Federal Deposit Insurance Corporation • Center for Financial Research

WORKING PAPER SERIES

Offsite Detection of Insider Abuse and Bank Fraud among U.S. Failed Banks 1989-2015

John P. O'Keefe
Federal Deposit Insurance Corporation

Chiwon A. Yom
Federal Deposit Insurance Corporation

October 2017

FDIC CFR WP 2017-06

fdic.gov/cfr

Offsite Detection of Insider Abuse and Bank Fraud among U.S. Failed Banks 1989 - 2015

John P. O'Keefe
Federal Deposit Insurance Corporation
550 17th Street, NW
Washington, DC 20429
Jokeefe@fdic.gov

And

Chiwon A. Yom
Federal Deposit Insurance Corporation
550 17th Street, NW
Washington, DC 20429
Cyom@fdic.gov

October 16, 2017

Key words: Bank Failure, Benford's Law, Fraud Detection

JEL classification code: C45, G21, G28, M49

Abstract

We find evidence that material insider abuse and internal fraud were present in approximately 457 (37 percent) of the 1,237 U.S. failed commercial and mutual savings banks (hereafter, banks) between 1989 and 2015. Using a unique dataset of the incidence of insider abuse and internal fraud among U.S. failed banks we analyze the characteristics of failed banks with the ultimate goal of developing fraud detection models—parametric (logistic regression, Benford digit analysis) and non-parametric (neural networks). We obtain information on the incidence of insider abuse and internal fraud among failed banks from failing bank cases prepared for the FDIC Board of Directors, restitution orders (fines) supervisors assessed for bank employee fraud, and bond claims the FDIC made to recover fraud-related losses on failed banks. The supervisory data we use to quantify fraud among failed banks has not been used previously in published research and, we feel, provides more comprehensive information on fraud among failed banks than that available to academic researchers. Since fraudulent behavior lies outside the realm of rationale behavior modelled in economics, we develop a framework for internal bank fraud that provides rationale and support for our fraud detection models. This framework is based on previous studies of financial fraud and internal bank fraud in particular. We test this framework using regression analysis of the determinants of fraudulent behavior among failed banks between 1989 and 2015 and find that banks with insider abuse and fraud present overstated income and asset values, under-reported losses and consequently overstated net worth. The regression models of fraudulent failed banks provide information on the financial statement line items that can be used to identify fraud. We next use a recently developed second-order Benford digit test to identify those banks whose financial statements suggest tampering and purposeful misstatement. Our results suggest that material insider abuse and fraud at banks is detectable using Benford digit analysis of bank financial data for a period one-to-four years prior to failure. Unfortunately, we are unable to develop an accurate neural network model for fraud prediction.

Table of Contents

1. Introduction

Insider abuse and fraud committed by bank employees can be difficult to detect, especially fraud committed by senior bank officers who have access to all areas of bank operations.[1] Insider abuse and internal bank fraud often contribute to bank failures. We estimate that of the 1,237 commercial and mutual savings banks (hereafter, banks) that failed between 1989 and 2015, approximately 457 (37 percent) had material insider abuse and/or internal fraud that was detected by bank regulators[2]

We use three sources of information on the incidence of internal fraud at failed banks—FDIC failing bank board cases, restitution orders and bond claims. FDIC failing bank board cases are prepared by the FDIC's Division of Resolutions and Receiverships for the FDIC Board of Directors to assist the Board in determining the most appropriate method to resolve bank failures. The failing bank board cases contain safety and soundness examination histories and describe events at banks that preceded bank failures, including insider abuse and internal fraud. Bank regulators can issue restitution orders with monetary fines on bank employees for fraud. Restitution orders can be issued before, during or after bank failure. Finally, for banks with bond insurance, the FDIC, in its role as failed-bank receiver, may file claims with failed-bank insurers to recover losses caused by bank employee fraud—bond claims.[3]

It is important to point out that our measures of bank insider abuse and fraud include instances where bank regulators suspected fraud, as well as instances of confirmed criminal activity. Section (8) (b) (6) of the Federal Deposit Insurance Corporation Act (FDI Act) authorizes the FDIC to issue restitution orders. Under FDI Act Section (6) (b) (6) (A) there are two statutory factors the FDIC must meet:

---

[1] We include in this definition of fraud behavior by bank employees that while deceptive, dishonest and costly to the bank, did not necessarily lead to criminal court convictions.

[2] Banks that received open bank assistance are not included in our failed-bank sample.

[3] Between 1989 and 2015 FDIC failing bank board cases identified 202 banks with material insider abuse and/or internal fraud, typically involving senior bank officers. Over this same period the FDIC made bond claims for bank employee fraud for 205 failed banks and bank supervisors issued material restitution orders on 213 failed banks; resulting in 457 banks with fraud-related penalties and/or insurance claims. Restitution orders can be for very small amounts, hence, we use a materiality threshold that requires the sum of restitution orders issued to a bank's employees (before, during and after failure) to be at least 25 percent of FDIC resolution costs for the bank and use the 213 material restitution order cases to obtain our total fraud-related bank failure count. We point out there is substantial overlap among our three fraud-related failed-bank flags—FDIC failing bank board cases, restitution orders and bond claims.

1) the bank was unjustly enriched through a violation of law, regulation or unsafe and unsound practice, 2) the act or practice involved a reckless disregard for the law or regulation.[4] Many restitution orders the FDIC issues are the result of criminal activity in which the defendant has been found guilty or plead guilty in court. Bond claims are based on dishonest and fraudulent activity by bank employees that may or may not have resulted in criminal court convictions. Finally, FDIC failing bank board cases discuss insider abuse, violations of bank regulation and instance of suspected criminal activity. Since we are interested in approaching the problem of insider abuse and internal bank fraud as a risk to the deposit insurer we do not limit our analysis to instances where fraudulent activity was confirmed by the courts. To acknowledge this approach, we use the terms insider abuse and bank fraud to include instances where dishonest and deceptive behavior by bank insiders were found by bank regulators regardless of the criminality of that behavior.

U.S. bank supervisors focus their surveillance programs on financial risks—credit, concentration, country, liquidity and market risks. U.S. bank supervisors also conduct onsite inspections of bank controls for money laundering and suspicious activity; however, these inspections are aimed at fraudulent activity by bank customers who may be acting with or without the cooperation of bank employees. The fraud detection framework we propose in this paper is designed for offsite detection of material insider abuse and fraud by bank employees and senior management.

We would like to point out that our paper uses an extensive literature review to support development of fraud detection models and because we are using existing techniques to detect bank fraud, our paper is intended to provide a proof of concept for offsite bank fraud detection using information on bank fraud that has not been previously used for empirical research. The remainder of the paper is organized as follows. Section 2 reviews the literature on fraud and bank fraud in particular. Section 3 presents our proposed framework for detecting insider abuse and internal bank fraud. Section 4 discusses the literature on offsite detection of fraud. Section 5 discusses our data on insider abuse, internal bank fraud and fraud risk indicators, followed by model calibration and results in Section 6. Section 7 concludes.

[4] See "Formal and Informal Action Procedures (FIAP) Manual, (December 21, 2015). FDIC, chapter 10.

2. Previous Literature on Fraud

Fraud is defined as "a deliberate deception practiced so as to secure unfair or unlawful gain".[5] Cressey (1951) interviewed violators of financial trust, e.g., embezzlers, at the Illinois state penitentiary at Joliet to understand the reasons why individuals in trusted positions committed fraud, i.e., became trust violators. Cressey (1951) found three conditions motivate all trust violations: 1) individuals must perceive they are under some form of financial pressure they cannot share with others, 2) be able to rationalize fraud with their trusted position and 3) have the opportunity to resolve their financial problems through fraud. Cressey (1951) found that all three of these conditions must be present for trust violations to occur. Cressey's scientific approach to understanding financial crime is a departure from moralistic explanations that the causes of trust violation are individuals' bad habits, e.g., gambling, and personal and business failures. In Cressey's model, these habits, personal and business failures create financial pressure; the trusted position provides opportunities for fraud and an individual's decision to not seek help in resolving financial pressure are the conditions necessary for trust fraud to occur.[6] Trust violators may feel perfectly legal and ethical failings, e.g., business losses, indicate personal deficiencies of such magnitude they will not share the financial pressure with anyone. The inability to share the financial pressure is based on the trust violator's perception; as Cressey (1951) points out, where one banker might seek help for his failing bank another might be too ashamed to seek help. Wheeler (1982) examines the nature of white-collar crime using information from pre-sentencing investigations (PSI) for eight categories of white-collar crime—antitrust violations, securities fraud, postal and wire fraud, false claims, credit and lending institution fraud, bank embezzlement, tax evasion, and bribery. The PSI sample covers fiscal years 1976 through 1978 and includes a national sample of antitrust and securities crimes and a sample of cases from seven federal district courts for the remaining six categories of white-collar crimes. The PSI data provide descriptions of the fraud and the context in which it was carried out, as well as details on individuals charged with the fraud. Wheeler (1982), using the PSI data, categorized offenders into three types—individual, occupational and organizational. Individual offenders committed the crime alone and did not use their occupation or an organization to carry out the crime. Occupational offenders may have committed the crime alone or with others and their occupation played a role in the crime. Finally, organizational offenders worked alone or with others

[5] See "Webster's II New Riverside University Dictionary", *The Riverside Publishing Company*, Boston MA (1984).
[6] Cressey (1951) reports that many trust violators he interviewed stated they did not spend stolen money on gambling or other illicit activity but were pressured by police to come up with a better explanation of where the money went than what they initially (truthfully) told police. Cressey (1951) also suggests courts anxious for conviction preferred low moral character as a factor in trials since it made convictions easier for prosecutors.

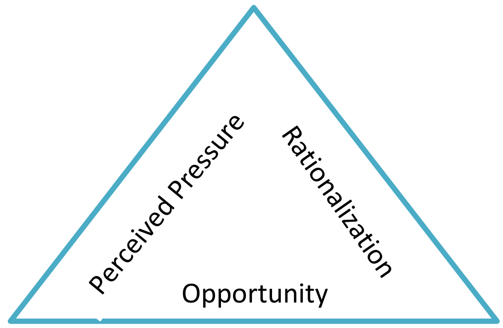
in carrying out the crime and their occupation and organization both played a role in the crime.[7] Wheeler's main hypothesis is that white-collar criminals can use the organization as a tool with which to carry out the crime. Wheeler (1982) found that organizational crimes occurred more frequently, lasted over longer time periods, had wider geographic scope, and had a greater impact in terms of both dollars stolen and number of victims adversely affected by the crime than did frauds carried out by individual and occupational offenders. Organizational offenders tended to be older, better educated, hold higher positions in companies and have fewer, if any, prior criminal offenses than did occupational and individual offenders.[8] Wheeler (1982) suggests that organizational offenders' relatively impeccable credentials allowed them to gain the trust that permits fraudulent activity to be more lengthy and widespread. The organization also allows offenders to hide the crime through falsification of documents. Wheeler (1982) concludes the organization is used by the offender to carry out a much grander crime than would be otherwise possible. While Wheeler (1982) found convicted organizational offenders served somewhat longer prison sentences than did occupational and individual white-collar offenders, the difference was small, suggesting less punishment relative to damage done compared by other white-collar criminals.[9]

Albrecht (1991) examines fraud in government entities and private companies. Albrecht (1991) explains that those who commit fraud are typically perceived to be honest and have earned trust in the organization. Albrecht (1991) introduced the term "fraud triangle" to combine the three conditions Cressey (1951) found necessary to motivate fraud—perceived pressure, opportunity and rationalization.[10]

---

[7] Wheeler combined occupational and organizational attributes of offenders because the nature of organizational offenders made it impossible to separate the two attributes.
[8] Wheeler (1982), pp. 1419–1420.
[9] Wheeler (1982) acknowledged that since organizational criminals tended to have higher rates of representation by private lawyers (over 90 percent of court cases) compared to other white-collar criminals, this may have also been a factor in length of incarceration.
[10] Albrecht (1991) states the fraud triangle is similar to the fire triangle in which oxygen, heat and fuel are necessary for a fire to exist and if any of these three factors is missing, fire cannot exist.

