of bank failure. These three predictor variables, which can be calculated from publicly available data on the FDIC website, are related to the CAMELS rating system, which the FDIC uses to rate the financial health of banks.

The three variables used in this study, the nonperforming loans ratio, the Tier 1 leverage capital ratio, and the noncore funding dependence ratio, are related to the

CAMELS ratings of asset quality, capital adequacy, and liquidity. Previous studies have included similar measures of asset quality, capital adequacy, and liquidity (Cox & Wang, 2014; Kerstein & Kozberg, 2013; Samitas & Polyzos, 2016).

- *Nonperforming loans ratio* was used as the proxy for the CAMELS rating of asset quality. Nonperforming loans include past-due loans, bankrupt and quasi-bankrupt assets, and doubtful assets (Hajialiakbari et al., 2013). The nonperforming loans ratio is calculated as total reported nonperforming loans divided by total loans (Filip, 2014). The higher the nonperforming loans ratio, the lower the perceived asset quality and the higher the probability of failure.
- *Tier 1 leverage capital ratio* was used as the proxy for the CAMELS rating of capital adequacy. The Tier 1 leverage capital ratio is calculated by dividing its tier 1 capital by its total risk-weighted assets, as reported on a bank's regulatory report (Federal Reserve Board of Governors, 2013). The lower the Tier 1 leverage capital ratio, the higher the probability of failure.
- *Noncore funding dependence ratio* was used as the proxy for CAMELS rating of liquidity. The noncore funding dependence ratio is the difference between non-core liabilities and short-term investments, divided by long-term assets (Horn, 2005). A higher noncore funding dependence ratio translates into a higher probability of bank failure.
- Bank failure or safety was the dichotomous dependent variable.

This study did not include instruments such as surveys, questionnaires, or other data collection mechanisms.

Asset quality was measured as the ratio of nonperforming loans in a bank's loan portfolio to the amount of outstanding loans (Filip, 2014). Capital was measured by the ratio of Tier 1 capital to average total consolidated assets minus amounts deducted from Tier 1 capital (Federal Reserve Board of Governors, 2013). Liquidity was measured by the difference between noncore liabilities and short-term investments, divided by long-term assets (Horn, 2005). Previous studies have included similar measures of asset quality, capital, and liquidity (Cox & Wang, 2014; Kerstein & Kozberg, 2013; Samitas & Polyzos, 2016). The dichotomous dependent variable was bank failure or safety. The raw data for this study are publicly available at the FDIC website. This study did not include instruments such as surveys, questionnaires, or other data collection mechanisms.

I downloaded the bulk data consisting of ratios using an identification number for each bank in the sample onto an Excel spreadsheet. The FDIC public database contained ratios commonly used to conduct research for bank failure prediction (Samitas & Polyzos, 2016). I then imported the data into SPSS for statistical analysis. I collected and analyzed data for 2014 and 2015. The period between 2008 and 2009 was the height of the financial crisis in the United States; during this period, a significant number of U.S. banks failed. This is a well-known historical phenomenon: bank failures typically increase during economic or financial recessions, such as the 2008 financial crisis (Cox & Wang, 2014). The period between 2014 and 2015 was a more prosperous time with far fewer bank failures. I imported the data from the FDIC website into SPSS for statistical analysis. I collected data on the independent variables and used these data to predict, via logistic regression, which banks would fail and which would survive in 2015. Analyzing sample statistics is a common approach for studies on bank failures (Kerstein & Kozberg, 2013). The approach I used mirrored the commonly used practice of obtaining data from public websites.

The analysis included three financial variables: nonperforming loans, Tier 1 leverage capital, and noncore funding dependence expressed as ratios. The study involved testing whether the variables predict bank failures. Nonperforming loans, Tier 1 leverage capital, and noncore funding dependence are all ratio variables. Bank failure, the outcome, was a categorical variable: failed or survived. Other researchers have used a similar scale of measurement such that the independent variables were ratios and the dependent variable, bank failure, was categorical: failed or survived (Gumbo & Zoromedza, 2016). Content validity, criterion-related validity, and construct validity were not applicable because the study did not include instruments. The data are in Section 3.

Data Collection Technique

The data for this study came from the Bank Data and Statistics subsection under the Industry Analysis section of the FDIC bank quarterly financial statements, or the Call Report, which are then aggregated into the Uniform Bank Performance Report. The FDIC database includes performance ratios to measure bank performance (de Claro, 2013). The specific data collected from the report included nonperforming loans, Tier 1 leverage capital, and noncore funding dependence of the banks; these measures comprised the study’s independent variables (FDIC, 2016). The data range was between 2014 and 2015. A similar study on predicting bank failure also included a data range for a specified time period (Samitas & Polyzos, 2016). The next step was to extract the data.

To extract the data, I selected the variables of interest and filtered the results from a search in the FDIC website. Researchers who conducted a similar study also extracted the data and filtered the results from the FDIC website (Lu & Whidbee, 2013). The data were downloaded to an Excel spreadsheet that included six columns: reporting period, unique bank identification number, three independent variables (nonperforming loans, Tier 1 leverage capital, and noncore funding dependence ratios), and the dependent variable expressed as 1 for failed and 0 for not failed.

