Risk-Based Capital Analysis in Punitive Damages Litigation

Susan W. Lanham
Craig Barton*

Montgomery and Nahrstadt (2010) and Zipursky (2005) have argued about the appropriateness of punitive damages in civil litigation. Punitive damages are not only intended to punish and deter bad behavior, but they are also intended to compensate plaintiffs for the malicious conduct they were subjected to, incentivize plaintiffs to file suit despite the costs, and encourage a good faith settlement (Davis & Palmer, 2010). Excessive and inappropriate awards, however, have resulted in a change in the way judges view punitive damages (Davis & Palmer, 2010). The United States Supreme Court in *Pacific Mutual Life Insurance Co. v. Haslip* (1991) ruled that excessive or inappropriate punitive damages awards could violate the 14th Amendment's due process clause. This ruling makes it necessary that juries be given better evidence so that they are able to determine an appropriate punitive damages award.

Since the 1970s, forensic accountants have presented evidence of a company's assets, liabilities, and equity position to a jury in punitive damages cases as evidence of their ability to pay a punitive award (Montgomery & Nahrstadt, 2010; Newman, 2007). Although information regarding the financial position of a defendant could be useful in determining an amount sufficient to punish and deter, no information is provided detailing what amount, if awarded, would destroy a defendant financially (Rustad, 2008). Organizations have a minimum capital retention level that is required so they are able to survive. This level is specific to each organization based on its size and risk it chooses to assume (Cummins & Phillips, 2009). Organizations require this minimum level of capital to support their business operations (Lev,

* The authors are, respectively, Assistant Professor of Accounting at Marshall University and Graduate School Dissertation Chair at Northcentral University.

Radhakrishnan, & Zhang, 2009). For this reason, jurors must not consider all of an organization's equity as available to service a punitive award.

Like other sorts of organizations, insurance companies and depository institutions are required to maintain a certain level of capital to reduce insolvency and protect the public (Smith, 2010). The required capital levels are calculated by each insurance company and depository institution (National Association of Insurance Commissioners, 1992). The calculations are made given risk-based reviews and guidelines established by the National Association of Insurance Commissioners (NAIC) for insurance companies and by the Board of Governors of the Federal Reserve System for depository institutions (Best's Rating Center, 2010; NAIC, 1992).

Four constructs are examined within this article: (a) the relationship between risk-based capital levels of insurance companies and their insolvency status, (b) the relationship between risk-based capital levels of depository institutions and their insolvency status, (c) the relationship between risk-based capital levels of property/casualty insurance companies and their financial strength ratings, and (d) the relationship between risk-based capital levels of life/health insurance companies and their financial strength ratings. Financial data was obtained from the NAIC for insurance companies and the FDIC for depository institutions. This data was organized in spreadsheet form. The study is retrospective in that data from the five year period from 2007 through 2011 was collected and reviewed for all insurance companies rated by A.M. Best and depository institutions operating during those years. Logistic regression was used to test the strength of the relationship between the chosen variables.

Determining whether risk-based capital levels are related to an organization’s financial strength or solvency status is important if testimony on this subject is to be provided in a court of law. In order to comply with the Federal Rules of Evidence, forensic accountants must be able

to show that the risk-based capital levels of defendants are significantly related to the financial health of the organization (Daubert v. Merrill Dow Pharmaceutical, Inc., 1993; Kumho Tire v. Carmichael, 1999; Philip Morris v. Williams, 2007; State Farm v. Campbell, 2003). The results of this study indicate that forensic accountants can consider risk-based capital analyses an authoritative source of data upon which to offer an opinion.

Although the results of this study are important for application purposes, it is more important that this study contributes to forensic accounting theory. Although accountants have provided forensic accounting services for several years, this field has grown exponentially within the last 20 years (DiGabriele, 2008). Additional contributions to forensic accounting and forensic economic theory are desperately needed (Browning-Ferris Industries, Inc. v. Kelco Disposal, Inc. 1989; TXO Prod. Corp. v. Alliance Resources, 1993; Pacific Mutual Life Insurance Co. v. Haslip, 1991). Justice Brennan was adamant that more guidance needs to be provided to juries who must make a determination of an appropriate punitive damages award (Browning-Ferris Industries, Inc. v. Kelco Disposal, Inc. 1989). This essay seeks to provide the sort of guidance Brennan calls for, ultimately helping jurors to make more decisions regarding damages awards that are punitive without bankrupting the defendant.

Definitions

There are multiple terms critical to the understanding of this study defined below. References are provided in support of each of the definitions when available. If no reference is provided, the author developed the definition.

Federal deposit insurance corporation (FDIC). The FDIC is an organization created by the United States government to provide insurance for deposits made into banks up to $250,000 (FDIC, 2012c). The FDIC also regulates the financial strength of member banks,

manages banks that have been taken over, and provides specific consumer-protection services (FDIC, 2012c).

Federal rules of evidence. The federal rules of evidence are laws covering the admissibility of evidence at trial (Paulo, 2009). The federal rules of evidence govern both the criminal law and civil law systems (Paulo, 2009).

Forensic accountant. A forensic accountant is an individual who specializes in preparing financial related reports that can be used in a court of law. A forensic accountant is hired to perform an analysis of damages in civil disputes, criminal matters, usually involving fraud, and marital or family matters involving divorce or child support.

Insurer financial strength rating. Best (2010) publishes a financial strength rating for all insurance companies stating an opinion regarding the strength of the insurance company's financial position and its ability to satisfy ongoing obligations. The financial strength of an insurance company is calculated given a qualitative and quantitative balance sheet evaluation, an analysis of the company's operating performance, and business profile (Best's Rating Center, 2010). The rating scale associated with the financial strength ratings published by A.M. Best is as follows:

Table 1

A.M. Best Financial Strength Ratings

Financial Strength Rating	Definition of Financial Strength Ratings
A++, A+	Superior
A, A-	Excellent
B++, B+	Good
B, B-	Fair
C++, C+	Weak
C, C-	Poor
E	Under Regulatory Supervision
F	In Liquidation
S	Suspended

National association of insurance commissioners (NAIC). The NAIC is an organization made up of the insurance commissioners from all 50 states in the United States, the District of Columbia, and five United States territories (Hersch, 2010). The NAIC is responsible for regulating the insurance industry and does so by creating model laws and rules for insurance companies to follow (Hersch, 2010).

Punitive damages. Punitive damages are monetary damages awarded by a jury or judge in addition to actual damages to punish a defendant in a civil lawsuit (Markel, 2009). Punitive damages are considered a civil punishment similar to a criminal fine. The purpose of imposing punitive damages is to punish a defendant for bad acts, and to deter others from committing the same bad acts (Markel, 2009).

Risk-based capital. Risk-based capital is a procedure for determining the minimum amount of capital that depository institutions and insurance companies must have to support business operations given the company's size and amount of risk it chooses to assume (NAIC, 1992). Risk-based capital requirements are established by the NAIC for insurance companies

(NAIC, 1992) through the Risk-Based Capital for Insurers Model Act Volume II-312 (1994). The requirements under this Model Act were established by the NAIC, however, most insurance jurisdictions within the United States have adopted the requirements through statutes, regulations, or bulletins (NAIC, 2009). The Basel II Accord was established in June 2004 and was the first in the banking industry to base capital requirements on risk levels (Hassan Al-Tamimi, 2008). In 2011, the Board of Governors of the Federal Reserve System, the FDIC, and the Office of the Comptroller of the Currency adopted a Final Rule. This Final Rule established a floor to risk-based capital levels as required under Section 171 of the Dodd-Frank Wall Street Reform and Consumer Protection Act, (Federal Reserve Board, 2011).

Solvent/Insolvent. The financial industry defines solvency as the ability of a company to satisfy its long-term financial obligations (Investopedia, 2014). In the accounting field, solvency is the degree to which the fair market value of assets of an individual or company exceed their liabilities (Schnee, 2000). The legal industry defines solvency as the ability to pay all legal debts when they are due (Merriam-Webster's Dictionary of Law, 1996). For the purpose of this study, companies that are considered solvent are still operating while companies considered insolvent have been placed into liquidation or ceased operation due to the inability to pay their debts when due.

Total adjusted capital. An insurance company's or depository institution's total adjusted capital is the statutory capital and surplus they have as calculated using statutory accounting practices associated with risk-based capital instructions (NAIC, 2009). The total adjusted capital for an organization is compared to their required capital level as determine by risk-based capital procedures to determine whether the company has the required minimum amount of capital according to regulatory standards.

II. REVIEW OF THE LITERATURE

Punitive damages in civil law have been in existence since the 18th century when utilized by England's common law courts to relieve an overburdened criminal justice system (Ellis, 1982). Punitive damages provided a civil alternative to a criminal prosecution of certain crimes. These damages were rarely assessed and were given little attention by scholarly writers (Zipursky, 2005). Within the past 40 years, however, punitive damage awards have increased substantially in number and magnitude (Rustad, 2008). The magnitude of punitive damage awards have led writers to question the methods forensic accountants utilize to assist juries in awarding an appropriate amount of punitive damages (Montgomery & Nahrstadt, 2010; Newman, 2007; Rustad, 2008).