Figure 1. Fraud Triangle



Albrecht (1991) comments that of the two most general ways to obtain money from organizations illegally—simple theft and theft by deception—the vast majority of crimes against organizations are thefts by deception; specifically, fraud carried out by employees of the organization. In terms of the mechanics of frauds committed against organizations, Albrecht (1991) states there are three main approaches: 1) receipts fraud, 2) theft of assets and 3) disbursements fraud. There are many ways in which frauds are carried out within each of these three general approaches. Receipts fraud can be accomplished by stealing duplicate payments, stealing payments on bad debt, or crediting accounts while stealing receipts, to name just three examples.[11] Theft of assets can be accomplished by, for example, theft of cash, inventory and fixed assets, as well as using company assets for personal use.[12] Perhaps the most elaborate frauds are designed to steal using disbursements made by the company and may involve collusion with individuals outside the company being defrauded. Examples of disbursements fraud include vendor fraud in which an employee arranges to overpay a vendor in return for cash kickbacks and/or other gifts from the vendor, payroll frauds in which ghost employees are paid, and health claims fraud. [13] In terms of impact, Albrecht (1991) states that business losses due to disbursements fraud exceeded the combined losses from receipts fraud and asset theft. Frauds against organizations can be prevented by reducing each of the three incentives for fraud—perceived pressure, opportunity and rationalization. Albrecht (1991) comments that a healthy work environment that encourages employee and management communication can reduce fraud by addressing low employee moral that can lead employees to rationalize fraud, as well as giving employees legal ways to address financial pressures. Finally, while improvements in companies' internal controls can reduce fraud,

[11] Albrecht (1991), p. 29.
[12] Albrecht (1991), p. 29.
[13] Albrecht (1991), p. 29.

Albrecht (1991) states that internal control systems are not designed to catch frauds involving collusion with other employees and individuals outside the organization.

Akerlof and Romer (1993) develop a theory of fraud to explain four financial crises that followed economic boom–bust cycles during the 1980s—U.S. savings and loan associations (S&Ls) crisis, Texas real estate market collapse, junk bond market collapse and the financial crisis in Chile. Akerlof and Romer (1993) model a firm whose owners have limited liability, i.e., owners can at most lose their ownership stake in the firm. Under normal circumstances firm owners will seek to maximize firm value, V, since their earnings from the firm, i.e., dividends, increase with V. Thus, under normal circumstances firms owners seek investments in projects with positive net present value. Normal circumstances are defined here as periods where V exceeds the maximum dividends owners can extract from the firm, M^*. Akerlof and Romer (1993) point out that the maximum amount of dividends that can be extracted from a bank or S&L is limited by regulatory minimum capital requirements. Under most circumstances it is unlikely that M^* can exceed V since capital requirements are set high enough to prevent this from occurring. In the 1980s, however, the S&L industry suffered a severe decline in capitalization due to a spike in short-term interest rates that resulted in negative net interest income generated by a severe mismatch in the maturities of S&Ls' assets and liabilities—S&Ls lent long on 30 year mortgages with fixed interest rates but borrowed short, relying on deposits with short-term maturities.[14] The result of the Treasury yield curve shock was most S&Ls had negative market value. S&L regulators—state and federal—permitted regulatory accounting rules that masked losses and allowed S&Ls to record false profits and high capital.[15] S&L regulatory capital requirements were also reduced.[16] The result was that M^* exceeded V for most S&Ls, hence thrift owners sought ways to extract funds from S&Ls, extracting enough to drive S&Ls into bankruptcy. Akerlof and Romer (1993) explain that the types of projects ideally suited to extracting M^* are those that allow a S&L to record paper profits even when the project generates no cash flow to the S&L. With a limited set of positive NPV project available, thrift owners turn to a much larger set of negative NPV projects that boom-bust cycles provide. Many types of negative NPV projects were ideally suited to generating false revenues and profits that S&L owners could extract from the thrift while still recording high S&L profits and capital under lax accounting rules. Akerlof and Romer (1993) point out that losses generated by the purposeful bankruptcy strategy greatly

---

[14] Akerlof and Romer (1993), p. 23.
[15] Akerlof and Romer (1993), p. 25.
[16] Akerlof and Romer (1993), p. 25.

exceed what owners were able to extract from thrifts, banks and other financial organizations during the four 1980s financial crises they studied, due in part to spillover effects on firms still pursuing firm value maximization and in part due to the bankruptcy for profit strategy's fueling of the economic boom–bust cycle. For these reasons, Akerlof and Romer (1993) characterize the bankruptcy for profit strategy as looting. In terms of the regulatory environment, Akerlof and Romer (1993) explain that in addition to reduced regulation and supervision and lax accounting standards there were changes to market regulation that allowed for increases in the concentration of S&L ownership which also contributed to the S&L crisis.[17] Akerlof and Romer (1993) comment that regulation that allowed for sole ownership of S&Ls made it easier for an owner to run the thrift for personal benefit.[18] Further, relaxed S&L regulation in two states—California and Texas—led to a competition in laxity, and further fueled the boom–bust cycle in those states as S&Ls changed from federal to state charters to take advantage of lax state regulation.[19]

In the case of the Texas real estate crisis the bankruptcy for profit strategy Akerlof and Romer (1993) describe was achieved by making loans for the acquisition, development and construction of commercial and residential real estate (hereafter, ADC loans). ADC loans are ideally suited to internal bank and thrift fraud since the true value of the project won't be known until it is completed three-to-five years after the lending begins. During the Texas real estate crisis ADC loans were made with no equity interest required of borrowers (real estate developers) and interest payments and fees borrowers "paid" to banks were made through interest reserves bank established (lent) for borrowers.[20] GAAP and regulatory accounting rules allowed banks and thrifts to record ADC loan interest and fees as income and effectively pay themselves all reported profits on the ADC loan during the real estate development period.[21] ADC loans were also often made with no property purchase or take-out financing commitments but rather were made on a speculative basis. [22] ADC loan growth was widespread during the 1980s Texas real estate sector boom period, allowing banks and thrifts to report high profits and growing capital. During the 1980s real estate crisis, Texas ADC lending persisted as real sector indicators,

---

[17] Akerlof and Romer (1993), pp. 24–25.
[18] Akerlof and Romer (1993), p. 25.
[19] In addition to charter changes, studies have shown there was a substantial increase in new bank charters (de novo banks) during the 1980s banking crises; see for example, O'Keefe (1990), FDIC (1997). New bank charters also increased prior to the 2007–2009 financial crises, as shown by Lee and Yom (2016).
[20] Akerlof and Romer (1993), pp. 27–28.
[21] Akerlof and Romer (1993), pp. 27–28.
[22] See, for example, O'Keefe (1990) and FDIC (1997).

such as commercial property vacancy rates and home sales, deteriorated.[23] As the real estate sector deteriorated many lenders tried to hide problem loans through various schemes such as making loans to real estate developers to purchase projects from the initial developer to hide defaults and manipulate real estate prices.[24] The junk bond market collapse and Chilean financial crisis also followed the bankruptcy for profit strategy according to Akerlof and Romer (1993); for brevity we do not discuss those crises here.

Green and Reinstein (2004) examine financial statement fraud among publicly traded banks and savings and loan associations (S&Ls) that was detected by the Securities and Exchange Commission (SEC). Green and Reinstein (2004) use a sample of 64 banks and S&Ls that the SEC identified as releasing fraudulent financial statements between 1979 and 1996.[25] This sample allowed Green and Reinstein (2004) to study how management fraud changed over time and to investigate the impact of changes in economic conditions, regulation and public scrutiny of bank and S&L financial statements, on the types of fraud that occurred. There were a number of changes to oversight and regulation of public accounting between 1979 and 1996 that tightened public scrutiny. Green and Reinstein (2004) find that increased regulation and scrutiny did not change the frequency of financial statement fraud but did alter how it was carried out. Specifically, the authors conclude that banks and S&Ls became more willing to withhold information than alter information in the latter part of their sample period. Green and Reinstein (2004) examine the frequency of fraud by audit area—Accounts Receivable, Cash, Investments, Loans Receivable, Reserves for Loan Losses, and Revenues, Gains and Losses. For both the 1979–1987 and 1988–1996 sub-periods the authors find the majority of frauds occurred in Investments, Reserves for Loan Loss reporting and Loans Receivable. The tenor of the financial reporting fraud in the Green and Reinstein (2004) sample was failure to recognize deterioration in asset value, e.g., overstate the value of investments and include uncollectable loans among loans receivable, and understate loss reserves.[26] In terms of the methods used to misstate financials, Green and Reinstein (2004) find inadequate or misleading disclosures and inaccurate accounting estimates comprised over 50 percent of the instances of fraudulent activity in their sample.[27] Other methods used to misstate financials in the Green and

---

[23] See, for example, O'Keefe (1990) and FDIC (1997).
[24] Akerlof and Romer (1993), p 17.
[25] The SEC issues enforcement actions against banks and S&Ls that SEC examiners found to be issuing fraudulent financial statements. The enforcement actions are available in the SEC's Accounting and Auditing Enforcement Releases (AAER).
[26] Green and Reinstein (2004), p. 96.
[27] Green and Reinstein (2004), p. 99.