The advantages of this approach are that the FDIC website has a listing of commercial banks needed to predict bank failure (Samitas & Polyzos, 2016) and that this listing of commercial banks is available to the public (Kerstein & Kozberg, 2013). A researcher can select the banks from the population using specific parameters to conduct bank failure prediction studies (Lin & Yang, 2016). The FDIC website was appropriate for selecting the population of banks for this study.

Secondary analysis of archival data, as used in this study, sometimes includes a number of disadvantages. These may include a lack of accuracy (Pernollet, Coelho, & van der Werf, 2017), the difficulty a researcher faces in understanding and interpreting the data (Schuster, Anderson, & Brodowsky, 2014), and the scarcity of data needed to conduct the research (Liu & Li, 2014). None of these were problems for this study. The data were accurate, complete, and easily understandable, especially for anyone with extensive experience in the field. There were no foreseeable disadvantages to using the FDIC website for this study.

Data Analysis

Research Question

For this study, the research question was as follows:

Do nonperforming loans, Tier 1 leverage capital, and noncore funding dependence predict the likelihood of bank failure?

Hypotheses

H_0: Nonperforming loans, Tier 1 leverage capital, and noncore funding dependence do not predict the likelihood of bank failure.

H_1: Nonperforming loans, Tier 1 leverage capital, and noncore funding dependence predict the likelihood of bank failure.

Data analysis involved using logistic regression. The statistical analysis was a logistic regression in which nonperforming loans, Tier 1 leverage capital, and noncore funding dependence were the independent variables and bank failure versus bank safety was the dependent variable. Researchers often use logistic regression to model categorical response data (Özkale, 2016) and in prediction studies (Elgmati et al., 2015). Previous researchers used logistic regression for predicting bank failure (Serrano-Cinca, Fuertes-Callén, Gutiérrez-Nieto, & Cuellar-Fernández, 2014). Logistic regression was the appropriate statistical analysis for this study.

It would have been possible to analyze the data using multiple regression, although it would have been less appropriate for several reasons. Multiple regression requires the assumption that the data are normally distributed (Alguraibawi, Midi, & Rana, 2015); however, the dependent variable for this study was not normally distributed, as 49 banks had failed and 201 had not failed. Therefore, multiple regression was not an appropriate method of analysis. Multiple regression lacks robustness for predictive studies, and logistic regression is a more robust alternative (Neykov, Filzmoser, & Neytchev, 2014). The ANOVA statistical method relates to measuring statistical mean differences (Rustam & Rashid, 2015) but did not apply because the study did not involve measuring statistical mean differences. Logistic regression was therefore the appropriate test for this study.

Researchers determined the statistical significance of their results based on the probability of values, odds ratios, and correlational coefficients (Fagerland, 2012). The results from a logistic regression can produce likelihood ratios, also known as odds ratios, which depict the likelihood of being in one of the categories of the dependent variable (fail or survive). A large odds ratio indicates a higher likelihood (Özkale, 2016). Researchers who have studied bank failure used similar inferential statistics to interpret their results (Di et al., 2016). Logistic regression was therefore appropriate for determining the statistical significance of the results for this study.

Data cleaning and screening procedures applied in this study because the data were archival and publicly available. Previous researchers who conducted bank failure prediction studies excluded cases with incomplete data (Alali & Romero, 2013). Bank failure prediction studies that have missing information were excluded from the analysis (Samitas & Polyzos, 2016). Incomplete data are disregarded in bank failure prediction studies (Cox & Wang, 2014). I did not include cases with incomplete data in the analysis.

There are three assumptions associated with logistic regression (a) sample size, (b) multicollinearity, and (c) outliers. The following discussion of these assumptions includes how they were assessed and actions taken if the assumptions were grossly violated. The first assumption of logistic regression is that the sample size will be adequate (Uprichard, 2013). If the sample is too small, there is a danger of making a Type II or a beta error; that is, concluding incorrectly that the model does not provide statistically significant results (Uprichard, 2013). In this case, that meant concluding that the three independent variables do not predict bank failure, when in fact they do. I used a sample of 250 banks, including about 49 that failed, and 201 that did not fail, between 2012 and 2015. Logistic regression requires a minimum sample size of 200 data collection points (McNeish & Stapleton, 2016); hence, this sample of 250 banks was adequate.

One of the assumptions of logistic regression is that there will not be a problem of multicollinearity. The absence of multicollinearity means that the independent variables included in the regression model do not correlate too highly with each other (Zahari, Ramli, Moktar, & Zainol, 2014). Independent variables highly correlated with each other pose a problem for both theoretical explanation and practical application. Theoretically, it would make it difficult to determine which of the closely correlated predictor variables is actually responsible for banks being at higher risk; from a more practical point of view, it would make it harder for bank regulators to decide which of several potential problems it is most urgent to address. To assess multicollinearity, I will review the variance inflation factors produced as part of the SPSS output. According to Zahari et al. (2014), variance inflation factor values greater than 10 indicate significant multicollinearity among the independent variables. I removed variables that had a variance inflation factor greater than 10 based on this rule.

Another assumption of logistic regression is that there are no outliers in the data. Outliers are cases with extreme scores on one or more of the independent variables; such cases may distort the regression equation (Yuen & Ortiz, 2017). A widely-accepted criterion is that a score should be considered an outlier if its distance from the mean of the distribution is more than 1.5 times the interquartile range (Yuen & Ortiz, 2017). To check for outliers, I used the descriptive statistics function of SPSS, and I deleted from the analysis any cases that appeared, on the basis of this rule, to be outliers.