In the late 1970s, judges began revising their jury instructions in punitive damages cases to include statements indicating the jury should consider a defendant's financial condition when assessing a punitive damages award (Scheuerman & Franze, 2008). The jury instructions also stated the award should not bankrupt or destroy a defendant financially (Scheuerman & Franze, 2008). Some writers questioned the appropriateness of these instructions (Neckers & Wikander, 2006). The trend among writers has been to support these jury instructions and to raise the issue that juries have had no way to determine what amount of punitive damages would destroy a defendant financially (Montgomery & Nahrstadt, 2010; Newman, 2007; Rustad, 2008). Review of the published body of knowledge regarding this problem offers no solution. Although much has been written regarding the use of risk-based capital requirements for regulatory purposes, no one has suggested utilizing risk-based capital requirements to assist juries in arriving at an appropriate punitive damages award.

A review of the literature makes it evident that there is a need for a uniform method of financial analyses that can be used by a forensic accountant to assist juries in awarding an appropriate level of punitive damages (Montgomery & Nahrstadt, 2010; Newman, 2007; Rustad, 2008). The methodology must be sound enough to withstand the strict tests of the Federal Rules of Evidence (Daubert, 1993; Kuhmo Tire, 1999; Philip Morris, 2007; State Farm, 2003). The Federal Rules of Evidence state that expert witnesses may only offer opinions based on a reliable foundation and only when those opinions are relevant to the specific case in which they are testifying. Testimony from a forensic accountant regarding a company's risk-based capital levels could be an important tool in ensuring a fair and appropriate punitive damages award.

Risk-based capital formulas are widely studied and disseminated and they may offer an accurate measurement of the capital required to support overall business operations (Hoyt & McCullough, 2010; Schroeder & Schauer, 2010; Smith 2010). Some have postulated that other solvency tests, such as the European Union's Solvency System or the Swiss Solvency Tests, are more successful at determining the amount of capital that organizations should retain to support business operations (Cummins & Phillips, 2009; Eling & Holsmüller, 2008). Although there are disagreements about the effectiveness of risk-based capital requirements, scholarly writers agree that risk-based capital requirements have helped to strengthen the financial positions of many organizations (Cummins & Phillips, 2009; Eling & Holsmüller, 2008; Hoyt & McCullough, 2010; Schroeder & Schauer, 2010; Smith 2010).

The literature pertaining to banking and insurance matters must be carefully considered. Kalbers (2009) argued that research into corporate governance and other accounting related issues was often in response to an event instead of in anticipation of some event. As a result, the research is narrow in scope and fails to grasp critical insight into phenomena. Kalbers (2009)

finds that research associated with corporate governance often assumes a tendency of causality that was not typically shown. For example, researchers assume that corporate governance resultes in an increase in the quality of financial disclosures (Kalbers, 2009). This research may have ignored whether the corporation chose to implement the monitoring practices on their own, or whether they were forced to implement the changes by regulators. Kalbers (2009) posited that this distinction could affect the outcome of the studies.

Researchers theorized that capital requirements based on risk instead of a flat percentage of assets are more effective at determining an organization's true capital needs (Cummings & Phillips, 2009; Eling & Holzmuller, 2008; Greenspan, 2010; Weber & Darbellay, 2008). This theory was applied practically within the insurance industry through the establishment of the Risk-Based Capital Model Act (NAIC, 1992) and within the banking industry through the Basel II Accord (Hassan Al-Tamimi, 2008; Mohanty, 2008). Although the risk-based capital theory was developed years ago, the application of the theory has been a fluid and evolving process, with writers addressing how revisions and adjustments to the theory should be applied occurring even today (Moore, 2011; Pera & Bird, 2011).

III. RESEARCH METHODS AND DESIGN

A non-experimental quantitative design plan was implemented for systematic empirical analysis of the data. A retrospective study using archived data was employed to determine the effectiveness of risk-based capital requirements for both insurance companies and depository institutions at predicting insolvency. The retrospective study was appropriate since historical data was available (Cummins & Phillips, 2009).

A binomial logistic regression analysis was performed to determine the relationship between risk-based capital ratios of insurance companies and banks and their solvency

propensity. The solvency status of organizations was used as the criterion variable and the ratio of an organization's total adjusted capital to its risk-based capital for insurance companies and total risk-based capital to risk-weighted assets for depository institutions was used as the continuous predictor variables. A multinomial logistic regression analysis was performed to determine the relationship between insurance companies and their financial strength ratings as determined by A.M. Best. The financial strength ratings of organizations were used as the criterion variable and the ratio of an organizations total adjusted capital to its risk-based capital was used as the continuous predictor variable.

The population of the study included the full population of United States domiciled insurance companies rated by A.M. Best and the full population of United States domiciled depository institutions. The review period for the study ranged from 2007 through 2011. Because the entire population of insurance companies rated by A.M. Best and the entire population of depository institutions operating from 2007 through 2011 were reviewed, organizations that became insolvent and organizations that remained solvent were included in the database. It was necessary to include companies in the database that have failed and that have not failed in order to test the predictability of risk-based capital levels at determining solvency status (De Andrés, Sanchez-Lasheras, Lorca, & De Cos Juez, 2011). De Andrés et al. posited (2011), "if the bankruptcy prediction models are eventually to be used in a predictive context, the estimation samples of failing and non-failing firms should be representative of the whole population of firms" (p. 357).

Given the nature of the data collection, it was no more difficult to obtain data on the complete population of subjects than it would have been to obtain data on just a sample of subjects. A census study was, therefore, performed utilizing the entire population of insurance

companies and commercial depository institutions for which data was available (Wyner, 2007). Utilizing the entire population of subjects ensured that no sampling errors exist and the results are accurate (Wyner, 2007). 1,917 property/casualty insurance companies and 537 life/health insurance companies were reviewed. Of the 2,454 insurance companies included in the database, 53 were placed into liquidation or ceased operation during the 2007 through 2011 review period. Of the 53 insolvent companies reviewed, 41 were property/casualty companies and 12 were life/health. The total number of depository institutions reviewed was 7,769. Of these institutions, 462 were placed into liquidation or ceased operation during the 2007 through 2011 review period.

Materials/Instruments

There were two predictor variables and three criterion variables for this non-experimental quantitative study. The predictor variable related to insurance company reviews was equal to the ratio of total adjusted capital to risk-based capital. The predictor variable related to depository institution reviews was equal to the ratio of total risk-based capital to total risk-weighted assets. The range of the ratio scale of measure was calculated for the databases pertaining to each research question and differed for each database and each year reviewed (Nerurkar, 2008).

The two criterion variables were the insolvency status and the A.M. Best financial strength rating. A nominal scale of measure was used with insolvency status with a range of yes or no, coded with a 0 for solvent and a 1 for insolvent (Nerurkar, 2008). The A.M. Best financial strength rating required an ordinal scale of measure given fourteen categories of ratings. Since this dependent variable did not contain enough data points for the lowest rating categories, these fourteen categories of ratings were grouped and recoded from 1 to 4 (Boslaugh & Watters, 2008).

Data Collection, Processing and Analysis

The first phase of the research involved the collection of a substantial amount of data. Insurance company financial data was obtained from the NAIC. To increase validity, random tests for accuracy were performed comparing an insurance company's financial data obtained from the NAIC with its annual reports. The annual reports were obtained from the company's web site or with its Form 10-Ks filed with the Security and Exchange Commission (Arcuri, el al., 2012; Gow, Ormazabal, & Taylor, 2010). Organizations were chosen at random and their data reviewed for accuracy (Khowaja, Ghufran, & Ahsan, 2011).

From 2007 through 2011, 57 insurance companies were placed into liquidation or ceased operation (Best's Review, 2008-2012). Data from the last annual statement filed with the NAIC was able to be collected for 53 of the 57 insurance companies that failed during 2007 through 2011. Annual statement data filed with the NAIC for these 53 companies was obtained from the West Virginia Insurance Commission.

Depository institution financial data was obtained from the FDIC, which provides the required financial information for each organization online at the Data Download section of Statistics on Depository Institutions, located at http://www2.fdic.gov/sdi/main.asp. A custom report was created with the following categories: date established, total assets, total risk-weighted assets, tier one RBC, tier two RBC and total RBC ratio. A report was created for each period from year-end 2007 through year-end 2011. Data was collected for 7,769 depository institutions.

To increase validity, random tests for accuracy were performed (Khowaja, et al., 2011). These tests compared a depository institution's financial data obtained from the FDIC with its annual reports published on the depository institution's web site or with its Form 10-Ks filed with

the Security and Exchange Commission (Arcuri, el al., 2012; Gow, et al., 2010; Khowaja, et al., 2011). No errors were found.

A logistic regression analysis was performed, utilizing the Statistical Package for the Social Sciences software (DeCesare, 2008). A binomial logistic regression analysis was performed to test the accuracy of the null hypothesis for research question one, with the dichotomous criterion variable equal to solvency (yes or no) for each insurance company (Baranoff, Papadopoulos, & Sager, 2007). The continuous predictor variable was the ratio of total adjusted capital to risk-based capital for each organization.