Reinstein (2004) sample include early recognition, fictitious documents, unsupported journal entries, lack of detail books, and entry misclassification of accounts.[28]

Black (2005) provides a detailed accounting of the S&L crisis of the 1980s and attributes the S&L failure waves to widespread internal fraud, specifically fraud carried out by the most senior thrift officers, which Black (2005) calls control fraud. Black (2005) finds that insider abuse and internal fraud by senior thrift officers occurs more frequently during economic growth periods when thrifts increase lending to support the real sector growth. During the early phases of the economic cycle thrift loan growth rates accelerate and loan concentrations in risky loan types increase as well. Black (2005) observes that loan growth is aided by relaxed internal lending standards, weak risk management and ineffective oversight by thrift boards of directors. According to Black (2005), during the economic growth phase the regulatory environment is characterized by lax bank supervision (de-supervision), accommodating bank regulation (de-regulation) and a supportive political environment. New lending is typically concentrated in those products where loan collateral value and loan repayment risk are difficult to estimate.[29] As the economic cycle slows fraudulent activity becomes increasingly difficult to hide as many frauds were Ponzi schemes that depended on loan growth for cash flow.[30] At the end of the economic cycle loan collateral value deteriorates rapidly when the bubble in asset prices (collateral values) bursts. These market conditions also occurred during the 2007–2009 U.S. financial crisis; therefore, Black (2005, 2009) finds increases in bank and thrift fraud during financial crises in general.[31]

Povel, Singh and Winton (2007) develop a theoretical model of corporate financial statement fraud designed to explain the increase in the frequency of fraud that tends to be revealed toward the end of economic boom periods in many industries.[32] Povel, Singh and Winton (2007) model the fraud that poorly performing firms might engage in to mask their true condition so as to attract investors. In the model invested funds allow for project finance that also confers benefits to the firm manager. Investors can choose to rely on publicly available information or more costly monitoring of firms when deciding whether or not to invest in firms. In the model, investors are more willing to rely on public information when overall economic conditions are good because they base their prior beliefs about firms' conditions

---

[28] Green and Reinstein (2004), p. 99.
[29] Black (2005), pp. 48–50.
[30] Black (2005), pp. 48–50.
[31] See, for example, O'Keefe (1990) and FDIC (1997).
[32] Previous studies have documented increases in bank fraud toward to end of economic boom periods that are followed by bank failure waves. See, for example, Akerlof and Romer (1993) and Black (2005, 2009).

on the average number of financially sound firms, i.e., become optimistic.[33] Since investors will monitor companies with poor performance and are less likely to invest in these firms, poorly performing companies have an incentive to misrepresent their financial condition when overall economic conditions are good. [34] Conversely, investors become pessimistic when economic conditions are bad, i.e., average company performance is poor, and will rely on monitoring to assess companies' conditions during these periods, thereby reducing incentives for financial statement fraud. [35]

Finally, Black (2009, 2010) uses a medical analogy to describe internal bank and thrift fraud.[36] Black (2009, 2010) states that the occurrence of internal thrift financial fraud is akin to the spread of infectious diseases that require an environment conducive to the pathogen (i.e., a virus or bacteria), a vector (i.e., mechanism that spreads the pathogen) and a host (i.e., infected individual). The environment, pathogens, vectors and hosts Black (2009) describe are based on the S&L crisis of the 1980s which Black (2009) argues was repeated during the 2007–2009 U.S. financial crisis.

3. Proposed Fraud Detection Framework

The literature discussed in section 2 provides information that we use to model bank fraud, i.e., the who, what, when, where, why and how questions about bank fraud. The bank fraud literature finds that bank frauds that contribute to bank failures are often organizational crimes in which the most senior bank officers use their positions of trust and the bank itself to carry out the fraud and this person will often be a dominant senior bank officer. While the exact manner with which fraud is carried out differs across banks, if the fraud is large enough in scale and scope it should result in under-recognition of loan losses, over-valuation of assets and over-statement of profits and capital. Hard to value assets, such as real estate acquisition, development and construction loans, are often used to carry out the fraud. The fraud will most likely occur during a national, regional or sectoral economic boom period accompanied by de-supervision and de-regulation.

Our reviews of FDIC failing bank board cases indicate that the findings of the academic literature on bank fraud are consistent with what bank examiners observed at FDIC-insured failed banks between 1989 and 2015. FDIC failing bank board cases contain confidential information; hence, we cannot

---

[33] Povel, Singh and Winton (2007), p. 1220.
[34] Povel, Singh and Winton (2007), p. 1220.
[35] Povel, Singh and Winton (2007), p. 1220.
[36] Black (2009) credits the now defunct regulator of savings and loans associations, the Federal Home Loan Bank Board, for applying the "health sciences metaphor" to describe internal bank fraud.

present case studies.[37] To give an indication of what examiners report in these cases, we next present a fictional failing bank board case that is designed to reflect the discussions of insider abuse and fraud we read in FDIC failing bank board cases:

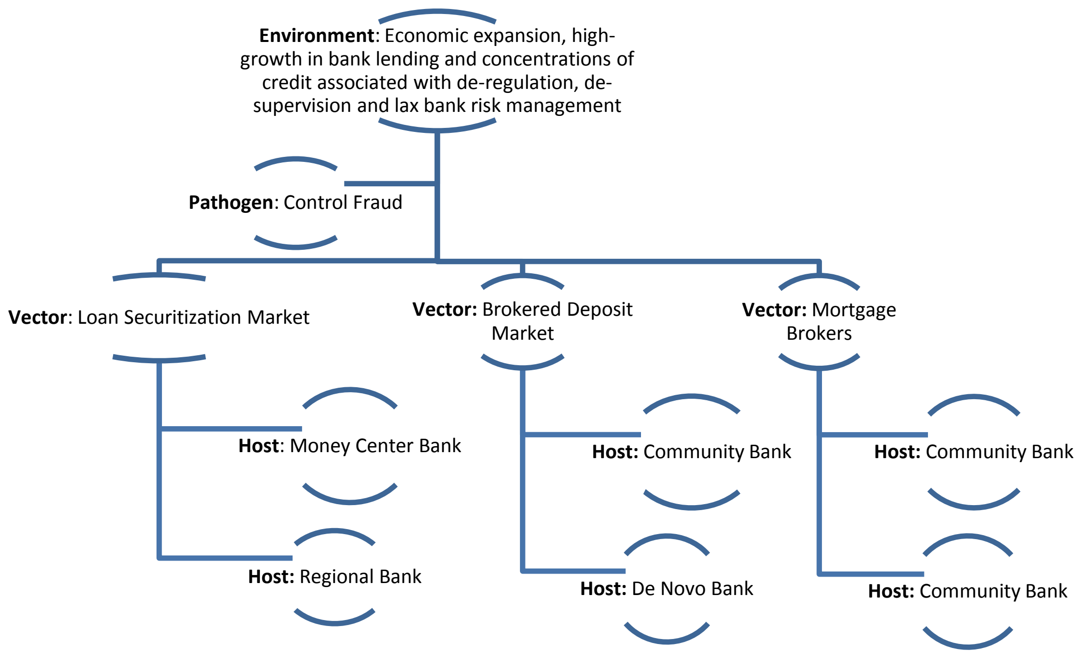
> The bank departed from the business plan approved by supervisors when its charter was approved in 2004. The bank's original business plan was to concentrate on local consumer and small business lending. In 2006 the bank changed its focus to lending for real estate acquisition, construction and development (ADC loans), as well as sub-prime residential real estate. Loan growth and loan concentrations have increased the bank's risk exposure substantially as the ADC loan-to-equity ratio increased from 50 percent to 600 percent between 2004 and 2008. Bank management has not put in place proper risk controls, used weak lending standards and questionable real estate appraisals. The bank's ADC loans allow for 100 percent financing with interest reserves, and a majority of the ADC and residential real estate lending has been well outside the bank's market area. The bank's board of directors has not exercised proper oversight of the bank and bank management. The bank's CEO and president holds a majority interest in the bank and dominates decision making at the bank. Examiners identified conflicts of interest for the CEO and two board members. Lending limits to insiders have been exceeded, resulting in the FDIC filing a notice of Reg. O violation. FDIC also issued a Section 8.e "removal of officers" enforcement action in 2008 to remove the bank CEO after examiners found loan files had been altered by the CEO to mask non-performing status. In addition, examiners identified potential fraudulent loans to real estate development companies in which the CEO had a business interest and FDIC has referred the matter to the Department of Justice. The bank's financial statements are not reliable since the bank has under-reported nonperforming loans. The new CEO, who joined the bank in 2009, has little previous experience in banking and has been unable to obtain new capital to cover loan losses, reduce the nonperforming ADC loans and residential mortgage loan exposures and has been otherwise unable to turn the bank around.

As this fictional/representative case study makes clear, many 1989–2015 failed banks exhibited the characteristics of fraudulent organizations described by Wheeler (1982), Albrecht (1991), Akerlof and Romer (1993), Green and Reinstein (2004), Black (2005) and Povel, Singh and Winton (2007). We now combine the previously discussed characteristics of the environment, vectors and hosts associated with insider abuse and internal fraud at failed banks to develop a framework for fraud detection (hereafter, *proposed fraud detection framework*). Figure 2 uses Black's (2009, 2010) health sciences metaphor to

[37] Each of the three federal bank regulators has an Office of Inspector General (OIG) that is required to conduct Material Loss Reviews of failed banks where failure resolution costs exceed minimum thresholds of materiality. The Material Loss Reviews are publicly available at federal bank regulators' websites. These reviews describe events surrounding bank failures and the reasons for failure and are similar in many ways to FDIC failing bank board cases but do not contain confidential material.

illustrate our *proposed fraud detection framework*. We use this framework to identify risk indicators that will serve as inputs for our fraud detection models.

Figure 2. Bank Control Fraud: Health Sciences Metaphor



We next discuss empirical approaches for fraud detection, followed by the application of these techniques to models based on our fraud detection framework.

4. Previous Literature on Fraud Detection

Financial fraud has been a persistent problem historically and, according to Bolton and Hand (2002), is expanding in frequency and severity with societies' increased reliance on technology. There is a correspondingly growing literature on fraud detection. In this section, we discuss commonly used empirical approaches for fraud detection.[38] Since there are a large number of diverse approaches for fraud detection we focus on those approaches that have successfully detected financial fraud.

Bolton and Hand (2002) review the literature on the detection of several types of fraud, such as credit card, money laundering, e-commerce, computer intrusion and telecommunications fraud. Bolton and Hand (2002) describe two general statistical methods for fraud detection—*supervised* and *unsupervised* methods. Supervised methods use datasets where instances of fraud have been confirmed to train

---

[38] Fraud prevention is outside the scope of this paper.

models that distinguish fraudulent from non-fraudulent patterns in the data.[39] Supervised statistical models such as linear discriminant analysis, logistic regression, neural networks and a variety of machine learning algorithms have been used to develop empirical fraud detection models by looking for patterns in the data on observations with fraud present and applying this information to classify new data as having high potential to be fraudulent.[40] Bolton and Hand (2002) state some types of fraud typically involve more than one individual—e.g., telecommunications fraud and money laundering—and that analyses such as record link and social network analysis have been used to relate individuals involved in fraud together. Unsupervised methods can be applied to datasets where instances of fraud need not be known a priori since the methods rely on pre-identified rules for detecting fraud (i.e., do not need to be trained on fraud data). Unsupervised methods look for outliers in the data relative to expected values. A widely used method of unsupervised fraud detection is statistical digit analysis based on the Law of Anomalous Numbers (aka, Benford's Law). Bolton and Hand (2002) point out that since statistical fraud detection can at best point to the likelihood of fraud, the output of these models is a *suspicion score* that indicates the likelihood an observation in the data represents an incidence of fraud.[41] Given the wide variety of statistical fraud detection approaches, there can be a correspondingly wide variety of suspicion scores. Bolton and Hand (2002) discuss using suspicion scores to rank order observations and focusing investigative efforts on those entities with the highest rank-ordered scores.[42] We next discuss popular approaches for statistical fraud detection, starting with unsupervised methods—Law of Anomalous Numbers—followed by supervised methods—logistic regression and neural networks.