I used SPSS Version 20 to analyze the data. The SPSS software is helpful to researchers who wish to use various statistical tests in their research (Kumar, 2014). Researchers often use the software to analyze studies with logistic regression techniques (Kim, Choi, & Emery, 2013). Researchers commonly apply regression and other statistical tests within SPSS to predict loan default (Vasilev, 2015). Bhunia (2013) used SPSS for data analysis. Researchers use the SPSS software for predictive analysis (Anton & Ivan, 2015). The SPSS software was appropriate for this study.

The findings appear in the form of a regression table that includes the following columns: (a) β, (b) *SE* (c) Wald, (d) *df*, (e) *p*, (f) odds ratio, and (g) 95% confidence interval for odds ratio. Beta (β) is the probability of making a Type II error in a hypothesis test by incorrectly concluding there is no statistical significance (Hollstein & Prokopczuk, 2016). Beta includes the values by which the researcher should multiply each independent variable in the logistic regression equation to predict the dependent variable (bank failure). These values provide a measure of the comparative importance of each independent variable. An independent variable whose beta has a larger absolute value has a greater impact on the dependent variable than does an independent variable with a smaller absolute value (Hollstein & Prokopczuk, 2016). More specifically, the beta values can be understood this way: For every increase of one unit in (a particular independent variable), the model predicts an increase of that variable's beta weight in the log-odds of the dependent variable, holding all other independent variables constant.

The *SE* are values associated with the beta coefficients. These values describe how precisely the model estimates each coefficient's real but unknown value (Bekker & Wansbeek, 2016). Researchers use the standard error for testing whether the value for each beta is significantly different from zero. The standard errors can also be used to form a confidence interval for the beta (Bekker & Wansbeek, 2016); that is, the likelihood that the beta falls between a specific higher and a lower value.

The Wald is a chi-square value (Voinov, 2015). Researchers can use the Wald value together with the *p* value to determine the likelihood that the beta coefficients differ significantly from those obtained by chance. The *df* are the number of values in the final calculation of a statistic that are free to vary (Gherekhloo, Chaaban, & Sezgin, 2016). There is one degree of freedom for each independent variable. The more degrees of freedom in the model, the higher Wald must be to reject the null hypothesis that the true value of the associated beta coefficient is actually zero.

The *p* value represents the statistical significance of each independent variable in the model (Stern, 2016). More specifically, the *p* value is the likelihood that the true value of the associated independent variable in the population is actually zero. By convention, *p* values less than .05 are accepted as statistically significant (Stern, 2016), that is, unlikely to have occurred by chance.

The Exp (β) is the probability, given a particular value for an independent variable, that an event will occur, divided by the probability that the event will not occur (Lui, 2016). The odds ratio is a measure of how much each independent variable increases the likelihood of an outcome, in this case the likelihood of bank failure. The values in this column indicated that when a particular independent variable is raised by one unit, the likelihood of bank failure is multiplied by the associated Exp (β) value.

The 95% confidence interval of the odds ratio is used to determine whether the association is statistically significant (Yimeng, Kopec, Cibere, Li, & Goldsmith, 2016). The 95% confidence interval of the odds ratio means there is a 95% likelihood that the true value of the odds ratio in the population falls between the upper and lower boundary values. The 95% confidence interval was used in this study.

Study Validity

Researchers who do experimental research must pay attention to threats to internal and external validity. Internal validity refers to how well a researcher conducts an experiment; more specifically, whether there are reasons to believe that the outcome was the result of something other than the independent variables (Burchett, Mayhew, Lavis, & Dobrow, 2013). External validity refers to the extent to which the results of an experiment are generalizable to other situations (Fernandez-Hermida, Calafat, Becoña, Tsertsvadze, & Foxcroft, 2012). It is especially important in arguing that an experiment conducted in a laboratory setting provides insights into what happens in the real world (Cahoon, Bowler, & Bowler, 2012). As this study is not an experiment, many of the issues of internal and external validity will not apply. For example, there are no threats to validity posed by statistical regression or experimental mortality. Furthermore, as this study did not include human subjects, there were no threats to validity posed by maturation or testing reactivity.

The main threat in this study was to statistical conclusion validity, which is the confidence a researcher can have in any conclusions about relationships among variables (Heale & Twycross, 2015). There are two types of statistical conclusion errors. A Type I error occurs when a researcher concludes that there is a relationship among variables when in fact there is no such relationship; a Type II error occurs when a researcher concludes that there is not a relationship among variables when in fact there is a relationship (Yin, 2013). Researchers exercise precautionary measures to minimize statistical conclusion errors.

To guard against making a Type I error, I used a two-tailed test with alpha $< .05$, which is a conventional level of statistical significance. Thus, I only reported results that had less than a 5% likelihood of having occurred by chance alone. If the results I obtained in my sample were unlikely to have occurred by chance, it meant that it was reasonable to generalize from the sample to the larger population. That is, any relationship between the predictor variables and the outcome measure (bank failure) was likely to exist in the larger population as well. The likelihood of a Type II error decreases when researchers use larger samples (Bradley & Brand, 2013; Gheondea-Eladi, 2014). To guard against making a Type II error, I used a sufficiently large sample, as determined by a power analysis (see above, in the section on sampling strategy).