A binomial logistic regression analysis was performed to test the null hypothesis for research question two with the dichotomous criterion variable equal to solvency (yes or no) for each depository institution. The continuous predictor variable was the ratio of risk-based capital to risk-weighted assets for each organization. The binomial logistic regression analysis was performed separately for research questions one and two with control variables for size of organization, as measured by total assets and number of years in business.

In logistic regression, the independent variable, or the ratio of total adjusted capital to risk-based capital, is the log of the odds ratio, or ln(p/[1-p]). A logit is a function of the average of Y used to make the relationship linear. The logit is a link function applied to the dependent variable. The equation for the logit is as follows:

$$(1)\ Logit(Y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k$$

where Y is insolvency status, X_1 is risk-based capital ratio, X_2 is organization size, X_3 is years in business, and β_0 through β_k are parameters to be estimated. In order to model the equation in terms of the odds, the antilog of both sides of the equation was taken. The resulting formula is as follows:

$$(2)\quad \frac{P}{1-P} = e^{\ln\left(\frac{P}{1-P}\right)} = e^{\beta_0+\beta_1X_1+\beta_2X_2+\ldots+\beta_kX_k}$$

where P is the probability that Y=1 and e is the base of the natural logarithm of approximately 2.718. The dichotomous criterion variable was equal to solvency with the answer yes equal to one and no equal to zero. To determine the change in the odds of success for a one-unit change in X, the ratio of the odds at two values of X that were one unit apart was taken.

$$(3)\quad b = \frac{\Delta Y}{\Delta X} = \frac{\Delta Y}{1}$$

$$(4)\quad b = \ln[odds(Y)]_{x=x+1} - \ln[odds(Y)]_{x=x}$$

An advantage of using the odds ratio is that it does not depend on the value of X.

A multinomial logistic regression was used to test the accuracy of the null hypothesis for research question three with criterion variables equal to the ratings of property/casualty insurance companies (for example, A+, B, C-) (Denham, 2010; Pampel, 2000). The continuous predictor variable was equal to the ratio of total adjusted capital to risk-based capital for each organization.

Consistent with research question three, multinomial logistic regression was also used with criterion variables equal to the ratings of life/health insurance companies when testing the null hypothesis for research question four (Denham, 2010). The continuous predictor variable was equal to the ratio of total adjusted capital to risk-based capital for each organization. A separate multinomial logistic regression analysis was required for research questions three and four, given that a separate risk-based capital formula exists for property/casualty insurance companies versus life/health insurance companies.

Finding the probability of an outcome when there are more than two categories using multinomial logistic regression is more difficult than the formula discussed above (Denham,

2010). For research questions three and four, there are fourteen categories of ratings grouped into four criterion variables. Because there were four categories of criterion variables, the number of equations required to determine the relationship between the dependent and independent variables was equal to 3 (Pampel, 2000). Category 3, or those companies rated A or A-, was chosen as the reference category since it had the highest frequency (Pampel, 2000). The formula for this reference category was as follows:

$$(5)\ \mathrm{P}(Y_i = 1) = \frac{1}{1+\sum_{h=2}^{4}\exp(X_{hi})}$$

The formula for each of the other categories was as follows:

$$(6)\ \mathrm{P}(Y_i = m) = \frac{\exp(X_{mi})}{1+\sum_{h=2}^{4}\exp(X_{hi})}$$

where X_{hi} are the independent variables as defined above. Each of the 3 log odds calculated was exponentiated and then the probability determined (Denham, 2010; Pampel, 2000).

Methodological Assumptions, Limitations, and Delimitations

The purpose of this non-experimental, retrospective, quantitative study is to determine whether a relationship exists between an organization's risk-based capital position and its financial strength or solvency status. The full population of insurance companies rated by A.M. Best and depository institutions operating from 2007 through 2011 was selected to participate in the study. Data from the participants was collected for the five-year review period covering 2007 through 2011.

Assumptions. The following assumptions were made:

1. A retrospective non-experimental quantitative design was appropriate for this study (Menard, 2011). The design determined if a relationship existed between the dependent and independent variables.

2. A census study was employed with the entire population of insurance companies rated by A.M. Best and depository institutions operating during 2007 through 2011 reviewed (Draugalis, Coons, & Plaza, 2008; Draugalis & Plaza, 2009). Data was available for most of them for 2007 through 2011.

3. The data used in the study was reported by the insurance companies and depository institutions accurately and honestly.

4. The SPSS statistical software that was utilized accurately performed the required statistical tests on the data (DeCesare, 2008).

Limitations. An inherent limitation is present in regression studies, given that the purpose of the study is to measure the strength of a relationship between variables instead of determining causality between variables (Simon, 2011). This lack of causality, however, minimizes threats to the internal validity of the study (Bleijenbergh, Korzilius, & Verschuren, 2011). External validity pertains to the ability of the researcher to substantiate that the results of the research can be generalized across other settings, times, and populations of people or organizations (Roe & Just, 2009). There are various factors that could have threatened the external validity of the study. This study reviewed all insurance companies and depository institutions operating during 2007 through 2011. No other periods were tested. Organizations that were very young and organizations that were very old were included in the study. To test the relationship between insurance company insolvency propensity and risk-based capital ratios,

property/casualty and life/health insurance companies had to be combined into one database. This was done because the number of insurance companies that became insolvent during the review period was low (53) when compared to the number that remained solvent (2,401).

The external validity of the study would also be threatened if companies reviewed had similar characteristics because the results could not be generalized to other companies or institutions that do not have the same characteristics (Creswell, 2009). This study is limited to insurance companies and depository institutions. If the risk-based capital levels of insurance companies and depository institutions only in the year 2011 were reviewed, then generalizations to periods other than 2011 would not necessarily be accurate or valid (Nerurkar, 2008). To assume the conclusions reached are likely for periods prior to 2011, a review of the data from periods covering a five-year range, or 2007 through 2011, was conducted (Nerurkar, 2008). The study is still limited, however, since periods prior to 2007 were not reviewed.

Delimitations. There are delimitations of this study, which may limit its scope. A review of insurance companies and depository institutions only was made. No other type of organization was included in the study. The study was also limited to a review of a specific five-year period. The study reviewed variables associated with risk-based capital, insolvency status, financial strength ratings, years in business, and total assets only. The relationship between other variables, such as equity position or liquidity position to insolvency rates or financial strength ratings were not tested.

Although data normality for independent variables is not required when performing logistic regression (Denham, 2010; Menard, 2011), an analysis of data normality was performed given the wide range in total assets and risk-based capital ratios between companies. As shown

on the histogram in Figure 1, the wide range in risk-based capital ratios for insurance companies results in data that is severely skewed to the right.

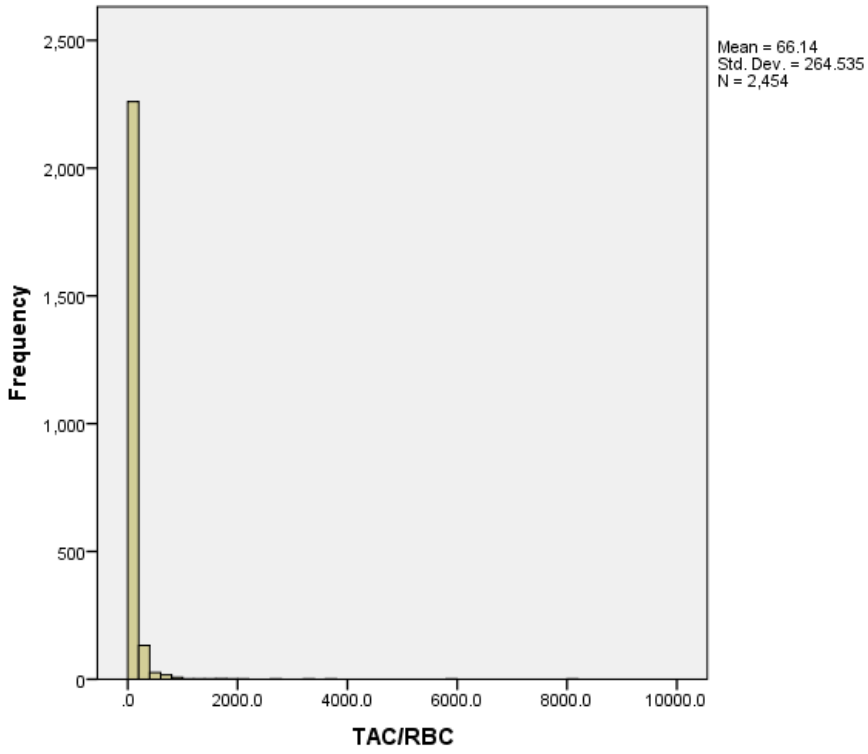

Figure 1. Insurance Company RBC Ratio: RQ1

When data is as severely skewed to the right as this data is, the few outliers far out in the tail exert undue influence on the results and make relationships difficult to interpret. As a result, it has been recommended that the data be transformed utilizing a natural log to make the data more normally distributed where the extreme ranges are shifted closer to the center (He, 2011; Boslaugh & Watters, 2008). Figure 2 shows a histogram of insurance company RBC Ratios after transformation of the data using natural logs.