4.1. Law of Anomalous Numbers

Newcomb (1881) and Benford (1938) are credited with independently discovering the Law of Anomalous Numbers; since Benford's exposition of the Law is more comprehensive than Newcomb's, we next discuss Benford's seminal paper on the Law of Anomalous Numbers. Benford (1938) was a physicist working for General Electric Company when he presented his paper on the Law of Anomalous Numbers at a meeting of the American Philosophical Society.[43] Benford (1938) states, "It has been observed that the pages of a much used table of common logarithms show evidences of a selective use

[39] Bolton and Hand (2002), p. 236.
[40] Bolton and Hand (2002), p. 237.
[41] Bolton and Hand (2002), p. 237.
[42] Bolton and Hand (2002), p. 236
[43] Benford (1938).

of the natural numbers."[44] More specifically, the observation was that the first pages of a table of common logarithms (base 10 logarithms) show more wear and tear than do subsequent pages. Benford (1938) refers to the Arabic numerals 1 through 9 as the natural numbers. The first pages of the common logarithm table cover numbers that begin with the digit 1, and show for example, the log of 1.10 is 0.0414 while the last pages of the table cover numbers that begin with the digit 9. Benford surmised that this reflected the possibility that engineers, mathematicians and scientists who used logarithmic tables to make calculations involving items that can be represented by numbers—e.g., areas around lakes, populations, death rates and air pressure—*used* numbers that began with the digit 1 more than they used numbers that began with the digit 9.[45] To be clear, a number is a measure such as the population of a city, e.g., 230,456, while the first digit is the specific Arabic numeral that appears at the beginning of the number, here "2", and the second digit appears second, here "3", and so on.[46]

Benford (1938) investigated his "selective use of natural numbers" hypothesis by obtaining 20,229 samples for 20 very different categories of measures—areas of rivers, size of populations, death rates, air pressure and atomic weights, to name but five measures.[47] The number of observations by measurement category varied from a low of 91 (Atomic Weight) to a high of 5,000 (mathematical functions of digits, e.g., square root). Benford (1938) measured the frequency of the first digit for the Arabic numerals 1 through 9 for all 20,229 observations. Table 1 shows the average frequency of the first digit for Benford's full sample.[48]

Table 1. Digit Frequency for a Set of 20,229 Measures

	First Digit Frequency as a Percent of Total Number of Observations								
Number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Average	30.6	18.5	12.4	9.4	8.0	6.4	5.1	4.9	4.7

[44] Benford (1938), p. 551.
[45] Benford (1938), p. 551.
[46] We would like to point out that logarithm table wear and tear could simply reflect the fact that English language books are read from left to right, so that individuals flipping through a book or tables will naturally include the initial pages of the book or tables in their search for specific pages more often then they reach the end of the book or table. Benford's (1938) research on digit frequency, however, lends credence to the logarithmic table hypothesis.
[47] Benford (1938) provides very little information about the 20 categories of measures, and does not define all of them; hence, categories such as "Design" and "Drainage" remain a mystery.
[48] Benford (1938), p. 553.

Benford (1938) imposed four restrictions on his experiment on digit frequency. First, the 20 categories of measures were unrelated to one another, e.g., population versus atomic weight. Second, for any number preceded by a decimal or a zero, preceding zeros were ignored and only the first digit between 1 and 9 was considered; hence for a number such as 0.01256 the first digit was taken as "1". Third, only measures with four digits or more were included in the sample; hence our prior example qualifies—1256. Fourth, Benford (1938) selected ..."data that is not too restricted in numerical range, or conditioned in some way too sharply…"[49] Benford (1938) did not give any examples of the measures in his sample and did not explain what "conditioned too sharply" means. We will assume Benford (1938) was explicitly acknowledging the possibility of some potential truncation and rounding of numbers in his sample but that the overall alteration of numbers was minimal. We return to this topic later in this section.

Benford (1938) does not address the treatment of negative numbers. Clearly, one cannot directly apply negative numbers to a logarithmic distribution function so absolute values of negative numbers would need to be taken before applying digit analysis. The Association of Certified Fraud Examiners (ACFE) recommends doing separate digit analyses on negative and positive numbers because the incentive to manipulate numbers works in opposite directions for negative versus positive numbers. ACFE explains that for measures such as net income, a company's management has an incentive to overstate positive net income, however, if net income is negative managements' incentive is to report as small a loss as is possible or understate losses.[50]

Benford (1938) made a deliberate effort to collect data from as many fields as was possible and to use measures with "various degrees of randomness".[51] Some of the measures, such the street address numbers of the first 342 people mentioned in one issue of *American Men of Science* magazine, are arguably random numbers.[52] At the other extreme, Benford (1938) points out that some measures in his sample follow fixed laws or are otherwise closely related, such as …"Molecular Weights, Specific Heats, Physical Constants and Atomic Weights".[53]

[49] Benford (1938), p. 552.
[50] See Association of Certified Fraud Examiners.
[51] Benford (1938), p. 552.
[52] Benford (1938), p. 560.
[53] Benford (1938), p. 557.

Benford (1938) observed that for the random numbers in his sample, the first digit frequencies closely follow a logarithmic distribution function:

> "The frequency of first 1's is then seen to be 0.306, which is about equal to the common logarithm of 2. The frequency of first 2's is 0.185, which is slightly greater than the logarithm of 3/2. The difference here, log 3 - log 2, is called the logarithmic integral. These resemblances persist throughout, and finally there is 0.047 to be compared with log 10/9, or 0.046."[54]

Benford First-Order Test

Based on these findings, Benford (1938) proposes that for sets of unrelated, random measures the frequency of the first digit, "a", follows a logarithmic function, $F_{a,}$ as shown is equation 1.[55]

$$F_a = log\left(\frac{a+1}{a}\right) \tag{1.}$$

Benford (1938) observed that a nonrandom numbers' first digit frequencies show the most divergence from the logarithmic distribution, hence he calls the logarithmic distribution rule the *Law of Anomalous Numbers*. Benford (1938) also finds that numbers with fewer than four digits do not follow the logarithmic distribution rule but rather follow a different, geometric distribution.[56] Benford (1938) points out that the Law of Anomalous Numbers is about events, i.e., frequencies of digits, and not about natural numbers and digits themselves.

Following the logic of the logarithmic distribution function, that second place digit frequencies must take the first digit into account. To see this, consider a two digit number, "ab", where "a" is the first digit and "b" is the second digit. The frequency of second digit "b" occurring in otherwise random sets of numbers, F_b, given first digit "a" occurred, is shown in equation 2:[57]

$$F_b = log\left(\frac{ab+1}{ab}\right) \Big/ log\left(\frac{a+1}{a}\right) \tag{2.}$$

---

[54] Benford (1938), p. 553.
[55] Benford (1938), p. 554.
[56] Benford (1938), p. 554.
[57] Benford (1938), p. 555.

Summing equation 2 over all possible combinations of a specific second digit, b, and the nine possible first digits, a, yield the probability of second digit b occurring.

We would like to point out that equation 2 follows Bayes' Theorem, where the conditional probability of "b" occurring given "a" has occurred is equal to the ratio of the joint probability of "a" and "b" to the probability of "a" occurring.

$$P(b|a) = P(b \cap a)/P(a) \tag{3.}$$

The logarithmic distribution functions can also be used to generate expected digit frequencies for higher order of digits, e.g., third, fourth, and fifth digit, as well as combinations of digits, e.g., first two digits, that follow Benford's Law. For brevity we do not derive those frequency functions here. The most common application of Benford's Law for fraud detection is to compare expected first, second and higher order digit frequencies with digit frequencies observed in the data, where the dataset used is take from measures suspected of reflecting fraudulent activity. Because the digit frequencies tests are applied directly to the data without any transformations of the data, comparisons of expected versus actual digit frequencies are known as Benford first-order tests. As we discuss in section 4.2 there are more recently developed Benford digit tests of data transforms, i.e., differenced in rank ordered data series, that address some of the weaknesses found in the Benford first order test.

Benford (1938) shows the first digit frequencies for random numbers follow the logarithmic distribution function well but that numbers that follow fixed rules, e.g., scientific constants, have first digit frequencies that diverge the most from the logarithmic distribution among the 20 measurement categories. Benford (1938) concludes, "these facts lead to the conclusion that the logarithmic law applies particularly to those outlaw numbers that are without known relationship rather than to those that individually follow an orderly course; and therefore the logarithmic relation is essentially a Law of Anomalous Numbers."[58] Benford (1938) next investigates the causes of the Law of Anomalous Numbers, and studies natural phenomena, such as individual's reactions to external stimuli. Benford (1938) explains that individual's reactions to light, sound, radiation and toxins closely follow a logarithmic

[58] Benford (1938), p. 557.

distribution law.[59] Conversely, man-made measures or scales for fields such as music and mechanical devices, such as drill bits and light bulb wattage, follow a geometric distribution.[60]

4.2. Fraud Detection Using the Law of Anomalous Numbers

Newcomb (1881) and Benford (1938) do not mention the application of the Law of Anomalous Numbers to fraud detection; however, its application to fraud detection and financial fraud in particular, has been widespread. Durtschi, Hillison and Pacini (2004) review the literature on Benford's Law, focusing on the application of the Law to detecting fraud in accounting data. Durtschi, Hillison and Pacini (2004) conclude that it is appropriate to apply Benford's Law to accounting data since studies by Carslaw (1988), Boyle (1994), Hill (1995), Nigrini (1996, 1999), Nigrini and Mittermaier (1997) and others show that most accounting numbers result from combining different, independent random data in several ways (addition, subtraction and division) and behave as anomalous numbers. Durtschi, Hillison and Pacini (2004) also point out that certain accounting numbers do not follow Benford's Law but rather follow an orderly course as evidence of human thought, such as assigned numbers, e.g., check numbers, order numbers, and other numbers resulting directly from human thought, e.g., ATM withdrawals. Further, Durtschi, Hillison and Pacini (2004) describe the prices of goods and services as reflecting "psychological barriers" that affect digit frequencies, and do not follow Benford's law. For example, retailers often prefer to price products at the next lowest price, e.g., $1.99 versus $2.00, apparently because shoppers place disproportionate significance on immaterially lower prices. Before applying the Law of Anomalous Numbers to financial fraud detection we consider two possible avenues for bank financial statements to reflect an orderly course—fraudulent and non-fraudulent.[61]

Fraudulent Orderly Courses

A bank employee who issues loans to fictitious borrowers is likely adding non-naturally occurring numbers to the bank's loan portfolio. Other examples of bank employee fraud include schemes to refinance nonperforming loans to hide defaults, using fictitious real estate appraisals and other fictitious documentation to get loans approved and altering past-due loan customers' records to make account payment status current. In the case of frauds committed by bank senior officers it is also possible that

---

[59] Benford (1938), p. 562.
[60] Benford (1938), p. 563.
[61] The empirical literature on financial fraud that we are aware of does not consider the possibility of non-fraudulent factors, other than number rounding and truncation, which might result in non-random financial statement entries.

the bank financial statements are directly altered to mask the fraud. Whether these frauds are detectable from analysis of banks' balance sheet and income statements depends on the duration and materiality of the fraud. **Our main hypothesis** is that material internal fraud is detectable by observing significant deviations in digit frequencies from the logarithmic distributions posited by Benford (1938) for relevant balance sheet and income statement entries. We will quantify what we mean by relevant entries and significant deviations in section 6.1.