Statistical conclusion validity depends on three considerations: (a) reliability of the instrument, (b) sample size, and (c) data assumptions. Reliability should not be an issue, because this study did not include any instrument such as a questionnaire. The sample size was adequate, as logistic regression requires a minimum sample size of 200 data collection points (McNeish & Stapleton, 2016); I used a sample of 250 banks, including 49 that failed, and 201 that did not fail.

The data assumptions related to using logistic regression included the risk of multicollinearity among predictor variables and the distorting influence of outliers. The absence of multicollinearity means the independent variables included in the regression model do not correlate too highly with each other (Zahari et al., 2014). Were these independent variables highly correlated with each other, it would pose a problem for both theoretical explanation and practical application. Theoretically, it would make it difficult to determine which of the closely correlated predictor variables was responsible for banks being at higher risk; from a more practical point of view, it would make it harder for bank regulators to decide which of several potential problems is most urgent to address. To assess multicollinearity, I reviewed the variance inflation factors produced as part of the SPSS output. According to Zahari et al. (2014), variance inflation factor values greater than 10 indicate significant multicollinearity among the independent variables.

Another assumption of logistic regression is there are no outliers in the data. Outliers are cases with extreme scores on one or more of the independent variables; such cases may distort the regression equation (Yuen & Ortiz, 2017). A widely-accepted criterion is to consider a score as an outlier if its distance from the mean of the distribution is more than 1.5 times the interquartile range (Yuen & Ortiz, 2017). To check for outliers, I used the descriptive statistics function of SPSS, and I deleted from the analysis any cases that appeared, based on this rule, to be outliers. Researchers exercise precautionary measures to minimize statistical conclusion errors. Using the appropriate statistical tests helped to alleviate any issues or errors that could arise with generalizing results to the population.

Transition and Summary

Section 2 included a restatement of the purpose of this study and an explanation of why I conducted the study. This section also included a description of the participants for the study, the research method and design, and the sample. The specific information contained in this section aligned with the research question and the hypotheses. Section 3 will include the findings of the data analysis, the ways the results may affect the professional community, and the implications for social change. Section 3 will also include my recommendations for future research, a summary, and conclusions for the study.

Section 3: Application to Professional Practice and Implications for Change

Introduction

The purpose of this quantitative correlational study was to examine if nonperforming loans, Tier 1 leverage capital, and noncore funding dependence predict the likelihood of bank failure. The independent variables were nonperforming loans, Tier 1 leverage capital, and noncore funding dependence, and the dependent variable was bank failure. Bank regulators use different types of performance measures to assist them in identifying events that occur prior to a bank failing (Liu, 2015). Banking regulators should understand the relationship between different banking financial performance measures and the potential for banks to fail (Di et al., 2016). In this section, I will present the findings of the data analysis. I will also indicate how the findings apply to professional practice, implications for social change, and recommendations for actions.

Presentation of Findings

In this subsection, I will describe the statistical test (logistic regression), evaluate statistical assumptions, present descriptive statistics and inferential results, provide a theoretical discussion of the findings, and conclude with a concise summary. The statistical test I used in this study was logistic regression. Logistic regression can be used to test the relationship between one or more independent variables and a dichotomous dependent variable (Lu & Whidbee, 2013). The dependent variable of bank failure was scored as bank failure = 1, bank nonfailure = 0.

Tests of Assumptions

This section includes the tests of assumptions. There are three assumptions associated with logistic regression: (a) sample size, (b) multicollinearity, and (c) outliers (Uprichard, 2013). In the following subsections, I will discuss the results of the assumption evaluation.

Sample Size. The first assumption of logistic regression is that the sample size will be adequate (Uprichard, 2013). If the sample is too small, there is a danger of making a Type II or a beta error; that is, concluding incorrectly that the model does not provide statistically significant results (Uprichard, 2013). In this study, I used a sample of 250 banks, including 49 that failed, and 201 that did not fail, between 2013 and 2015. As previously noted, logistic regression requires a minimum sample size of 200 data collection points (McNeish & Stapleton, 2016).

Multicollinearity. The data assumptions related to using logistic regression included the risk of multicollinearity among predictor variables and the distorting influence of outliers. The absence of multicollinearity means the independent variables included in the regression model do not correlate too highly with each other (Zahari et al., 2014). Were these independent variables highly correlated with each other, it would pose a problem for both theoretical explanation and practical application. I evaluated multicollinearity by examining the correlation coefficients among the predictor variables. There was no evidence of multicollinearity among the predictor variables (see Table 1).

Table 1

Correlation Coefficients Among Study Predictor Variables

Variable	*1*	*2*	*3*
1. Nonperforming loans	—		
2. Tier 1 leverage capital	-.500	—	
3. Noncore funding dependence	-.011	-.072	—

Note. $N = 250$.

Outliers. Outliers are cases with extreme scores on one or more of the independent variables; such cases may distort the regression equation (Yuen & Ortiz, 2017). A widely-accepted criterion is that a score should be considered an outlier if its distance from the mean of the distribution is more than 1.5 times the interquartile range (Yuen & Ortiz, 2017). I evaluated outliers in this study by examining the normal probability plot (P-P) of the regression standardized residual (see Figure 1) and the scatterplot of the standardized residuals (Figure 2). Figure 1 includes two potential outliers, evidenced by variances exceeding +/- three standard deviations. Figure 2 shows a potential violation of the outlier assumption. Therefore, bootstrapping, using 1,000 samples, will be reported where appropriate.