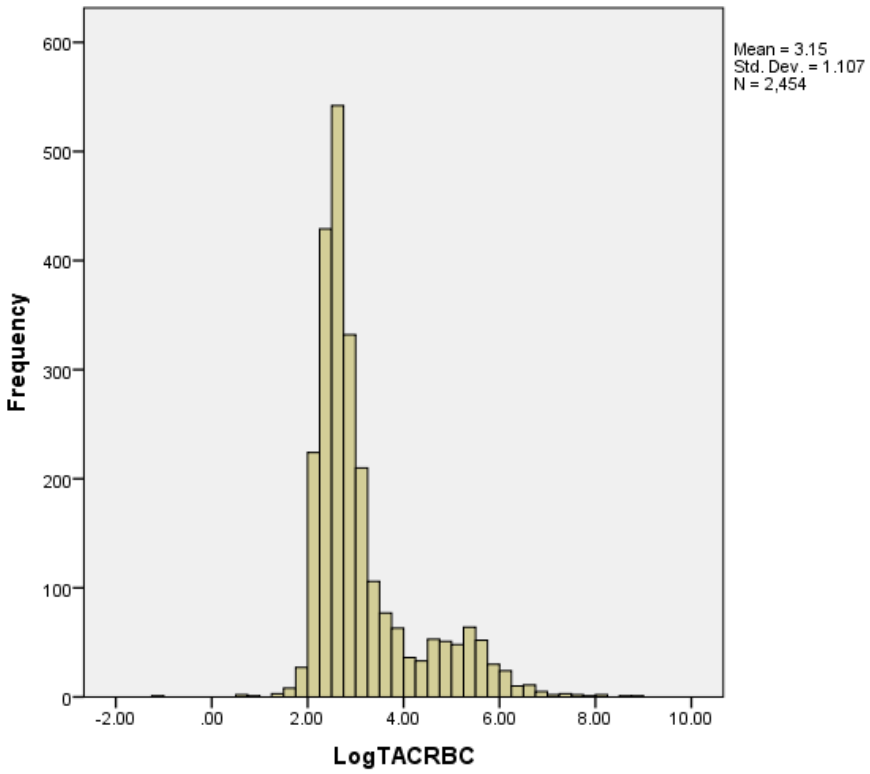

Figure 2. Insurance Company RBC Ratio after Transformation: RQ1

The same exercise was performed for the total assets within each data set. Figure 3 shows a histogram of total assets for research question 1.

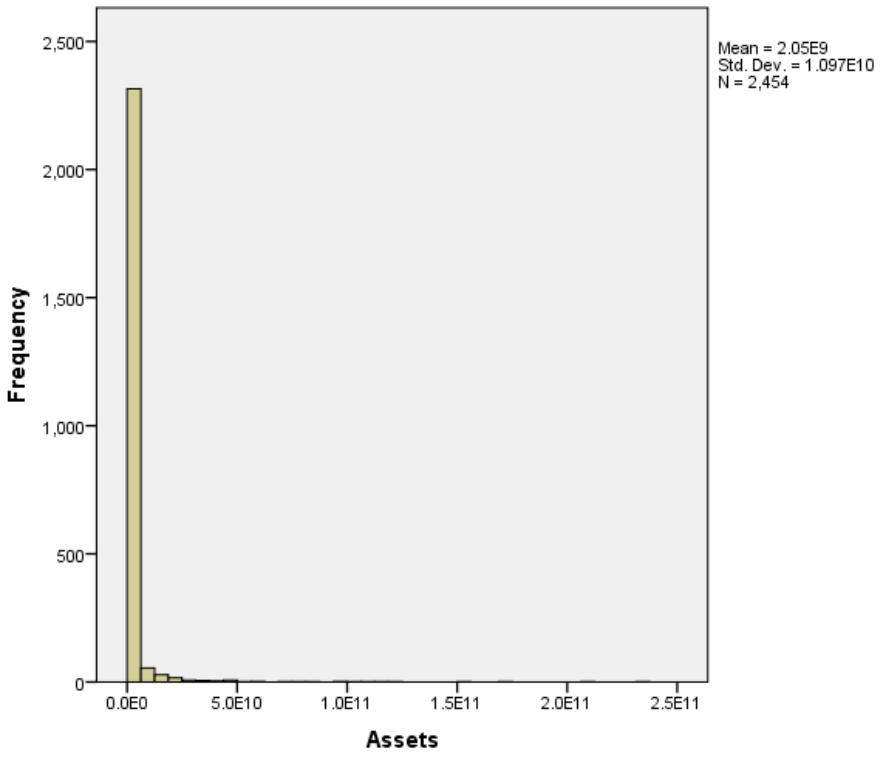

Figure 3. Insurance Company Total Assets: RQ1

Figure 4 shows the total assets of insurance companies in research question 1 after transformation of the data using natural logs.

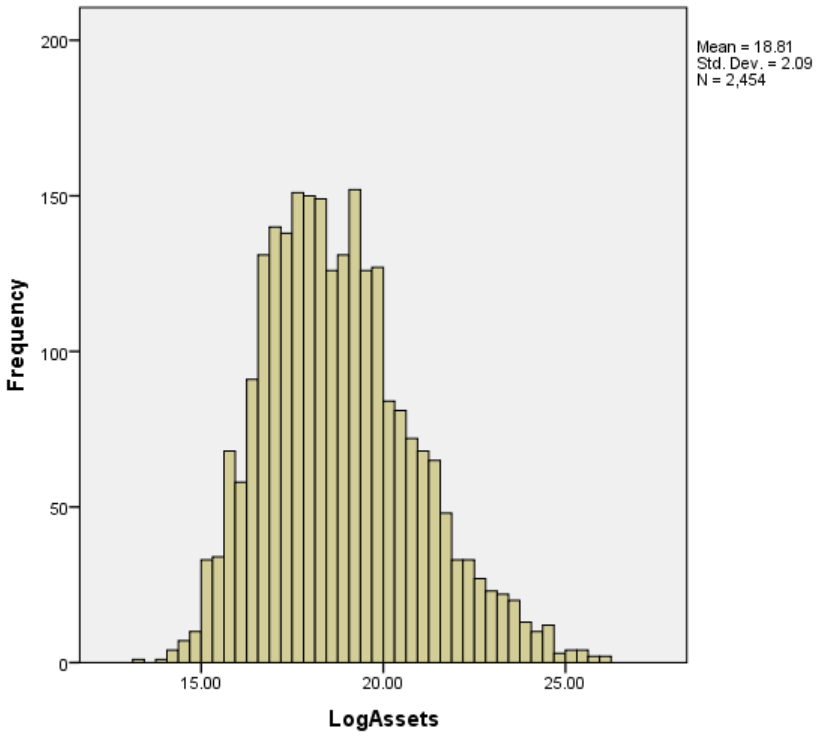

Figure 4. Insurance Company Total Assets after Transformation: RQ1

Histograms were performed for each data set utilized in each research question, showing risk-based capital ratios and total assets skewed severely to the right for all data sets except one. The risk-based capital ratio for depository institutions used in research question 2 did not have the same significant range as the risk-based capital ratios of insurance companies. Therefore, no transformation of the risk-based capital ratio was made. All other risk-based capital ratios and all assets figures were transformed utilizing natural logs (He, 2011; Boslaugh & Watters, 2008).

The results of logistic regression analysis are affected by the correlation of independent variables (Kock & Lynn, 2012). Multicollinearity was, therefore, examined prior to the performance of any logistic regression analysis. Specifically, to test for multicollinearity, an analysis of the Variance Inflation Factor (VIF) was made (Hair, Black, Babin, & Anderson, 2009; Kock & Lynn, 2012). Although there is no set VIF value that indicates unacceptable levels of collinearity, it is commonly posited that values over 10, 5, and 3.3 are problematic

(Hair, Black, Babin, & Anderson, 2009; Kock & Lynn, 2012). The tests showed that multicollinearity in this study was not an issue since the VIF values were all under 1.5.

Binomial and multinomial logistic regressions were used to analyze the differing hypotheses. Binomial logistic regression allows for the analysis of categorical dependent variables with only two categories, while multinomial logistic regression allows for the analysis of categorical dependent variables with more than two categories (Denham, 2010). The results of these regressions are presented to show the strength of the relationship between solvency status and financial strength ratings, respectively, to the variables of age of company, size of company, as determined by total assets and risk-based capital ratio as predictors.

IV. RESULTS

The dependent variables for this study were solvency status for RQs 1 and 2, and financial strength rating for RQs 3 and 4. The independent variables in each research question were risk-based capital (RBC) ratio, total assets, and the age in years of each company. Descriptive statistics have been provided for all variables. The descriptive statistics for the independent variables utilized to answer RQs 1, 2, 3, and 4 are shown in Tables 5, 6, 7, and 8 respectively.

Table 2

Distribution of Independent Variables: RQ1

	N	Minimum	Maximum	Mean	Std. Dev.
Years Old	2454	0	259	49.43	39.47
Log Assets	2454	13.21	26.18	18.81	2.08
Log RBC Ratio	2454	-1.20	9.00	3.15	1.10

The minimum years old was calculated as a zero when companies were less than one year old.