Non-fraudulent Orderly Courses

To begin, consider the dominant activity at banks—lending. The amounts that bank customers seek to borrow largely depend on loan purpose and borrowers' ability to repay the loan. Banks approve loan applications based on customer credit worthiness, bank credit policies, bank condition, local economic conditions and bank regulation. The degree of randomness in loan amounts will depend on these demand- and supply-side factors. The influence of these factors on loan amounts might also vary across loan categories. For this reason, **our second hypothesis** is that the degree of randomness in loan amounts and related financial variables—loan charge-offs, recoveries and nonperforming loans—can vary across loan categories for reasons unrelated to fraud. Specifically, we hypothesize that certain categories of loans reflect an orderly course that is non-fraudulent while other categories of loans reflect random processes from a digit perspective. Two potential sources of non-fraudulent, non-random digits in bank financial statements are retail pricing and negotiated prices.

Retail Pricing

To understand the "physiological price barriers" described by Durtschi, Hillison and Pacini (2004), consider retail automobile prices. The manufacturer suggested retail price (MSRP) as of February 2017 for a Jeep Cherokee was $23,595 and a Cadillac CT6 Sedan listed for $53,795; the authors found similar pricing for other models of automobiles. The MSRP is a starting point in a sales price negotiation, so why not set the MSRP at $23,600 for the Jeep and $53,800 for a Cadillac? A Northern Virginia Ford dealership listed the "easy price" of a Ford F150 truck as $18,999. The "easy price" is a price one can lock in and is not a starting point for price negotiation; so why not round up to $19,000? Does a 0.005% difference in price really matter to consumers? Automobile dealers apparently think it does and appear to manage the digits in prices to the lowest digit "available" in the price. That is, the Ford F150 "easy price" of $18,999 suggests second digit management perhaps because the automobile features do not qualify it for first digit management that might move the price into the $20,000 price range. Similarly, the MSRP's of the Jeep Cherokee and Cadillac suggest the dealerships are also managing prices to the second digit since customers rarely pay more than MSRP.

Asking prices for automobiles are just that, starting points for price negotiations. What are the implications of digit-managed asking prices on final sales prices? Automobile price negotiations are not a random process, rather both participants in the negotiation—automobile salesperson and customer—seek to get the most favorable price from their perspectives. We hypothesize negotiations of sales prices that start with digit-managed asking prices can only lead to digit-managed final sales prices.

The same retail pricing phenomenon is seen in the list prices for residential properties. A random selection of residential home listing prices in Northern Virginia as of February 2017—$1,599,000; $899,000; $449,900; and $729,000—suggests realtors, like automobile dealerships, are managing listing prices at the second digit. As was the case for automobiles, mortgage loans will reflect not only list prices but final negotiated prices. We believe our previous conclusion about the cost of automobiles also applies to the cost of residential housing, i.e., it is a digit-managed number.

The existence of non-fraudulent, orderly courses in data from bank financial statements contributes to type 1 error in the application of the Law of Anomalous Number to fraud detection. In our empirical approach we control for this possibility by testing for fraud across different segments of the loan portfolio, as well as areas of the balance sheet and income statement we believe are not driven by non-fraudulent, digit-managed processes. We also apply a recently developed second-order test of Benford's Law that greatly reduces the likelihood of type 1 error found in Benford first order tests, which we describe next.

Benford Second-Order Test

Nigrini and Miller (2009) introduce a second-order test of Benford's Law that greatly reduces the large type 1 error rate associated with standard first-order digit tests of Benford's Law. Miller and Nigrini (2008) provide mathematical analysis of the differences between adjacent ordered random numbers that follow Benford's Law and show the digits of these differences "approximately" follow Benford's Law. Nigrini and Miller (2009) provide empirical examples that show that an important advantage of using the differences of order-ranked random numbers for Benford digit analysis is that the differences in digits tend to follow Benford's Law for most statistical distributions of numbers, including many that do not follow Benford's Law, e.g., normal and uniform distributions. Nigrini and Miller (2009) conclude that one can expect Benford's Law to "almost" apply to most random number data distributions or mixture of distributions, although the usual caveats about numbers altered by human intervention still apply. Nigrini and Miller (2009) provide empirical case studies of the second-order test, applying the test to a corporation's accounts payable data, corporate journal entry data, franchise restaurant data on food sales and cost data (cost done separately) for approximately 5,000 restaurants, and tests of annual food costs-to-sales ratios by restaurant.

Since the second-order tests are conducted on difference values that "almost" follow Benford's Law for all digits and two-digit combinations, there will be small differences between the Benford expected digit frequencies and the frequencies one observes even when the underlying data are truly random. Nigrini and Miller (2009) therefore suggest that one should apply statistical tests of expected and observed digit frequencies, such as Chi Square tests, with caution since statistical tests may tend to reject the null hypothesis that the data follow Benford's Law due to the inexact following of Benford digit frequencies. Nigrini and Miller (2009) suggest one can supplement statistical tests of digit frequencies departure from the Benford's distribution with graphical analysis of observed digit frequencies and simple measures of divergence in distributions, such as the mean absolute deviation between expected and observed digit frequencies. We apply the second-order Benford test in section 6.

5. Data

Our measure of whether there was insider abuse or fraudulent activity in a failed bank is compiled from three sources. The first source is the FDIC Board of Directors *failing bank cases (FBC)*. Before a bank is closed by the state or national bank chartering authority, the FDIC Division of Resolutions and Receiverships prepares a failing bank case to request the authority to choose the least costly method for resolving the bank failure from the FDIC Board of Directors. The failing bank case states the reasons why the bank should be closed and a preliminary, model-based estimate of the cost of the failure to the FDIC Deposit Insurance Fund (DIF). In many cases the least costly resolution method is not known at the time the failing bank board case is prepared. To utilize the FBC for this paper, the FBC for each failed bank was reviewed by three FDIC staff that made independent judgments on whether insider abuse and/or fraud played a role in the bank's failure. For each failed bank, a final decision was made on whether insider abuse and/or fraud was present if at least two staff agreed on that finding. This process served as a control on the potential subjectivity in fraud assessments.

The *restitution orders* are also used to identify banks where insider abuse or fraudulent activities were present. When fraud is detected, the FDIC issues a restitution order to the perpetrator with a fine. Issuing a restitution order can be a punitive action or a corrective action since a restitution order can be issued before, during, or after the bank failure. Banks with restitution ordered amounts of more than 25 percent of the estimated resolution cost are defined as insider abuse and/or fraud present. To ensure the restitution order amounts are material we also required resolution costs to be at least 5 percent of the failed-bank's assets.

Our third source of fraud information is from FDIC *bond claims*. A bank with bond insurance is protected from insider abuse and fraud up to the amount of the policy. A bank can file a claim on its bond insurance when insider abuse and/or fraud cause a loss. In its role as failed-bank receiver the FDIC can file a claim on the bond insurance when it discovers insider abuse and/or fraud while resolving the bank failure. A bank is defined as an insider abuse and/or fraud failure if the FDIC filed a bond insurance claim. Information on fraud claims made by the bank is not used to define fraud failures because we do not have information on bond claims made by the bank.

Table 2 presents the number of failed banks where insider abuse and/or fraudulent activities were identified in each data source for bank failing between 1989 and 2015 period. Each data source identified a similar number of instances of insider abuse and fraudulent activities and there is significant overlap in these measures.

Table 2. Insider Abuse and Fraud among U.S. Failed Banks: 1989–2015

FDIC Failing Bank Board Case	227
Bond Claims	205
Restitution Orders (> 25% of resolution costs)	215
Net Number of Insider Abuse and/or Fraud Failures	457
Number of Failed Banks	1,257

Table 3 presents a list of the types of insider abuse and/or internal fraud activities documented in failing bank cases. It is possible that more than one type of insider abuse is observed at a bank. We acknowledge that specific activities used to carry out insider abuse and internal bank fraud will likely change over time.

Table 3. Types of Insider Abuse or Fraudulent Activity, Post 2006
(Identified in FDIC Failing Bank Board Cases)

Types of Insider Abuse or Fraudulent Activity	Frequency
Alteration of financial statements / manipulation of records / concealing information from BoD or regulator / inflated appraisals / inflated financial statements	20
Loans to insiders / Violation of Reg O	9
Transactions with affiliates (BHC, mortgage affiliate, etc.) / Violation of Reg W Section 23A	4
Self-dealing, e.g. excessive compensation, nepotism	8
Embezzlement	1
Fictitious loans or generating loans for inappropriate usage or forgery on loan documentation	11
Inappropriate transactions such as check-kiting, money-laundering, withdrawal of funds from customer accounts	7
Bank's inappropriate transaction with a firm affiliated with a bank owner, officer, director, or employee	2
All Other	6
Total	68

We use banks' income statement and balance sheet data reported quarterly to their primary federal regulator (aka, Call Reports) to detect fraud. We selected explanatory variables for the logistic regression model of bank fraud based on the previously discussed fraud detection framework. The following financial ratios are used to measure a bank's financial condition in the fraud failure model.

- *Equity* is a ratio of equity capital to total assets and measures shareholders' ownership of the bank.
- Bank's liquidity is measured by *Liquid assets ratio*. *Liquid assets* ratio is a sum of securities and federal funds sold divided by total assets.
- *Nonperforming loans ratio* is the sum of past due loans 90+ days and nonaccruals divided by total assets and measures a bank's asset quality.
- *Income earned but not collected ratio* is a bank's interest earned or accrued on earning assets that has not yet been collected to total assets. This includes accrued interest receivable on loans, leases, debt securities, and other interest-bearing assets.
- *One-year asset growth rate* is a change in bank's merger-adjusted asset size from one year ago.
- *Investments in a bank's subsidiaries* ratio is a bank's investments in subsidiaries, associated companies, joint ventures, and partnerships where the bank exercises significant influence to total assets.
- *Earnings* is a ratio of income before taxes to total assets and measures a bank's profitability. It is not clear whether reported earnings of a bank close to failing with fraudulent activities would differ

from that of those without fraud. Although actual earnings of a bank with fraudulent activities may be lower, it might hide its true condition by reporting higher earnings.

The financial ratios control for differences in bank performance and evidence of insider abuse and/or fraud. Table 4 presents the mean and median financial ratios of banks two years prior to failure. Among failures, banks with insider abuse and/or fraud have a higher average loss rate, a bank resolution cost to total assets ratio, compared to all other failed banks. For instance, the mean loss rate for bank with insider abuse and/or fraud is 23.9% compared to 20.2% for all other failed banks.