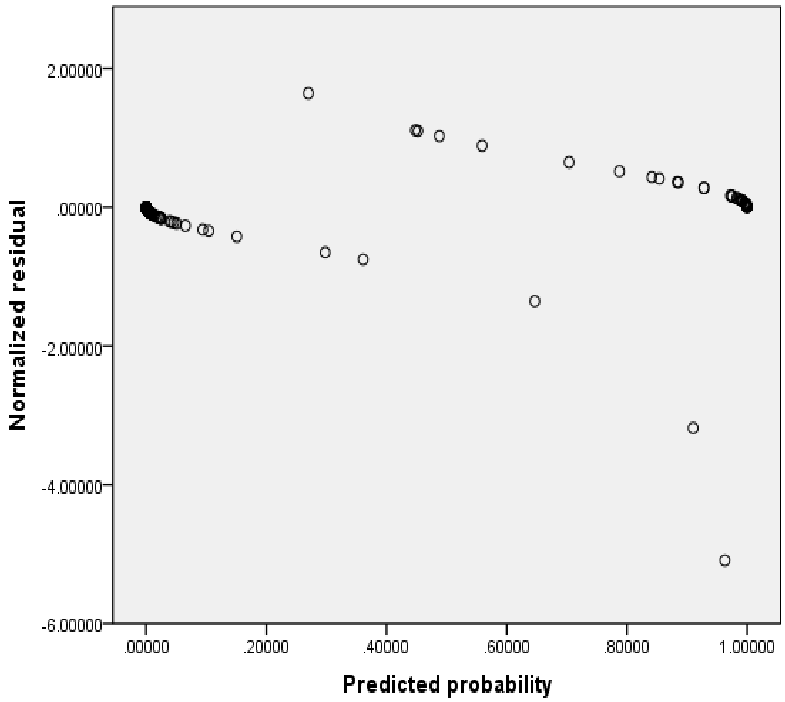

Figure 1. Probability plot of normalized residuals against predicted probability of bank failure.

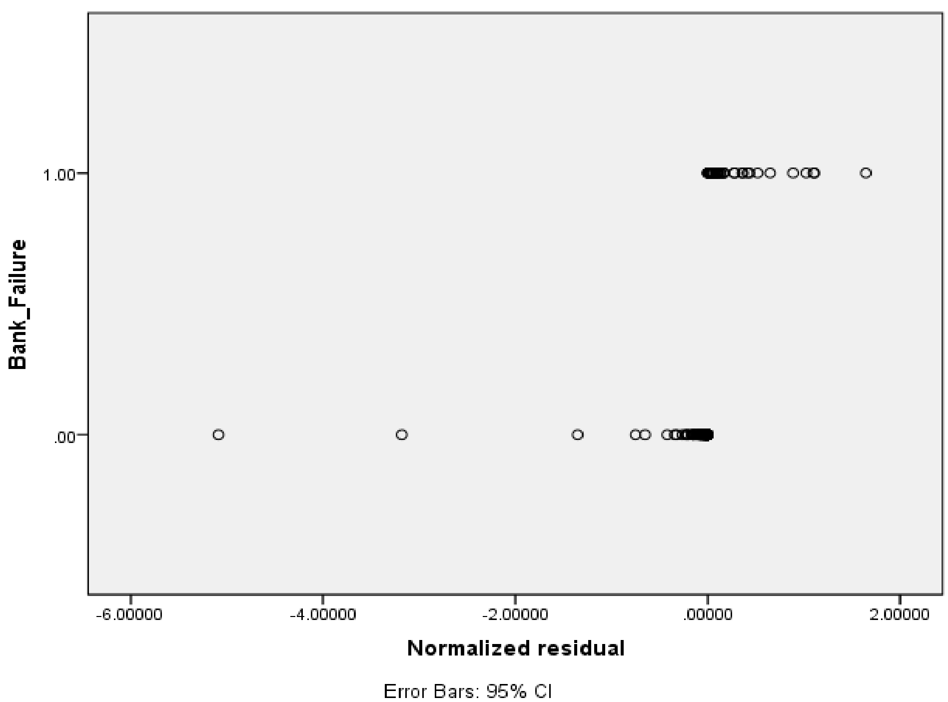

Figure 2. Scatterplot of the normalized residuals.

Descriptive Statistics

Table 2 shows the descriptive statistics for the predictor variables for 49 failed banks and 201 banks that did not fail (safe banks). Several differences between failed and safe banks were apparent. Compared to the safe banks, failed banks had a larger portion of their loan portfolio as nonperforming loans, they had less Tier 1 leverage capital, and they had higher levels of noncore funding dependence.