Table 3

Distribution of Independent Variables: RQ2

	N	Minimum	Maximum	Mean	Std. Dev.
Years Old	7768	0	239	71.25	44.52
Log Assets	7768	8.01	21.32	12.15	1.34
Log RBC Ratio	7768	-16.50	757.50	18.97	22.34

Table 4

Distribution of Independent Variables: RQ3

	N	Minimum	Maximum	Mean	Std. Dev.
Years Old	1876	1	259	47.70	40.42
Log 2011 Assets	1877	14.00	25.47	18.49	1.83
Log 2010 Assets	1877	14.02	25.44	18.48	1.83
Log 2009 Assets	1873	13.77	25.34	18.44	1.83
Log 2008 Assets	1860	14.14	25.25	18.43	1.82
Log 2007 Assets	1848	13.58	25.38	18.42	1.84
Log 2011 RBC	1874	-2.30	9.00	2.88	1.42
Log 2010 RBC	1871	-2.30	8.84	2.91	1.40
Log 2009 RBC	1866	-2.30	10.40	2.91	1.41
Log 2008 RBC	1851	-2.30	8.65	2.83	1.40
Log 2007 RBC	1839	-2.30	10.45	2.83	1.44

Table 5

Distribution of Independent Variables: RQ4

	N	Minimum	Maximum	Mean	Std. Dev.
Years Old	525	1	168	56.93	34.93
Log 2011 Assets	525	15.10	26.18	20.15	2.38
Log 2010 Assets	525	15.11	26.15	20.08	2.39
Log 2009 Assets	524	15.17	26.11	20.05	2.38
Log 2008 Assets	521	14.75	26.14	20.04	2.36
Log 2007 Assets	519	14.98	26.11	20.03	2.33
Log 2011 RBC	524	-.69	6.77	2.39	.75
Log 2010 RBC	525	-1.61	8.10	2.40	.82
Log 2009 RBC	523	-.69	8.77	2.34	.84
Log 2008 RBC	520	.00	8.44	2.28	.85
Log 2007 RBC	519	.41	7.11	2.37	.79

The frequencies and percentages for the dependent variables utilized to answer research questions 1, 2, 3, and 4 are shown in Tables 5, 6, 7, and 8 respectively.

Table 6

Distribution of Dependent Variables: RQ1

Variable	Frequency	Percent
Solvency Status		
Solvent	2401	97.8
Not Solvent	53	2.2

Table 7

Distribution of Dependent Variables: RQ2

Variable	Frequency	Percent
Solvency Status		
Solvent	7306	94.1
Not Solvent	462	5.9

Table 8

Distribution of Dependent Variables: RQ3

Variable	Frequency	Percent
2011 P/C Financial Strength Rating		
1 (C++ and below)	16	.9
2 (B++ to B-)	254	13.6
3 (A and A-)	1217	65.0
4 (A++ and A+)	386	20.6
2010 P/C Financial Strength Rating		
1 (C++ and below)	15	.8
2 (B++ to B-)	242	12.9
3 (A and A-)	1196	63.9
4 (A++ and A+)	400	21.4
2009 P/C Financial Strength Rating		
1 (C++ and below)	11	.6
2 (B++ to B-)	244	13.1
3 (A and A-)	1168	62.6
4 (A++ and A+)	405	21.7
2008 P/C Financial Strength Rating		
1 (C++ and below)	7	.4
2 (B++ to B-)	261	14.1
3 (A and A-)	1125	60.8
4 (A++ and A+)	407	22.0
2007 P/C Financial Strength Rating		
1 (C++ and below)	6	.3
2 (B++ to B-)	269	14.6
3 (A and A-)	1059	57.6
4 (A++ and A+)	420	22.8

Table 9

Distribution of Dependent Variables: RQ4

Variable	Frequency	Percent
2011 P/C Financial Strength Rating		
1 (C++ and below)	7	1.3
2 (B++ to B-)	147	28.1
3 (A and A-)	240	45.8
4 (A++ and A+)	130	24.8
2010 P/C Financial Strength Rating		
1 (C++ and below)	6	1.1
2 (B++ to B-)	152	29.0
3 (A and A-)	235	44.8
4 (A++ and A+)	129	24.6
2009 P/C Financial Strength Rating		
1 (C++ and below)	7	1.3
2 (B++ to B-)	147	28.1
3 (A and A-)	237	45.3
4 (A++ and A+)	123	23.5
2008 P/C Financial Strength Rating		
1 (C++ and below)	5	1.0
2 (B++ to B-)	149	28.7
3 (A and A-)	238	45.8
4 (A++ and A+)	115	22.1
2007 P/C Financial Strength Rating		
1 (C++ and below)	3	.6
2 (B++ to B-)	138	26.6
3 (A and A-)	225	43.4
4 (A++ and A+)	136	26.2

Research Question 1

Q1. What predictive relationship exists between risk-based capital ratios, as measured in the last available financial statement, of property/casualty and life/health insurance companies and insolvency propensity of property/casualty and life/health insurance companies within the years 2007 to 2011?

RQ1 Hypothesis

$H1_0$. There is no significant relationship between risk-based capital ratios, as measured in the last available financial statement, of property/casualty and life/health insurance companies and insolvency propensity of property/casualty and life/health insurance companies within the years 2007 to 2011.

$H1_a$. There is a significant relationship between risk-based capital ratios, as measured in the last available financial statement, of property/casualty and life/health insurance companies and insolvency propensity of property/casualty and life/health insurance companies within the years 2007 to 2011.

The dependent variable was insurance company solvency status with two categories of results: a numeral one indicated insolvent, while a numeral zero indicated solvent. The continuous predictor variables were risk-based capital ratio (after natural log transformation), size of insurance company as measured by total assets (after natural log transformation), and age of insurance company. A test of the full model compared to an intercept only model was statistically significant, $\chi^2(3, N = 2454) = 180.389$, $p<.001$. Table 9 shows the logistic regression coefficient, standard error, Wald test, and odds ratio for the three predictors.

Table 10

Binomial Logistic Regression Analysis Predicting Insurance Company Solvency Status

Predictor	B	S.E.	Wald	Odds Ratio
Log RBC Ratio	-2.360***	.356	43.968	.094
Log Assets	-.919***	.117	61.906	.399
Years Old	-.001	.004	.105	.999

*Note: ***p<.001*

Assuming a .05 criterion of statistical significance, risk-based capital ratio and total assets were both significant predictors of insolvency propensity. We can, therefore, reject the null hypothesis for RQ1. Table 9 shows that for each one unit increase in the log of the Risk-Based Capital ratio, the odds of a company being insolvent is approximately 90% lower. As the log of assets increase one unit, the odds of a company being insolvent is approximately 60% lower. The age of insurance companies was not a significant predictor of solvency status.

Research Question 2

Q2. What predictive relationship exists between risk-based capital ratios, as measured in the last available financial statement, of depository institutions and insolvency propensity of depository institutions within the years 2007 to 2011?

RQ2 Hypothesis

$H2_0$. There is no significant relationship between risk-based capital ratios, as measured in the last available financial statement, of depository institutions and insolvency propensity of depository institutions within the years 2007 to 2011.

$H2_a$. There is a significant relationship between risk-based capital ratios, as measured in the last available financial statement, of depository institutions and insolvency propensity of depository institutions within the years 2007 to 2011.

The dependent variable was depository institution solvency status with two categories of results: a numeral one indicated insolvent while a numeral zero indicated solvent. The continuous predictor variables were risk-based capital ratio, size of insurance company as measured by total assets (after natural log transformation), and age of insurance company. A test of the full model compared to an intercept only model was statistically significant, $\chi^2(3, N = 7768) = 2228.93, p<.001$. Table 10 shows the logistic regression coefficient, standard error, Wald test, and odds ratio for the three predictors.

Table 11

Binomial Logistic Regression Analysis Predicting Depository Institution Solvency Status

Predictor	B	S.E.	Wald	Odds Ratio
RBC Ratio	-.644***	.024	715.640	.525
Log Assets	.301***	.055	30.378	1.351
Years Old	-.006**	.002	10.966	.994

*Note. **p<.01; ***p<.001*

Assuming a .05 criterion of statistical significance, risk-based capital ratio, total assets, and the company age were all significant predictors of insolvency propensity. We can, therefore, reject the null hypothesis for RQ2. Table 10 shows that for each one unit increase in the Risk-Based Capital ratio, the odds of a company being insolvent is approximately 47% lower. The log of assets had an unexpected effect. The results showed for each one unit increase in the log of assets, the odds of a company being insolvent increased approximately 65%. The age of depository institutions was determined to have a significant predictive relationship to solvency status.

Research Question 3

Q3. What predictive relationship exists between risk-based capital ratios of property/casualty insurance companies and A.M. Best financial strength ratings of property/casualty insurance companies in each year from 2007 to 2011 (Best's Rating Center, 2010)?

RQ3 Hypothesis

$H3_0$. There is no significant relationship between risk-based capital ratios of property/casualty insurance companies and A.M. Best financial strength ratings of property/casualty insurance companies in each year from 2007 to 2011 (Best's Rating Center, 2010).