On average, banks with insider abuse and/or fraud (hereafter, fraud banks) reported better financial condition and performance, e.g., higher equity and lower nonperforming loans than other failed banks (hereafter, non-fraud banks). Two years prior to failure, both fraud and non-fraud banks have negative earnings but fraud banks lose less money, on average. Overall, fraud banks report better financial condition than do non-fraud banks two years prior to failure. At the same time, fraud banks also display greater risk-taking with higher asset growth.

Table 4. Descriptive Statistics of Failed Institutions 2 Years Prior to Failure

	Insider abuse and/or fraud not detected by regulators	**Insider abuse and/or fraud detected by regulators**	**Insider abuse and/or fraud not detected by regulators**	**Insider abuse and/or fraud detected by regulators**
	MEAN	**MEAN**	**MEDIAN**	**MEDIAN**
Loss rate[1]	20.17	23.91***	19.01	21.51
Equity	7.24	8.35***	6.75	7.94
Nonperforming loans	3.96	3.05***	3.25	1.89
Income earned but not collected	0.80	0.77	0.68	0.61
One year asset growth	8.05	11.49**	1.99	7.22
Liquid assets	26.12	21.40***	23.45	19.09
Investment in subsidiaries	0.05	0.03	0.00	0.00
Earnings	-1.41	-0.50***	-0.96	0.32
# observations	758	451	758	451

[1]Loss rate is a ratio of cost of a bank resolution to total assets as of quarter before failure.
***Indicate that the mean value for banks with insider abuse/fraud present differs from banks without insider abuse/fraud with statistical significance at 1 percent.

6. Model Calibration and Results

We next present the results for alternative fraud-detection approaches—logistic regression, Benford digit analysis and neural network analysis—followed by a discussion of how these various models might be used in a fraud-detection framework.

6.1. Logistic Regression

In this section, we estimate a parametric model to predict bank failures where insider abuse and/or fraud was detected by regulators. In equation 4 we denote bank failures where insider abuse and/or fraud were detected by regulators by y=1 and all other failures by y=0 and model the probability of a insider abuse and fraud-related bank failure as a function of bank's balance sheet and income statement variables previously discussed in section 5.

$$y_i = x_i\beta + \mu_i \tag{4}$$

In equation 4, β is a vector of regression coefficients, X_i is a vector of variables measuring bank characteristics and μ_i is the regression error term. The probability of bank failure is modelled by bi-variate logistic regression.

The regression model of fraud-related failures can be used to support or refute the fraud detection framework we devised based on the academic literature and will provide information on which financial variables to include in more general fraud detection models, i.e., Benford digit analysis and neural networks. Because we only observed fraud among failed banks we are unable to develop a logistic regression model of fraud detection for the population of banks, failed and non-failed. This is because our fraud bank indicator is also essentially a failed-bank indicator; hence there is overlap in what the measure means when applied to the population of banks. We can, however, avoid the dilemma of dual meanings of the fraud bank indicator with unsupervised fraud detection models, here, Benford digit analysis.

Regression Results

Table 5 reports the results of the logit models using banks' last financial ratios before failure. Columns (1), (2), and (3) of table 5 report the estimates of the models using the full (1989-2015), early (1989-2004), and the recent (2007-2015) periods, respectively. Table 5 shows that fraud banks detected by regulators reported higher equity on their last call reports compared to failing banks without insider abuse and/or fraud. Fraud failures also tended to report lower earnings compared to non-fraud failures. In the full and early periods, fraud failures are characterized by higher asset growth and lower liquid assets. In contrast, the fraud failures in recent periods reported higher income earned but not collected.[62]

Table 5. Logistic Regression of Fraud vs. Non-fraud failures using Last Financial Ratios before Failure

	(1)	(2)	(3)
	Full (1989-2015)	Early (1989-2004)	Recent (2007-2015)
Intercept	-0.859***	-0.774**	-1.524***
Equity	0.118***	0.090***	0.077**
Nonperforming loans	0.017*	0.003	0.012
Income earned not collected	0.036	0.097	1.674***
One year asset growth	0.017***	0.020***	0.005
Liquid assets	-0.016***	-0.021***	-0.0002
Investment in subsidiary	0.187	0.219	0.545
Income before taxes	-0.113***	-0.099***	-0.092***
Likelihood ratio	106.42***	50.94***	35.84***
Number of observations	1,236	718	518

*** Indicates statistical significance at 1%. ** indicates statistical significance at 5%. * indicates statistical significance at 10%.

Table 6 reports the estimation results using data four quarters prior to failure. For full, early, and recent periods, fraud banks reported higher equity. In full and early periods, banks with insider abuse and/or fraud grew more rapidly. Due to rapid growth, banks may outgrow their rules, procedures, or internal control systems and make it easier for an insider abuse.

Moreover, fraud banks had lower liquid assets ratio and invested more in the bank's subsidiaries in full and early periods. In recent periods, failed fraud banks had higher income earned but not collected. Fraud banks reported higher earnings one year before failure. This differs from the results in Table 5 where banks with insider abuse and/or fraud reported lower earnings on their last call reports.

[62] According to McDill (2004), a high level of income earned but not collected is an indication that loans have gone bad but have not been written off.

Table 6. Logistic Regression of Fraud vs. Non-fraud failures using Data 4 Quarters before Failure

	(1)	(2)	(3)
	Full (1989-2015)	Early (1989-2004)	Recent (2007-2015)
Intercept	-0.136	0.023	-1.100**
Equity	0.071***	0.034**	0.074**
Nonperforming loans	0.006	-0.027	0.006
Income earned not collected	0.010	0.094	1.388***
One year asset growth	0.007**	0.014***	-0.003
Liquid assets	-0.027***	-0.034***	0.0002
Investment in subsidiary	0.369*	0.423**	0.594
Income before taxes	0.064***	0.051	0.056
Likelihood ratio	96.25***	60.96***	30.19***
Number of observations	1,228	710	518

*** Indicates statistical significance at 1%. ** indicates statistical significance at 5%. * indicates statistical significance at 10%.

Table 7 reports the estimation results using data eight quarters prior to failure. Fraud banks reported lower nonperforming loan ratios than did banks without insider abuse and/or fraud for the full and early periods. While the estimated coefficient is negative, it is not statistically significant for the recent period. This finding is consistent with fraud banks with insider abuse and/or fraud failing to recognize deterioration in the bank assets (Green and Reinstein (2004)).

Similarly, fraud failures reported lower liquid assets but the estimated coefficient is significant only for the full and early periods. Higher reported earnings are also observed at fraud failures but the estimated coefficient is statistically significant only for the full sample. For the recent period, income earned but not collected to total assets ratio is positive and statistically significant.

Table 7. Logistic Regression of Fraud vs. Non-fraud failures using Data 8 Quarters before Failure

	(1)	(2)	(3)
	Full (1989-2015)	Early (1989-2004)	Recent (2007-2015)
Variable	Fraud failure	Fraud failure	Fraud failure
Intercept	0.168	-0.065	-0.486
Equity	0.028*	0.025	-0.015
Nonperforming loans	-0.060**	-0.098***	-0.017
Income earned not collected	-0.029	0.095	1.307***
One year asset growth	-0.002	0.001	-0.003

Liquid assets	-0.026***	-0.028***	-0.001
Investment in subsidiary	-0.250	-0.589	0.600
Income before taxes	0.059**	0.036	0.054
Likelihood ratio	65.13***	36.36***	23.71***
N	1,203	689	514

*** Indicates statistical significance at 1%. ** indicates statistical significance at 5%. * indicates statistical significance at 10%.

The findings that fraud banks have higher equity, lower nonperforming loans, and higher earnings are consistent with these banks reporting more favorable financial numbers than banks without insider abuse and/or fraud. Possibly, these findings are a reflection of fraud banks reporting fictitious accounting numbers at higher frequency. The exception is liquid assets which are negatively related to fraud failures. Plausibly, it is more difficult to report false level of liquid assets. Loan quality is not readily observable which makes it easier for the bank to hide problems. In contrast, it is more difficult to hide in treasury or other liquid securities.

6.2. Benford Digit Analysis

Following the conclusions of section 4.1.2 we conduct second-order Benford digit tests of bank Call Reports. Based on Nigrini and Miller (2009) we feel it is appropriate to apply the second-order test to financial data from multiple balance-sheet and income statement entries for a bank over time. Specifically, we use eight consecutive calendar quarters of financial data for certain areas of bank financial reports that previous research suggests might be manipulated by fraudulent banks—loans past due 30-89 days, loans past due 90 days or more, nonaccrual loans and gross loan charge-offs for six categories of loans—1-4 family residential mortgages, loans for multifamily properties, loans for nonfarm, nonresidential properties, loans for real estate construction and development, consumer loans and commercial and industrial loans. We conduct the second-order tests on banks individually and group our results based on bank status in terms of whether regulators detected material insider abuse and/or internal fraud by bank employees or not. To that end we have three groups of banks: 1) failed banks where insider abuse and/or fraud was detected by regulators, 2) failed banks where no insider abuse and/or fraud was detected by regulators, and 3) non-failed banks where no insider abuse and/or fraud was detected by regulators. For the non-failed bank group, we use a random sample of 300 banks for the second-order tests.

We chose to apply the second-order test to the first digit frequencies (1 through 9) since the data requirements for a first digit test are much lower than for a first-two digit test where there are 89 possible digit combinations. To ensure there are sufficient data to observe all nine first digits we require there be at least 40 observations on some portion of the previously discussed financial variables (bank variable-quarter observations) to compute banks first digit frequencies and we all require that each of the nine first digits be observed at least once. This later requirement is intended to give acceptance of the null hypothesis that the digits follow the Benford distribution the greatest chance of being accepted, thereby reducing type 1 error. We focus on type 1 error because the burden on regulators of conducting a follow-up investigation for potential bank fraud is likely to be high. Finally, Nigrini and Miller (2009) point out that when combining different datasets in a second-order test, all the variables should span the same relative range in values, else differencing ranked ordered variables will not result in numbers that follow the Benford distribution. For this reason we chose the loan subcategories discussed previously and did not mix together variables whose ranges in values are not likely to overlap significantly, e.g., total assets and consumer loan charge-offs.

The intent of the fraud detection model is to be able to detect fraud well before bank failure; therefore we used eight quarters of financial data over the period one-to-two years before failure for failed banks and a contemporaneous period for the samples of non-failed banks. To evaluate the divergence between expected and observed digit frequencies we use two second-order test statistics—chi square (CHI) and mean absolute deviation (MAD). Equation 5 defines the chi-square statistic as the sum of the squared differences between observed and expected digit frequencies for bank *j*, divided by the expected digit frequencies for each digit, k. We use the 99 percent confidence level for rejecting the null hypothesis that the digits follow the Benford first digit distribution.

$$Chi\ Square_j = \sum_{k=1}^{9} \left(observed_{j,k} - expected_{j,k}\right)^2 / expected_{j,k} \qquad (5)$$

The mean absolute deviation for bank *j* is defined in equation 6 where all terms are as defined previously in equation 5.

$$MAD_j = \sum_{k=1}^{9} \left(observed_{j,k} - expected_{j,k}\right) / 9 \qquad (6)$$

We conduct second-order tests using data from the two most recent U.S. banking crises—late 1980s–early 1990s and 2007–2009, and use overlapping two-year periods around each crisis period to test for model robustness. Tables 8 and 9 present the results of the second-order Benford tests.