Table 2

Descriptive Statistics for Nonperforming Loans, Tier 1 Leverage Capital, and Noncore Funding Dependence

Banks	*N*	*M*	*SD*
Failed banks			
Nonperforming loans	49	11.52	7.01
Tier 1 leverage capital	49	3.91	1.81
Noncore funding dependence	49	-5.39	21.48
Safe banks			
Nonperforming loans	201	1.71	1.86
Tier 1 leverage capital	201	10.69	2.97
Noncore funding dependence	201	- 1.50	15.96
Total banks			
Nonperforming loans	250	3.64	5.24
Tier 1 leverage capital	250	9.36	3.87
Noncore funding dependence	250	-2.26	17.20

Inferential Results

I used binary logistic regression ($a \leq .05$) to test the efficacy of a model that could predict bank failure. The independent variables in this study were nonperforming loans, Tier 1 leverage capital, and noncore funding dependence, and the dependent variable was bank failure. My null hypothesis was that nonperforming loans, Tier 1 leverage capital, and noncore funding dependence would not significantly predict bank failure; my alternative hypothesis was that these three independent variables would significantly predict bank failure. Preliminary analyses were conducted to assess whether the assumptions related to sample size, multicollinearity, and outliers were met. The sample size was adequate and there was no evidence of multicollinearity. The established research practice is to test assumptions for violations in binary logistic regression studies (Zahari et al., 2014). There was evidence that two banks were outliers; therefore, bootstrapping with 1000 samples was used. I will report the 95% confidence intervals in the following paragraph.

The model as a whole was able to significantly predict bank failure, $X^2(3, N = 250) = 218.862$, $p < .001$. In the final model, nonperforming loans, Tier 1 leverage capital, and noncore funding were all statistically significant, with Tier 1 leverage capital ($\beta = -1.485$), $p < .001$) accounting for a higher contribution to the model than nonperforming loans ($\beta = .354$, $p < .001$) and noncore funding dependence ($\beta = -.057$, $p = .015$). The model as a whole explained between 58% (Cox and Snell R^2) and 93% (Nagelkerke *R2*), respectively. The final predictive equation was: bank failure = 6.752 + .354 (nonperforming loans) - 1.485 (Tier 1 leverage capital) -.057 (noncore funding dependence). The logistic regression equation correctly predicted 45 of the 49 banks that failed, for an accuracy of 91.8%. The equation also correctly predicted 198 of the 201 banks that did not fail, for an accuracy of 98.5%. Overall, the equation correctly predicted

243 out of 250 cases, for an accuracy of 97.2% using the SPSS data analysis software. Table 3 shows the values associated with variables in the equation. Table 4 depicts the β bootstrap 95%.

Table 3

Variables in the Equation

Variable	β	*S.E.*	Wald	*df*	*p*	Exp(*B*)	95% CI for EXP(*B*) Lower	Upper
Nonperforming loans	.354	.105	11.284	1	.001	1.424	1.159	1.751
Tier 1 leverage capital	-1.485	.359	17.149	1	.000	.226	.112	.457
Noncore funding dep.	-.057	.023	5.947	1	.015	.944	.902	.989
Constant	6.752	2.132	10.032	1	.002	855.892		

Note. CI = confidence interval.

Table 4

β Bootstrap 95% CIs Based on 1000 Samples

	β	Lower	Upper
Nonperforming loans	.354	-4.943	52.629
Tier 1 leverage capital	-1.485	-2.631	-1.309
Noncore funding dependence	-.057	-.143	-.013
Constant	6.752	1.039	1367.265

Note. N = 250.

Nonperforming loans. In this study, I found nonperforming loans to be a significant predictor of bank failure; the resulting odds ratio of 1.42 means that a bank was 1.42 times more likely to fail when nonperforming loans increased by one unit. This finding is consistent with previous research, which has found that nonperforming loans are a significant driver of a bank's financial health and that they influence a bank's credit quality and performance (Canicio and Blessing (2014)). Lu and Whidbee (2013) found a significant relationship between higher performing loans and bank success. Deteriorating asset quality, as measured by nonperforming loans to assets, contributes to bank failure (Lu & Whidbee, 2013). Canicio and Blessing (2014) maintained that an unsustainable level of nonperforming loans resulted in bank failure. Cox and Wang (2014) concluded that the likelihood of bank failures was predicted with higher accuracy when statistical models included financial indicators such as nonperforming loans. In contrast, de Claro (2013) found that nonperforming loans are a compelling driver of a bank's financial health but noted that operational measures such as earnings and profitability were the most effective indicators of bank failure.

Tier 1 leverage capital. In this study, I found Tier 1 leverage capital to be the most significant predictor of bank failure; the odds ratio of .226 means that a bank was .226 times more likely to fail when Tier 1 leverage capital decreased by one unit. This finding is also consistent with previous research, which has found that lower Tier 1 leverage capital ratios predict bank failure (Merle, 2013). Cherpack and Jones (2013) found that banks with lower Tier 1 leverage capital failed at higher rates than banks with higher Tier 1 leverage capital ratios. The minimum requirements can vary, but the Tier 1 leverage capital ratio in safe banks typically ranges from 4% to 6% (Camara et al., 2013). Capital standards are important in banking because of their ability to predict default risk (Merle, 2013). Lower Tier 1 leverage capital potentially leads to bank failure. In a study on U.S. bank failures, Abreu and Gulamhussen (2015) found an association between lower capital, as measured by equity to assets, and a higher probability of failure. In contrast, Schenck (2014) found that regulatory capital measures such as the Tier 1 leverage capital ratio are not a significant predictor of distress for large financial institutions. The findings of this study are consistent with the majority of previous studies, which indicated that a low Tier 1 leverage capital ratio is an important predictor of bank failure.