$H3_a$. There is a significant relationship between risk-based capital ratios of property/casualty insurance companies and A.M. Best financial strength ratings of property/casualty insurance companies in each year from 2007 to 2011 (Best's Rating Center, 2010)

The dependent variable was P/C insurance company financial strength rating with four differing categories of financial strength. A numeral one indicated the lowest category of financial strength, with a number four representing the highest category of financial strength. Category number 3, or A and A-, was chosen as the reference variable because this category had the highest number of observations. The continuous predictor variables were age of P/C insurance company, size of P/C insurance company as measured by total assets (after natural log transformation), and risk-based capital ratio (after natural log transformation). The model was tested for five different years from 2007 through 2011. A test of the full model compared to an intercept only model was statistically significant in all years: $\chi^2(9, N = 1873) = 508.81, p < .001,$

2010, $\chi^2(8, N = 1871) = 468.706$, $p < .001$, 2009 $\chi^2(8, N = 1866) = 447.312$, $p < .001$, 2008 $\chi^2(8, N = 1766) = 396.769$, $p < .001$, 2007 $\chi^2(8, N = 1778) = 444.681$, $p < .001$. Table 11 shows the logistic regression coefficient, standard error, Wald test, and odds ratio for the three predictors.

Table 12

Multinomial Logistic Regression Analysis Predicting P/C Insurance Company Financial Strength Rating

Predictor	B	S.E.	Wald	Odds Ratio
2011 Rating[a]				
1 Log RBC Ratio	-1.895***	.338	31.419	.150
1 Log Assets	-.980***	.206	22.702	.375
1 Years Old	-.001	.006	.012	.999
2 Log RBC Ratio	-.855***	.078	119.389	.425
2 Log Assets	-.698***	.060	135.036	.497
2 Years Old	-.003	.002	2.510	.997
4 Log RBC Ratio	-.473***	.054	78.181	1.605
4 Log Assets	-.500***	.045	125.614	1.648
4 Years Old	-.002	.002	.828	.998
2010 Rating[a]				
1 Log RBC Ratio	-1.958***	.367	28.425	.141
1 Log Assets	-.846***	.203	17.337	.429
2 Log RBC Ratio	-.863***	.081	112.594	.422
2 Log Assets	-.722***	.062	137.811	.486
4 Log RBC Ratio	-.400***	.053	58.050	1.493
4 Log Assets	-.424***	.042	103.111	1.527
2009 Rating[a]				
1 Log RBC Ratio	-2.495***	.487	26.203	.083
1 Log Assets	-1.096***	.268	16.784	.334
2 Log RBC Ratio	-.860***	.081	111.618	.423
2 Log Assets	-.705***	.061	134.426	.494
4 Log RBC Ratio	-.319***	.051	38.967	1.376
4 Log Assets	-.367***	.045	82.451	1.444
2008 Rating[a]				
1 Log RBC Ratio	-2.185**	.513	18.157	.113
1 Log Assets	-.714*	.291	6.038	.489
2 Log RBC Ratio	-.661***	.072	85.221	.516
2 Log Assets	-.643***	.058	124.018	.526
4 Log RBC Ratio	-.368***	.051	51.100	1.445
4 Log Assets	-.382***	.041	87.283	1.466
2007 Rating[a]				
1 Log RBC Ratio	-1.668***	.381	19.118	.189
1 Log Assets	-1.017**	.358	8.045	.362
2 Log RBC Ratio	-.701***	.074	90.447	.496
2 Log Assets	-.630***	.057	121.671	.533
4 Log RBC Ratio	-.368***	.050	55.156	1.445
4 Log Assets	-.399***	.041	96.610	1.491

*Note: *p<.05; **p<.01; ***p<.001*

[a] *The reference category is 3, A and A-*

Assuming a .05 criterion of statistical significance, risk-based capital ratio and total assets were both significant predictors of financial strength in each year from 2007 through 2011. We can, therefore, reject the null hypothesis for RQ3. Table 11 shows, in 2011, for each one unit increase in the log of the risk-based capital ratio, the odds of a company having a C rating or below (compared to an A or A- rating) is about 85% lower. Also, for each one unit increase in the log of the risk-based capital ratio, the odds of a company having a B++ rating or below (compared to an A or A- rating) is about 57% lower. The years 2010 through 2007 also showed that as the log of risk-based capital ratios go up, companies are less likely to have lower ratings. The log of assets had a similar effect. In each year, the results showed that as the log of assets go up, companies are less likely to have lower ratings. The age of P/C insurance companies was not a significant predictor of financial strength in 2011. Since it would have been redundant to include age in the models for 2007 through 2010, the category was left out of these models.

Research Question 4

Q4. What predictive relationship exists between risk-based capital ratios of life/health insurance companies and A.M. Best financial strength ratings of life/health insurance companies in each year from 2007 to 2011 (Best's Rating Center, 2010)?

RQ4 Hypothesis

$H4_0$. There is no significant relationship between risk-based capital ratios of life/health insurance companies and A.M. Best financial strength ratings of life/health insurance companies in each year from 2007 to 2011 (Best's Rating Center, 2010).

$H4_a$. There is a significant relationship between risk-based capital ratios of life/health insurance companies and A.M. Best financial strength ratings of life/health insurance companies in each year from 2007 to 2011 (Best's Rating Center, 2010).

The dependent variable was L/H insurance company financial strength rating, with four differing categories of financial strength. A numeral one indicated the lowest category of financial strength, with a number four representing the highest category of financial strength. Category number 3, or A and A-, was chosen as the reference variable since this category had the highest number of variables. The continuous predictor variables were age of L/H insurance company, size of L/H insurance company as measured by total assets (after natural log transformation), and risk-based capital ratio (after natural log transformation). The model was tested for five different years from 2007 through 2011. A test of the full model compared to an intercept only model was statistically significant in all years: 2011, $\chi^2(9, N = 524) = 232.714$, $p < .001$, 2010, $\chi^2(8, N = 525) = 237.871$, $p < .001$, 2009 $\chi^2(8, N = 523) = 265.916$, $p < .001$, 2008 $\chi^2(8, N = 520) = 275.656$, $p < .001$, 2007 $\chi^2(8, N = 519) = 307.482$, $p < .001$. Table 12 shows the logistic regression coefficient, standard error, Wald test, and odds ratio for the three predictors.

Table 13

Multinomial Logistic Regression Analysis Predicting L/H Insurance Company Financial Strength Rating

Predictor	B	S.E.	Wald	Odds Ratio
2011 Rating[a]				
1 Log RBC Ratio	-3.370***	.916	13.531	.034
1 Log Assets	-.842**	.323	6.813	.431
1 Years Old	.012	.015	.688	1.012
2 Log RBC Ratio	-.615***	.160	14.795	.540
2 Log Assets	-.621***	.078	64.083	.538
2 Years Old	-.012	.004	7.789	1.012
4 Log RBC Ratio	.295***	.197	2.233	1.343
4 Log Assets	.463***	.069	44.558	1.589
4 Years Old	-.007	.004	3.693	.993
2010 Rating[a]				
1 Log RBC Ratio	-2.032***	.489	17.283	.131
1 Log Assets	-1.340**	.399	11.262	.262
2 Log RBC Ratio	-.685***	.157	19.026	.504
2 Log Assets	-.592***	.072	67.888	.553
4 Log RBC Ratio	.488**	.172	8.074	1.628
4 Log Assets	.435***	.065	44.786	1.545
2009 Rating[a]				
1 Log RBC Ratio	-2.951***	.726	26.544	.052
1 Log Assets	-1.359***	.374	13.189	.257
2 Log RBC Ratio	-.595***	.154	14.952	.551
2 Log Assets	-.653***	.077	72.123	.521
4 Log RBC Ratio	.533**	.167	10.255	1.705
4 Log Assets	.458***	.067	46.079	1.580
2008 Rating[a]				
1 Log RBC Ratio	-2.286**	.740	9.550	.102
1 Log Assets	-1.343***	.369	13.252	.261
2 Log RBC Ratio	-.600***	.160	14.064	.549
2 Log Assets	-.724***	.082	77.909	.485
4 Log RBC Ratio	.580**	.175	11.031	1.786
4 Log Assets	.448***	.069	42.420	1.565
2007 Rating[a]				
1 Log RBC Ratio	-2.743*	1.111	19.118	.189
1 Log Assets	-1.321**	.474	8.045	.362
2 Log RBC Ratio	-.603***	.170	90.447	.496
2 Log Assets	-.696***	.085	121.671	.533
4 Log RBC Ratio	.750***	.196	55.156	1.445
4 Log Assets	.607***	.076	96.610	1.491

*Note: *p<.05; **p<.01; ***p<.001*

[a] *The reference category is 3, A and A-*

Assuming a .05 criterion of statistical significance, risk-based capital ratio and total assets were both significant predictors of financial strength in each year from 2007 through 2011. We can, therefore, reject the null hypothesis for RQ4. Table 12 shows, in 2011, for each one unit increase in the log of the risk-based capital ratio for L/H companies, the odds of a company having a C rating or below (compared to an A or A- rating) is about 97% lower. Also, for each one unit increase in the log of the risk-based capital ratio, the odds of a company having a B++ rating or below (compared to an A or A- rating) is about 46% lower. The years 2010 through 2007 also showed that as the log of risk-based capital ratios go up, companies are less likely to have lower ratings. The log of assets had a similar effect. In each year, the results showed that as the log of assets go up, companies are less likely to have lower ratings. The age of L/H insurance companies was not a significant predictor of financial strength in 2011. Since it would have been redundant to include age in the models for 2007 through 2010, the category was left out of these models.