The data requirements of the second-order Benford test and available observations on fraud and non-fraud related failures reduce the sample of banks to which we can apply the second-order test. Thus not all fraud-related failures are included in tables 8 and 9.

Table 8. Second-order Benford Tests: Late 1980s–Early 1990s Banking Crisis

Benford Second-order Tests					
Bank Group		Financial Data Period	# Banks Screened	# Banks w/ Benford Rejected Chi-Square test (p-value 1%)	# Banks w/ Chi-Square > 30 and Mean Absolute Deviation > 4
Failed Banks	Insider Abuse and/or Fraud Detected by Regulators	1988–1989	28	5 (18%)	1 (4%)
		1987–1988	25	4 (16%)	0 (0%)
		1986–1987	23	4 (17%)	1 (4%)
	Insider Abuse and/or Fraud Not Detected by Regulators	1988–1989	126	15 (12%)	3 (2%)
		1987–1988	107	24 (22%)	6 (6%)
		1986–1987	126	15 (12%)	3 (2%)
Non-failed Banks (Random Sample)	Insider Abuse and/or Fraud Not Detected by Regulators	1988–1989	67	13 (19%)	3 (4%)
		1987–1988	52	7 (13%)	1 (2%)
		1986–1987	71	15 (21%)	4 (6%)

Table 9. Second-order Benford Tests: 2007–2009 Banking Crisis

Benford Second-order Tests					
Bank Group		Financial Data Period	# Banks Screened	# Banks w/ Benford Rejected Chi-Square test (p-value 1%)	# Banks w/ Chi-Square > =30 and Mean Absolute Deviation >= 4
Failed Banks	Insider Abuse and/or Fraud	2008–2009	73	6 (8%)	1 (1%)
		2007–2008	97	12 (12%)	1 (1%)

	Detected by Regulators	2006–2007	80	6 (8%)	0 (0%)
	Insider Abuse and/or Fraud Not Detected by Regulators	2008–2009	60	10 (17%)	5 (8%)
		2007–2008	61	9 (15%)	3 (5%)
		2006–2007	42	2 (5%)	2 (5%)
Non-failed Banks (Random Sample)	Insider Abuse and/or Fraud Not Detected by Regulators	2008–2009	155	8 (5%)	2 (1%)
		2007–2008	127	7 (6%)	0 (0%)
		2006–2007	118	9 (8%)	0 (0%)

Tables 8 and 9 show that a typical statistical threshold for rejecting the null hypothesis that the data follow the first digit Benford distribution, i.e., 1 percent significance level, results in relatively high rejection rates. If we were to apply the second-order test to all banks, a 1 percent significance level would likely lead to over 8 percent of all banks or over 400 banks failing the test and requiring follow-up analysis by regulators. Nigrini and Miller (2009) suggest the “almost” Benford characteristic of first differences in ranked data contributes to false positives in the second-order test. To limit the burden of unnecessary follow-up analysis by regulators we consider a simple threshold test based on both chi square statistics and MAD; if a bank’s chi square is 30 or more and MAD is 4 or more then the bank fails the second-order test for random numbers. This latter, simpler test is much more restrictive and generally results in 1 percent of banks or less (40 or less banks) failing the second-order test.

As we discussed previously, our fraud suspicion flag includes activities that may not have resulted in banks altering their financial statements. We therefore investigated banks that failed the chi-square test using a p-value of 1 percent, as well as banks that failed the chi square and MAD thresholds test. Among all screened banks with suspected fraud in tables 8 and 9, 37 banks failed the chi-square test using a p-value of 1 percent and 33 of those banks had significant restitution orders and/or FDIC bond claims. Among all banks with suspected fraud in tables 8 and 9 that failed the chi-square and MAD thresholds test, we find that in all cases the banks had indications of material internal fraud due to FDIC bond claims, restitution orders and/or news reports of deliberate financial misstatements. We believe restitution orders and bond claims are tangible proof of internal bank fraud, as opposed to the suspected fraud discussed in FDIC failing bank board cases.

As a check on the second-order test accuracy we compared the first digit frequencies of banks with insider abuse and/or fraud against those where no fraud was suspected graphically. While Nigrini and Miller (2009) recommend one use graphical analysis to confirm non-Benford behavior, visual inspection may not be practical for large samples of banks regulators wish to screen. Figures 3 and 4 show the expected and observed second-order test digit frequencies for a failed bank where insider abuse and/or fraud was detected by regulators, and statistical test statistics support that finding, versus those of a non-failed bank. The graphical analysis agrees our simple threshold second-order test base in a chi square of 30 or more and MAD of 4 or more. Figures 3 and 4 are representative of those for the population of banks.

Figure 3.

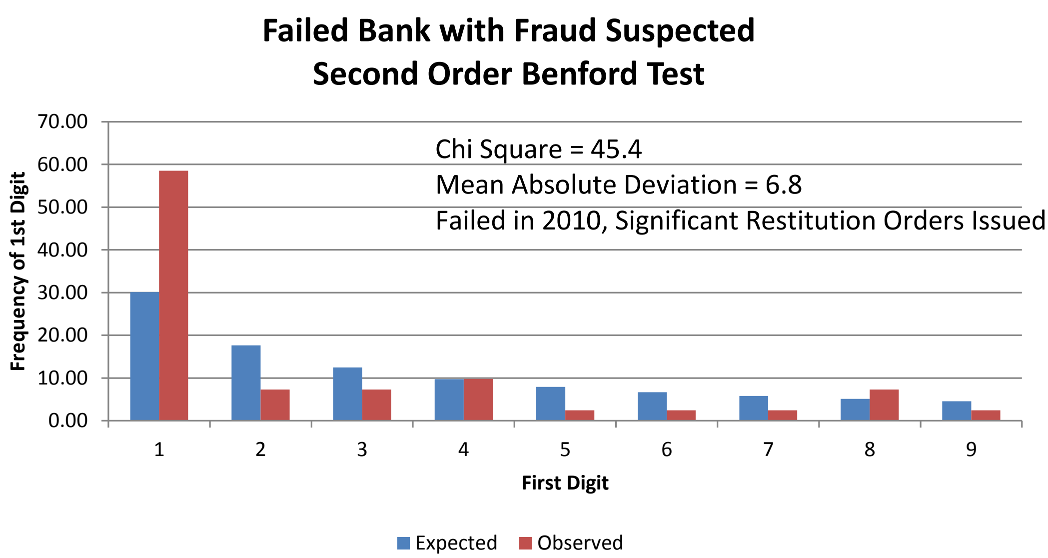
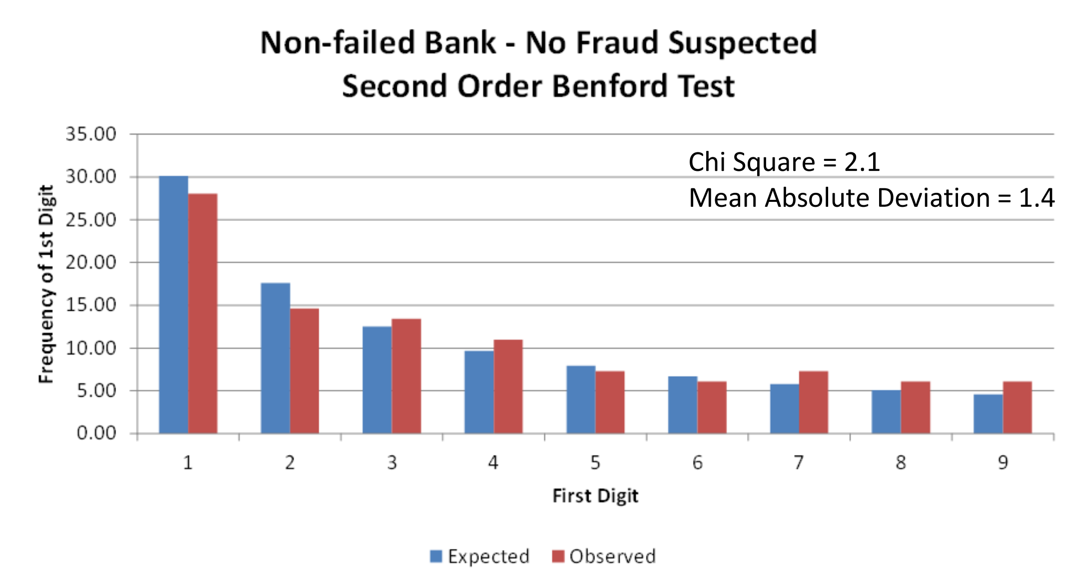


Figure 4.



Another approach to reducing type 1 error is to combine tests of first and second digit frequencies. The tests of the distribution of the 10 possible second digits (i.e., 0 through 9) can be made using the same approach as was used to test first digit frequencies. By combining first and second digit tests we hope to increase the accuracy of fraud detection while reducing the potential number of banks regulators would need to analyze in subsequent screening processes.

Tables 10 and 11 present results for the combined first and second digit tests for the late 1980s–early 1990s banking crisis and 2007–2009 global financial crisis period, respectfully, using digits from the second-order Benford test. To enhance the comparability of results we only include those banks where both first and second digit chi square tests of digit frequencies could be estimated. Tables 10 and 11 show that banks fail the second digit test at much higher rates than for the first digit test. Further, our results show that combining first and second digit tests reduce the pool of potential fraud candidates to a manageable number of banks to review.

We investigated the role that insider abuse and fraud played in the failure of the **seven banks** in table 11 where regulators detected insider abuse and/or fraud that did not pass both the first and second digit tests. For these seven banks, five banks had bond claims and six banks had substantive restitution orders. We also conducted an internet search for news reports on these seven failed banks and found five had news reports of substantive insider fraud and/or charges of insider fraud.