Noncore funding dependence. In this study, I found noncore funding dependence to be a significant predictor of bank failure; the odds ratio of .944 means that a bank was .944 times more likely to fail when noncore funding dependence increased by one unit. This finding is also consistent with previous research. Bologna (2015) found a positive correlation between higher noncore funding dependence and bank failure. More expensive or temporary large brokered or government deposits, as measured by noncore funding dependence, could strain a bank's liquidity position because of the potential of immediate runoff (Li et al., 2013). When a bank's loan-to-deposit ratio is significant, bank regulators seek corrective action to alleviate further bank distress (Handorf, 2014). Almansour (2015) used logistic regression analysis to show that the liquidity ratio was a significant indicator of bankruptcy for firms. Almansour justified the liquidity ratio as a strong indicator of bankruptcy because managers reduce the level of current assets relative to total assets when businesses incur consistent operating losses.

Application to Professional Practice

Banking regulators are required by law to monitor the safety and soundness of the financial institutions that they regulate (Kupiec, Lee, & Rosenfeld, 2017). Early warning systems are an essential part of risk monitoring that identifies which banks are likely to fail (Cleary & Hebb, 2016). Although it is impossible to predict bank failure with absolute certainty, banks that are less financially sound have a higher probability of failure. In this study, the use of logistic regression analysis improved the accuracy with which bank failure could be predicted from 80% to 97%. Erdogan (2016) found logit regression accurate in the prediction of Turkish bank failure. The results from this study have several implications for the professional practices of banking regulators.

First, banking regulators should use publicly available financial data to supplement their on-site assessments of which banks are at a higher risk of failing. Currently, bank regulators conduct on-site bank examinations, using data that is not publicly available, on a 12- to 18-month basis (Kerstein & Kozberg, 2013). The infrequency of such on-site bank assessments limits banking regulators' ability to detect distressed financial conditions and implement corrective action. By using publicly available data, bank examiners could supplement their yearly, on-site examinations with more frequent, off-site examinations; this might allow them to detect signs of trouble earlier, at a point when a timely correction could save a bank from failure.

By using publicly available data, banking regulators could make more frequent examinations of banks; this would allow bank managers, who work with banking regulators, to develop more timely corrective action plans to alleviate the risk of bank failure. When bank managers identify negative trends, they could diversify or reduce their reliance on activities and practices that lead to bank distress (Alvarez-Franco & Restrepo-Tobon, 2016). A collective effort by both the banking regulators and bank managers in monitoring and identifying negative trends promotes financial stability and reduces bank distress (Chiaramonte & Casu, 2017).

Second, banking regulators should use logistic regression to analyze these publicly available data. Currently, logistic analysis is not widely used by banking regulators and instead they rely on the CAMELS rating system to assess the health of a bank (Kupiec et al., 2016). If banking regulators added logistic regression analysis to their arsenal of tools, they would improve their accuracy in assessing the risk of bank failure. Banking regulators who use logistic regression to supplement their analyses of bank risk should focus primarily on the Tier 1 leverage capital ratio, and second, on the nonperforming loans ratio. Based on the results of this study, these are the ratios that best predict bank failure. The noncore funding dependence ratio, while statistically significant, added less than the other predictor variables to the overall accuracy of the logistic regression equation.

Implications for Social Change

The results of this study may impact individuals, organizations, and communities if bank regulators use logistic regression with publicly available information for predicting bank failure. If this practice were widely adopted, the frequency of bank failure might be reduced, and several benefits to society might follow. Bank employees would be less likely to lose their jobs; people owning the bank's stock would be less likely to lose the value of their investments (Babajide et al., 2015). Organizations would be better able to secure funds to undertake worthwhile activities or investments, leading to an improvement in local employment and production generation (Ghosh, 2016).

Financially sound banks would be better able to continue lending within the community, and sustain organizations or provide loans to start-up businesses (Amador et al., 2013). This process of reinvesting in the community can lead to economic growth and new opportunities for job expansion.

When members of a community perceive sustained economic growth, they tend to have more time for community services, in addition to the freedom to consider new business development. Overall, social change is derailed when banks fail as banking activities such as lending contribute to the sustainability of the local community (Jizi et al., 2014). If the risk of bank failure can be predicted more accurately and those risk factors addressed in a timely fashion, banks will be better able to contribute to sustainable economic development in ways that are good for organizations and the larger community (Jizi et al., 2014).

Recommendations for Action

The findings reported here are likely to be of interest to banking regulators who have the responsibility for overseeing the financial condition of U.S. banks and training programs that have the responsibility for improving the skills of banking examiners. Bank managers who have the responsibility of adjusting bank policies to alleviate risk are likely to be interested in this study's findings. Several recommendations follow from the findings reported here.

One recommendation is that banking regulators incorporate logistic regression analysis, with publicly available data, to supplement existing tools such as on-site bank examinations (Cleary & Hebb, 2016). The use of these data and statistical tools may improve efficiency, as bank regulators could conduct offsite analyses with greater frequency. These off-site examinations could be performed quarterly and then compared with on-site examination results. Bank regulators, in turn, learn more of where to focus their efforts and resources earlier in the process (Mitsiolidou & Kritsa, 2017).

A second recommendation concerns training for bank regulators. Federal regulators have curriculums designed for the education of bank regulators (FDIC, 2017). The results of this study suggest that those curriculums should be updated to include training in the use of logistic regression with publicly available financial data, especially nonperforming loans, Tier 1 leverage capital, and noncore funding dependence. Instructors with the necessary expertise in logistic regression should teach the concepts to examination staff, preferably using simulation exercises to ensure practical application.