V. EVALUATION OF FINDINGS

The results of this study showed a significant predictive relationship between risk-based capital levels of insurance companies and depository institutions to insolvency propensity. As the log of risk-based capital ratios went up, the likelihood of insolvency went down. The results also showed a significant predictive relationship between risk-based capital levels of insurance companies to their financial strength ratings. As the log of risk-based capital ratios went up, the likelihood of having a lower rating went down. The significant relationships are present in every year from 2007 through 2011. This indicates that forensic accountants can consider evidence of a defendant's risk-based capital position accurate and appropriate for use in punitive damages cases. This study was required to show that risk-based capital levels are related to an

organization's financial health to withstand the strict tests of the Federal Rules of Evidence (Daubert, 1993; Kuhmo Tire, 1999; Philip Moris, 2007; State Farml, 2003). The Federal Rules of Evidence state that expert witnesses may only offer opinions based on a reliable foundation, and only when those opinions are relevant to that specific case.

The theoretical framework of this study pertains to the development of a specific analytical model addressing discrepancies related to the law and academia as they correspond to social and political culture. Discrepancies occur when judges inform jurors that any award of punitive damages in a case must not bankrupt or destroy a defendant financially but offer no guidance to the jury as to what that amount is. Academia has offered no solution to this problem. This is the first study which addresses this issue and tests a model that could be used to assist a jury in making an appropriate determination.

Although no similar studies have been performed testing the relationship between risk-based capital ratios and solvency propensity or financial strength in recent periods, previous research did review the period from 1989 to 1991 and found risk-based capital ratios to be less predictive of insurance company weakness than the NAIC's Financial Analysis Surveillance Tracking System (Grace, Harrington, & Klein, 1998). Despite risk-based capital ratios being less predictive of solvency issues than the Financial Analysis Surveillance Tracking (FAST) system, Grace, Harrington and Klein found that RBC ratios in combination with FAST were stronger than any one category alone. The authors stated, "RBC ratios may reveal new information about insolvency risk in spite of their relatively low power on a univariate basis" (Grace, et al., 1998, p. 213).

Another study reviewing data from 1990, 1991 and 1992 to predict insurance company insolvencies during 1991-1993, 1992-1994, and 1993-1995 respectively showed similar results.

The FAST system, again, proved to be a stronger predictor of insurance company solvency status than RBC ratios (Cummins, Grace, & Phillips, 1999). Pottier and Sommer compared four measures of insurance company risk: FAST, RBC, A.M. Best Capital Adequacy Relativity ratios and A.M. Best Ratings (2002). The study used data from 1995 to predict insolvencies occurring from 1996 to 1998. The research found that A.M. Best data were better predictors of insurance company insolvency than FAST or RBC ratios (Pottier & Sommer, 2002).

VI. APPLICATION OF RISK-BASED CAPITAL

Risk-based capital data for insurance companies can be obtained online from the annual statements published with the NAIC at www.naic.org. Hard copies of these annual statements are also available with the insurance commissioner of each state. The Risk-Based Capital for Insurers Model Act (1994) as established by the NAIC and adopted by the individual states requires the following ratios of Total Adjusted Capital to Risk-Based Capital to avoid any regulatory action:

1. Company Action Level – with respect to any insurer, the product of two and its authorized control level RBC (RBC ratio of 200%).
2. Regulatory Action Level – the product of one and one-half and its authorized control level RBC (RBC ratio of 150%).
3. Authorized Control Level RBC – the number determined under the risk-based capital formula in accordance with RBC instructions (RBC ratio of 100%).
4. Mandatory Control Level RBC – the product of seven-tenths and the authorized control level RBC (RBC ratio of 70%).

If, for example, a property/casualty insurance company has Total Adjusted Capital of $50,000,000 and Risk-Based Capital of $20,000,000, their RBC ratio would total 250% ($50,000,000/$20,000,000). Given that the company must maintain $40,000,000, or an RBC ratio of 200%, to avoid the Company Action Level, the company has $10,000,000 in capital above the required minimum. To avoid the Regulatory Action Level, the company must

maintain $30,000,000 in capital, and would, therefore, have $20,000,000 in capital above this minimum. These figures could be presented to the jury in addition to the total adjusted capital figure of $50,000,000.

Bank risk-based capital data can also be obtained online through the FDIC at www.fdic.gov. The FDIC established different risk-based capital standards for banks. These standards, called Prompt Correction Action Thresholds, will be revised as of January 1, 2015 and defined as follows (FDIC, 2012):

1. Well Capitalized refers to a Total Risk-Based Capital Ratio equal to or greater than 10 percent, and Tier 1 Risk-Based Capital Ratio equal to or greater than 8 percent, and Tier 1 Leverage Capital Ratio equal to or greater than 5 percent.
2. Adequately Capitalized is not well capitalized and refers to a Total Risk-Based Capital Ratio equal to or greater than 8 percent, and Tier 1 Risk-Based Capital Ratio equal to or greater than 6 percent, and Tier 1 Leverage Capital Ratio equal to or greater than 4 percent.
3. Undercapitalized is neither well capitalized nor adequately capitalized and refers to a Total Risk-Based Capital Ratio less than 8 percent, and Tier 1 Risk-Based Capital Ratio less than 6 percent, and Tier 1 Leverage Capital Ratio less than 4 percent.
4. Significantly Undercapitalized refers to a Total Risk-Based Capital Ratio less than 6 percent, and Tier 1 Risk-Based Capital Ratio less than 4 percent, and Tier 1 Leverage Capital Ratio less than 3 percent.

The risk-based capital ratio, as defined by the FDIC, is the ratio of total capital to risk-weighted assets. If, for example, a company has total capital of $50,000,000 and risk-weighted assets of $400,000,000, for a ratio of 12.5%, the company has $10,000,000 above the amount required to maintain the "Well Capitalized" level of 10%, and $18,000,000 above the amount required to maintain the "Adequately Capitalized" level of 8%.

VII. CONCLUSION

A significant predictive relationship was found between the risk-based capital position of insurance companies and depository institutions and their insolvency status as evidenced by a p-value in each analysis < 0.01. We also confirmed a significant predictive relationship existed

between the risk-based capital position of insurance companies and their financial strength ratings as evidenced by a p-value in each analysis < 0.01. Given this significant relationship, it is recommended that forensic accountants hired to present evidence of a defendant insurance company or depository institution's financial position in punitive damage cases include evidence of the defendant's risk-based capital position. This evidence will assist jurors in knowing the amount of an award that could destroy the defendant financially.

Further research is needed to explore the relationship between the risk-based capital position and financial strength ratings of depository institutions. This is a study that could easily be performed if CAMELS ratings determined by the FDIC are released into the public domain (Corcoran, 2010). This research could also be performed if a rating agency would provide a numerical identifier recognized by the FDIC with each company along with a greater number of companies reviewed and rated.

There are other areas of research left open at the conclusion of this study. Is there a better way to measure the amount of capital an organization must retain to support business operations that could be used to assist a jury in punitive damages cases? Are the minimum risk-based capital requirements for insurance companies and depository institutions appropriate? This research explores one aspect of forensic accounting evidence in relation to punitive damages cases. It has provided a foundation for future research to explore other areas related to forensic accounting theory and forensic accounting evidence.

VII. REFERENCES

Arcuri, A., Iqbal, M. Z., & Briand, L. (2012). Random testing: Theoretical results and practical implications. *IEEE Transactions on Software Engineering, 38*(2), 258-277. doi:10.1109/TSE.2011.121

Baranoff, E. G., Papadopoulos, S. & Sager, T. W. (2007). Capital and risk revisited: A structural equation model approach for life insurers. *Journal of Risk & Insurance, 74*(3), 653-681.

Best's Rating Center. (2010). Guide to financial strength ratings-insurer. Retrieved from http://www.ambest.com/ratings/guide.asp

Best's Review's: Annual Corporate Changes 2007. (2008). *Best's Review*, *109*(2), 73.

Best's Review's: Annual Corporate Changes 2008. (2009). *Best's Review*, *110*(2), 85-91.

Best's Review's: Annual Corporate Changes 2009. (2010). *Best's Review*, *111*(2), 76-83.

Best's Review's: Annual Corporate Changes 2010. (2011). *Best's Review*, 112(2), 82-90.

Best's Review's: Annual Corporate Changes 2011. (2012). *Best's Review*, 113(2), 66-71.

Bleijenbergh, I., Korzilius, H., & Verschuren, P. (2011). Methodological criteria for the internal validity and utility of practice oriented research. *Quality and Quantity, 45*(1), 145-156. doi:10.1007/s11135-010-9361-5

Blundell-Wignall, A., & Atkinson, P. (2010). Thinking beyond Basel III: Necessary solutions for capital and liquidity. *OECD Journal, 2*(1), 9-33. doi:10.1787/19952872.

Boslaugh, S., & Watters, P. A. (2008). *Statistics in a nutshell*. Sebastopol, CA: O'Reilly Media, Inc.