Table 10. Second-order Benford Tests of First and Second Digits: Late 1980s–early 1990s Banking Crisis

Benford Second-order Tests						
Bank Group		Financial Data Period	# Banks Screened	# Banks Failing 1st Digit Chi-Square Test (p-value 1%)	# Banks Failing 2nd Digit Chi-Square Test (p-value 1%)	# Banks Failing 1st and 2nd Digit Chi-Square Test (p-value 1%)
Failed Banks	Insider Abuse and/or Fraud Detected by Regulators	1988–1989	16	1 (6%)	6 (38%)	0 (0%)
		1987–1988	13	0 (0%)	4 (31%)	0 (0%)
		1986–1987	7	2 (29%)	2 (29%)	0 (0%)
	Insider Abuse and/or Fraud Not Detected by Regulators	1988–1989	33	5 (15%)	15 (45%)	2 (6%)
		1987–1988	49	12 (24%)	18 (37%)	6 (12%)
		1986–1987	62	7 (12%)	27 (43%)	6 (10%)
Non-failed Banks (Random Sample)	Insider Abuse and/or Fraud Not Detected by Regulators	1988–1989	33	7 (21%)	17 (52%)	4 (12%)
		1987–1988	20	3 (15%)	12 (60%)	2 (10%)
		1986–1987	22	5 (23%)	12 (55%)	1 (5%)

Table 11. Second-order Benford Tests of First and Second Digits: 2007–2009 Banking Crisis

Benford Second-order Tests						
Bank Group		Financial Data Period	# Banks Screened	# Banks Failing 1st Digit Chi-Square Test (p-value 1%)	# Banks Failing 2nd Digit Chi-Square Test (p-value 1%)	# Banks Failing 1st and 2nd Digit Chi-Square Test (p-value 1%)
Failed Banks	Insider Abuse and/or Fraud Detected by Regulators	2008–2009	60	6 (10%)	17 (28%)	2 (3%)
		2007–2008	129	13 (10%)	3 (2%)	2 (2%)
		2006–2007	62	6 (10%)	20 (32%)	3 (5%)
	Insider Abuse	2008–2009	46	7 (15%)	14 (30%)	4 (9%)

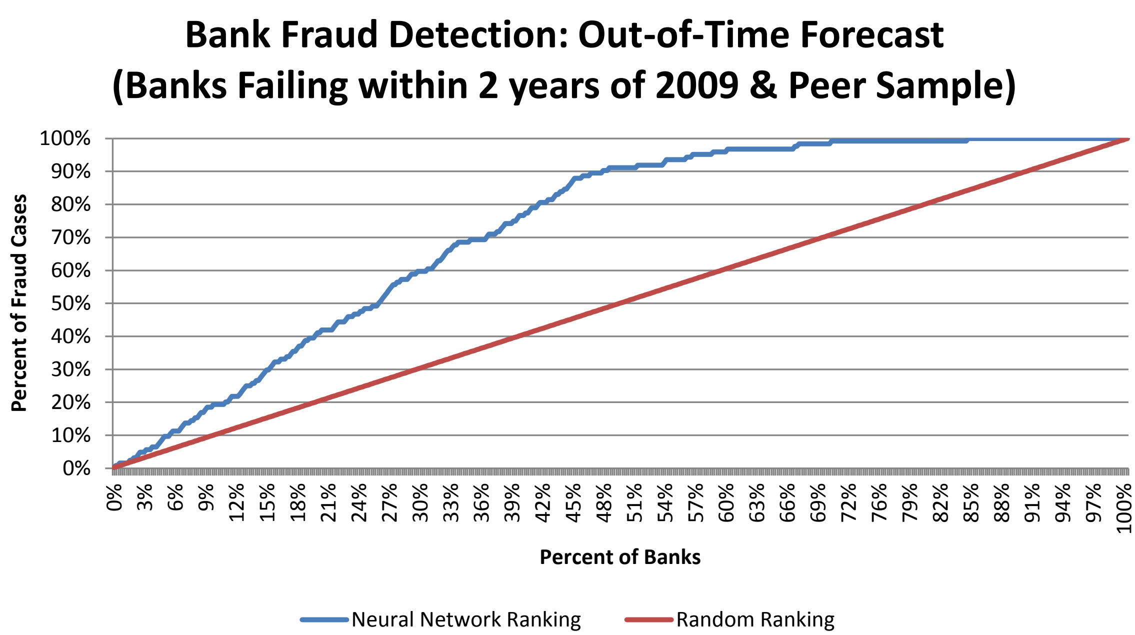
	and/or Fraud Not Detected by Regulators	2007–2008	38	7 (18%)	11 (29%)	2 (5%)
		2006–2007	24	0 (0%)	13 (54%)	0 (0%)
Non-failed Banks (Random Sample)	Insider Abuse and/or Fraud Not Detected by Regulators	2008–2009	84	2 (2%)	29 (34%)	1 (1%)
		2007–2008	73	2 (3%)	31 (42%)	0 (0%)
		2006–2007	53	6 (11%)	18 (34%)	3 (6%)

Collectively, tables 8 through 11 do not suggest that banks where regulators suspected fraud and/or issued restitution orders and bond claims fail Benford expected digit frequency tests more often than do non-failed banks and failed banks where no fraud was suspected or found. This seemingly counter-intuitive result can be explained by two factors that we discussed previously: 1) the presence of non-fraudulent orderly courses for digit frequencies, and 2) the “almost Benford” nature of second-order digit frequencies.

6.3. Neural Networks

Our third approach to developing an off-site fraud detection model was to use a neural network pattern recognition algorithm supplied by Matlab. Published research has found that neural network analysis can successfully detect the types of outliers in data that insider abuse and fraud might produce in bank financial statements. We trained neural network models using data from the same two pervious banking crises as we used for the Benford and logit models. The variables we used to detect fraud were informed by the regression model of fraud as well as the literature on bank fraud. Specifically, the neural network input variables were total loans secured by real estate, loans secured by commercial properties, nonaccrual real estate construction loans, gross chargeoffs on total loans and leases, equity capital, brokered deposits, income earned by not collected, income before taxes and extraordinary items, investment in unconsolidated subsidiaries, liquid assets, noncore deposits, reserve for loan and lease losses, total nonperforming assets (i.e., the sum of loans and leases past-due 30-89, past due 90 days or more and nonaccrual loans), all measured as a percentage of gross assets (i.e., net assets plus loss reserves), plus the ratio of expenses on employee compensation-to-number of employees, asset growth over prior year and annual asset growth 3 year ago.[63] The majority of our tests showed the neural network model did not detect failed banks where insider abuse and/or fraud were detected by bank regulators at a level of accuracy sufficient to merit use by bank regulators. For illustration, figure 5 presents the results of one test of the neural network model. Specifically, a neural network model using the aforementioned input variables measured as of year-end 2008 was used to identify fraud among all banks that failed with two years, where fraud was said to occur if one or more of our three fraud measures indicated fraud. To test the model's ability to discern fraud among failed banks versus non-failed banks, we included a matched set of non-failed peer banks, based on bank lending specialization group, in the estimation sample. After fitting the model using year-end 2008 input data and 2009-2010 failed banks plus nonfailed peers, we used the estimated network to predict fraud among a set of similarly selected failed and non-failed banks as of year-end 2009. The results of out-of-time fraud detection accuracy tests are shown in figure 5. While the results shown in figure 5 suggest the neural network model has some predictive capability, the level of accuracy is too low for bank supervisory purposes since it would require screening about 45 percent of all banks to ensure coverage of 100 percent of fraud cases.

Figure 5.



[63] Details on inputs definitions here…..

7. Conclusions

Our results suggest that material insider abuse and/or fraud at banks is detectable using Benford digit analysis of bank financial data for a period one-to-four years prior to failure. Specifically, we use a recently developed second-order Benford digit test to identify those banks whose financial statements suggest tampering and purposeful misstatement. Unfortunately, we are unable to develop an accurate neural network model for fraud prediction. Finally, regression analysis of the determinants of failure among banks with insider abuse and/or fraud compared to other types of failed banks are in general agreement with the literature on fraud in banking, which finds banks with insider abuse and fraud present will overstate income and asset values, under-report losses and consequently overstate capitalization.

References

Akerlof, George A and Paul M. Romer. Looting: The Economic Underworld of Bankruptcy for Profit. *Brookings Papers on Economic Activity*, No. 2 (1993).

Albrecht, Steve W. Fraud in Government Entities: The Perpetrators and the Types of Fraud. *Government Finance Review, Vol. 7, No. 6* (December 1991) pp. 27–30.

Association of Certified Fraud Examiners. Using Benford's Law to Detect Fraud. *Sample Chapter from Course on Fraud Detection*, undated.

Benford, Frank. The Law on Anomalous Numbers. *Proceedings of the American Philosophical Society*, Vol. 78, No. 4 (March 1938), pp. 551–572.

Black, William K. The Best Way to Rob a Bank is to Own One: How Corporate Executives and Politicians Looted the S&L Industry*. University of Texas Press*, Austin, Texas (2005).

_____________. Those Who Forget the Regulatory Successes of the Past are Condemned to Failure. *Economic and Political Weekly*, (March 28–April 3, 2009), Vol. 44, No. 13, pp. 80–86.

_____________. Why Regulators Must Fight 'Control Fraud' Like Public Health Specialists (January 14, 2010). Working Paper available at SSRN https://ssrn.com/abstract=1536527

Bolton, Richard J. and David J. Hand. Statistical Fraud Detection: A Review, *Statistical Science*, Vol. 17, No. 3 (2002), pp. 235-255.

Cressey, Donald R. "Why Do Trusted Persons Commit Fraud? A Social-Psychological Study of Defalcators", *Journal of Accountancy*, Vol. 92, No. 5 (November 1951), pp. 576–581.

Durtschi, Cindy, William Hillison and Carl Pacini. The Effective Use of Benford's Law to Assist in Detecting Fraud in Accounting Data. *Journal of Forensic Accounting*, 1524-5586/Vol.V (2004), pp. 17-34.

FDIC staff study. History of the Eighties – Lessons for the Future. (1997).

FDIC. Formal and Informal Action Procedures (FIAP) Manual, (December 21, 2015).

Green, Brian Patrick and Alan Reinstein. Banking Industry Financial Statement Fraud and the Effects of Regulation Enforcement and Increased Public Scrutiny. *Research in Accounting Regulation*, Vol. 17 (2004), pp. 87–106.

Kupiec, Paul and Chiwon Yom. Identifying Fraud in Failed Banks, unpublished paper (November 2007).

Lee, Yan and Chiwon Yom. The Entry, Performance, and Risk Profile of De Novo Banks, *FDIC CFR WP 2016-03*, (April 2016).

McDill, Kathleen. Resolution Costs and the Business Cycle, FDIC Working Paper 2004-01, (March 2004).

Miller, Steven J. and Mark J. Nigrini. Order Statistics and Benford's Law. *International Journal of Mathematics and Mathematical Sciences*, Vol. 2008, article ID 382948, pp. 1-19.

Newcomb, Simon. Note on the Frequency of Use of the Different Digits in Natural Numbers *American Journal of Mathematics*, Vol. 4, No. 1. (1881), pp. 39-40.

Nigrini, Mark J. and Steven J. Miller. Data Diagnostics Using Second-Order Tests of Benford's Law. Unpublished Working Paper (June 1, 2006) and *AUDITING: A Journal of Practice & Theory*: November 2009, Vol. 28, No. 2, pp. 305-324.

O'Keefe, John. The Texas Banking Crisis: Causes and Consequences 1980–1989. *FDIC Banking Review,* Vol. 3, No. 2. (Winter 1990).

Povel, Paul, Rajdeep Singh and Andrew Winton. Booms, Busts and Fraud. *The Review of Financial Studies*, Vol. 20, No. 4 (July, 2007), pp. 1219–1254.

Wheeler, Stanton. The Organization as Weapon in White-Collar Crime (1982). *Faculty Scholarship Series.* Paper 4128. http://digitalcommons.law.yale.edu/fss_papers/4128