A third recommendation concerns the dissemination of these results. The findings of this study should be disseminated through regulatory bank examination conferences and publications in professional accounting, banking, and finance journals. The results should also be presented at regulatory bank examination conferences. Banking regulators, accountants, and other financial services professionals have an interest in attaining resources relevant for improving competence (Baxter, Holderness, & Wood, 2017).

Recommendations for Further Research

As noted in an earlier section, this study was limited in a number of ways; several recommendations for future research follow from these limitations. One limitation is that this study included proxies for only three of the six CAMELS ratings that are ordinarily used to assess the financial health of banks: nonperforming loans, Tier 1 leverage capital, and noncore funding dependence. Although this logistic regression model was effective in predicting bank failure, the model might be improved by including additional independent variables.

As noted earlier, other researchers, including Cox and Wang (2014), and Kerstein, and Kozberg (2013), used many variables, including enforcement action, return on assets, and net interest margin, as proxies for the remaining regulatory examination components in the CAMELS ratings to assess commercial banks' financial condition, and found each of these effective for predicting the likelihood of bank failure. Additional variables might include those that assess management, earnings, and sensitivity to interest rate risk, and corporate governance (Jizi et al., 2014). The first recommendation, therefore, is that future studies include proxies for all six CAMELS ratings.

Another limitation of this study was the lack of access to confidential regulatory examination data. This made it impossible to compare the effectiveness of the model tested here with that of more traditional, onsite examinations. A second recommendation, therefore, would be to replicate the model tested here, and compare its effectiveness in predicting bank failure with predictions based on confidential regulatory examination data.

A third limitation concerns the size of the banks that made up most of this sample. Most of the banks tested in this study were small to mid-sized; it is possible that among larger banks, with assets of $1 billion, a different set of variables would be better predictors of bank failure (Clarke, 2016). Larger banks have access to substantially larger amounts of Tier 1 leverage capital, and therefore this factor may be a less important predictor of their risk of failure than it was in the sample of chiefly smaller-to mid-sized banks (Chiaramonte & Casu, 2017). In contrast, liquidity constraints, as measured by the ability of bank managers to pay debts as they become due, have led to financial distress for banks with assets of $1 billion or more (Clarke, 2016). The third recommendation, therefore, is that this logistic regression model be tested with a sample of larger banks.

Reflections

My experience with the DBA Doctoral Study process was positive. I am a banking regulator with over 30 years of experience in the field. Over that period, I have examined hundreds of banks for safety and soundness using the standard practices of the profession; those practices differ from the approach explored here in two ways. First, traditional bank examinations make use of financial records that are not publicly available, which means that they must be conducted by on-site visits. This in turn limits the frequency with which any bank can be examined.

Second, on-site bank examinations typically do not make use of logistic models to estimate the likelihood of bank failure; this means that bank examiners are not making use of a statistical model of proven effectiveness. After doing this study, I am persuaded that an alternative approach would be of value: one that made use of publicly available data, and that analyzed this data, using logistic regression, to estimate the likelihood of bank failure. Examinations of this sort would not, in my view, replace traditional, onsite examinations; instead, the two approaches would complement each other.

The advantage of this approach would be that the use of publicly available data would make possible more frequent, off-site bank examinations; the use of logistic regression models might allow regulators, like me, to increase the accuracy of their risk assessments. Bank managers, in turn, would be able to use this information to respond more quickly to signals that their banks are in danger of failing. I appreciate the opportunity to expand practical knowledge, and to contribute to the existing body of literature on estimating the likelihood of bank failure.

Conclusion

As noted earlier, the implications of bank failure extend beyond the cost to employees, who lose their jobs, and stockholders, who lose the value of their investments. Healthy banks play a vital role in the larger community: loans to individuals increase home ownership; commercial loans increase the development of new businesses. When banks fail the community at large suffers (Babajide et al., 2015). Although the likelihood of bank failure is typically higher in times of economic crisis, as witnessed in the 2007 global recession, bank failures are a problem even in better times: six banks have failed so far in 2017 (FDIC, 2017).

Banking regulators and bank managers share the responsibility for identifying and implementing measures that would prevent bank failures so as to lessen the negative effects that such failures have on all stakeholders. Although all FDIC banks are examined regularly, current practices are not as strong as they might be. First of all, the current practice depends primarily on onsite examinations, which limits their frequency. More frequent, off-site examinations would be possible if bank regulators made use of publicly available data. This would allow banking regulators to be better informed about where to focus their efforts and resources earlier in the process (Mitsiolidou & Kritsa, 2017). Second, bank regulators do not currently make use of logistic regression models to estimate the likelihood of bank failure. If banking regulators incorporated such statistical analysis as part of their regulatory monitoring tools, this might improve their effectiveness in identifying distressed banks (Cleary & Hebb, 2016).

In this study, it was found that logistic regression with three, publicly available predictor variables, nonperforming loans, Tier 1 leverage capital, and noncore funding dependence, could significantly improve the prediction of bank failure. Further refinement of this approach, possibly through the use of additional predictor variables, might improve this model still further. If this approach were adopted more widely, possibly through a broad program of training for banking regulators, the risk of bank failure might be reduced and the financial well-being of the larger community enhanced.

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