Browning-Ferris Industries, Inc. v. Kelco Disposal, Inc., 492 U.S., 267-272, 1989.

Corcoran, C. (2010). A reassessment of regulated bank capital on profitability and risk. *The International Business & Economics Research Journal, 9*(3), 97-100.

Cummins, J., Grace, M. F., & Phillips, R. D. (1999). Regulatory solvency prediction in property-liability insurance: risk-based capital, audit ratios, and cash flow simulation. *Journal Of Risk & Insurance, 66*(3), 417-458.

Cummins, J., & Phillips, R. (2009). Capital adequacy and insurance risk-based capital systems. *Journal of Insurance Regulation, 28*(1), 25-72.

Daubert v. Merrill Dow Pharmaceutical, Inc., 509 U.S. 579 (1993).

Davis, R., & Palmer, L. (2010). Punitive damages law in West Virginia. *West Virginia Supreme Court of Appeals*. Retrieved from http://www.state.wv.us/wvsca/PunitiveDamages2010.pdf

De Andrés, J., Sanchez-Lasheras, F., Lorca, P., & De Cos Juez, F. (2011). A hybrid device of self-organizing maps (SOM) and multivariate adaptive regression splines (MARS) for the forecasting of firms' bankruptcy. *Accounting and Management Information Systems, 10*(3), 351-374.

DeCesare, M. (2008). Using SPSS for social statistics and research methods. *Teaching Sociology, 36*(2), 165-167.

Denham, B. E. (2010). Measurement of risk perceptions in social research: A comparative analysis of ordinary least squares, ordinal and multinomial logistic regression models. *Journal Of Risk Research, 13*(5), 571-589. doi:10.1080/13669870903172386

DiGabriele, J. A. (2008). An empirical investigation of the relevant skills of forensic accountants. *Journal Of Education For Business*, *83*(6), 331-338.

Draugalis, J., Coons, S., & Plaza, C. M. (2008). Best practices for survey research reports: A synopsis for authors and reviewers. *American Journal Of Pharmaceutical Education*, *72*(1), 1-6.

Draugalis, J., & Plaza, C. M. (2009). Best practices for survey research reports revisited: Implications of target population, probability sampling, and response rate. *American Journal Of Pharmaceutical Education, 73*(8), 1-3.

Eling, M., & Holzmüller, I. (2008). An overview and comparison of risk-based capital standards. *Journal of Insurance Regulation, 26*(4), 31-60.

Ellis, D. (1982). Fairness and efficiency in the law of punitive damages. *Southern California Law Review, 56*, 12-20.

Federal Deposit Insurance Corporation. (2012). Financial Institution Letters, Regulatory Capital Rules. Retrieved from http://www.fdic.gov/news/news/financial/2012/fil12025.html

Gow, I. D., Ormazabal, G., & Taylor, D. J. (2010). Correcting for cross-sectional and time-series dependence in accounting research. *Accounting Review*, 85(2), 483-512.

Grace, M. F., Harrington, S. E., & Klein, R. W. (1998). Risk-based capital and solvency screening in property-liability insurance: hypotheses and empirical tests. *Journal of Risk & Insurance*, *65*(2), 213-243.

Greenspan, A. (2010). The Crisis/Comments and discussion. *Brookings Papers on Economic Activity*, (00072303), 201-261.

Hair, J., Black, W., Babin, B., & Anderson, R. (2009). *Multivariate data analysis*. Upper Saddle River, NJ: Prentice Hall.

Hassan Al-Tamimi, H. (2008). Implementing basel II: An investigation of the UAE banks' basel II preparations. *Journal of Financial Regulation and Compliance, 16*(2), 173-187. doi.10.11081135819808108698l4

He, L. (2011). Issues in statistical data analysis in applied linguistics: Data normality, transformations and power analysis. *US-China Foreign Language*, *9*(10), 647-658.

Hoyt, R. E., & McCullough, K. A. (2010). Managerial discretion and the impact of risk-based capital requirements on property-liability insurer reserving practices. *Journal of Insurance Regulation*, 28(2), 207-228.

Investopedia. (2014). Definition of solvency. Investopedia US, A Division of IAC. Obtained from http://www.investopedia.com/terms/s/solvency.asp

Kalbers, L. (2009). Fraudulent financial reporting, corporate governance and ethics: 1987-2007. *Review of Accounting & Finance*, *8*(2), 187-209. doi.10.1108/14757700910459510

Khowaja, S., Ghufran, S., & Ahsan, M. J. (2011). Estimation of population means in multivariate stratified random sampling. *Communications In Statistics: Simulation & Computation*, *40*(5), 710-718. doi:10.1080/03610918.2010.551014

Kock, N., & Lynn, G. S. (2012). Lateral collinearity and misleading results in variance based SEM: An illustration and recommendations. *Journal of the Association for Information Systems*, *13*(7), 546-580.

Kumho Tire Co. v. Carmichael, 526 U.S. 137 (1999).

Lev, B., Radhakrishnan, S., & Zhang, W. (2009). Organization Capital. *Abacus*, *45*(3), 275-298. doi:10.1111/j.1467-6281.2009.00289.x

Menard, S. (2011). Standards for standardized logistic regression coefficients. *Socia Forces, 89*(4), 1409-1428.

Merriam-Webster's Dictionary of Law. (1996). Merriam-Webster, Incorporated. Obtained from http://public.findlaw.com/LCsearch.html?restrict=consumer&entry=insolvent

Mohanty, S. (2008). Basel II: Challenges and risks. *Academy of Banking Studies Journal, 7*(1), 109-130.

Montgomery, C., & Nahrstadt, B. C. (2010). Preventing the runaway verdict in

catastrophic injury cases. *FDCC Quarterly*, *60*(3), 220-250.

Moore, J. (2011). Bank performance prediction during the 'great recession' of 2008-'09: A pattern-recognition approach. *Academy Of Banking Studies Journal*, *10*(2), 87-104.

National Association of Insurance Commissioners. (1992). Risk-based capital for insurers model act. *2*(312).

National Association of Insurance Commissioners. (2009). Risk-based capital general overview. Retrieved from http://www.naic.org/documents/committees_e_capad_RBCoverview.pdf

Neckers, C. S., & Wikander, M. L. (2006). Daubert and the soft sciences: Can a forensic economist ever make it past the gatekeeper?. *FDCC Quarterly*, *57*(1), 27-49.

Nerurkar, R. (2008). Basics of statistics for postgraduates. *Indian Journal of Dermatology, Venereology and Leprology*, *74*(6), 691-5.

Newman, T. R. (2007). Is there an expert in the house? Expert evidence in insurance coverage cases. *Defense Counsel Journal*, *74*(4), 307-312.

Pacific Mutual Life Insurance Company v. Haslip, 499 U.S. 1, 20 (1991).

Pampel, F. (2000). *Logistic regression: A primer*. Thousand Oaks, California. Sage Publications, Inc.

Pera, E., & Bird, S. (2011). Basel III: Restoring confidence in the banking sector. *Accountancy SA*, (02587254), 24-25.

Philip Morris v. Williams, No. 05-1256 (U.S. February 20, 2007).

Pottier, S. W., & Sommer, D. W. (2002). The effectiveness of public and private sector summary risk measures in predicting insurer insolvencies. *Journal of Financial Services Research*, *21*(1/2), 101.

Roe, B. E., & Just, D. R. (2009). Internal and external validity in economics research: tradeoffs between experiments, field experiments, natural experiments, and field data. *American Journal of Agricultural Economics*, *91*(5), 1266.

Rustad, M. (2008). The uncert-worthiness of the court's unmaking of punitive damages. *Suffolk University Law School Legal Studies Research Paper Series*. *08-05*, 453-514.

Scheuerman, S., & Franze, A. (2008). Instructing juries on punitive damages: due process revisited after Philip Morris v. Williams. *Journal of Constitutional Law*. *10*(5), 1147-1204.

Schnee, E. J. (2000). Calculating insolvency. *Journal of Accountancy, 189*(4), 71. Retrieved from http://search.proquest.com/docview/206766890?accountid=139631

Schroeder, R., & Schauer, D. (2010). The impact of SFAS No. 157 on commercial banks. *International Advances in Economic Research, 16*(2), 175-189.

Simon, M. K. (2011). Dissertation and scholarly research: Recipes for success. 2011 Ed. Seattle, WA.

Smith v. Lightning Bolt Prods., Inc., 861 F.2d 363, 373 (2d Cir.1988).

Smith III, D. (2010). The financial crisis: implications for regulatory capital. *Bank Accounting & Finance* (08943958), *23*(2), 9-15.

State Farm v. Campbell, No. 01-1289 (U.S. April 7, 2003).

TXO Production Corporation v. Alliance Resources Corporation, 509 U.S. 443, 464-465 (1993).

Weber, R., & Darbellay, A. (2008). The regulatory use of credit ratings in bank capital requirement regulations. *Journal of Banking Regulation*, *10*(1), 1-16. doi.10.1057/jbr.2008.22

Wyner, G. A. (2007). Survey errors. *Marketing Research*, *19*(1), 6-8.

Zipursky, B. C. (2005). A theory of punitive damages. *Texas Law Review*, 84(1), 105-171.