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## Article

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## Research Article

Karina Kasztelnik\*

# Innovative Empirical Model for Predicting National Banks' Financial Failure with Artificial Intelligence Subset Data Analysis in the United States

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**Abstract:** The principal objective of this research study was to investigate the impact of the Great Economic Recession of 2008 on national banks' equity investment valuations and create an empirical model for predicting national banks' financial failure in the United States. The focal period of the study was from 2009 to 2012, and public data sources used. It is not known to what extent national banks' stock value investments are based on the return on equity. This causal-comparative study explores the degree to which national banks' value investment in terms of the price to earnings ratio impacts their return on equity and the extent to which these banks' stock value investment in terms of dividend yield impacts their return on equity. We used statistical modeling and the machine learning model to find hidden patterns in the input data. The principal finding of this research is that the median earnings per share in 2012 and the dividend yield in 2009 were significantly larger than the median return on equity in 2009 and 2012. Additionally, the dividend yield in 2012 was significantly smaller than the median return on equity in 2012. These findings can contribute to improving our understanding of how banks can predict financial failure using the new machine learning features of artificial intelligence to build an early warning system with the innovative risk measurement tool.

**Keywords:** ROE, Equity Valuations, Financial Institutions, Economic Recession, Dividend Yield, Price to Earnings, Banks

**JEI Classifications:** M21, M41, O51, G24, N20

## 1 Introduction

In this research article, we develop an innovative model to measure possible contagion bank risk, which is defined as the risk that an initial bank failure may spill over to the rest of the banking industry and cause further bank failures. It is not known to what extent national banks' stock value investment based on the return on equity (ROE) changed in the four-year period from 2009 to 2012 after the Great Economic Recession of 2008 in the United States. The purpose of this study is to assess the impact of the Great Economic Recession of 2008 on national banks' stock value investment based on the reported ROE and create an empirical model for predicting national bank financial failures in the United States.

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The Great Economic Recession resulted in a loss of confidence among investors, thus making it challenging for them to regain full trust and confidence in the market system. However, Gottschalk and Moffitt (1994) identified an increase in earnings volatility during the slowdown that occurred in the 1970s. While the post-World War II period's growth also showed higher volatility in economic growth after a period of low growth, the most recent downturn (2008 to 2015) showed a weaker period of growth (Khanal & Mishra, 2017). This trend seems unique in the historical data.

In Rabbania, Grable, Wookjae, Nobre, and Kuzniak's (2017) study, the authors found that the increased volatility contributed to the increased risk-tolerant attitude individuals had toward the equity markets, resulting in sluggish economic growth compared to prior downturns. However, this relationship did vary. Supporting evidence only showed a relationship 64% of the time. This result, which was substantiated by Born, Breuer, and Elstner (2018), suggested that only a minor part of population uncertainty drove the exogenous uncertainty of stocks during the Great Economic Recession.

Even so, one may ask how the Great economic recession influenced equity. Chan-Lau, Liu, and Schmittmann (2015) analyzed how the Great Economic Recession of 2008 influenced the ongoing debt crisis in the euro area. Despite its large centralized banks, euro area banks still faced significant operating challenges. Banks in the euro area held significant sovereign bonds as an investment base that made their portfolios sizable. The effects of the Great Economic Recession put an excess drain on the portfolios, thus hurting countries' ability to repay their bonds and increasing the sovereign risk. While the authors did reiterate the positive impact on the equity to asset ratio of retained earnings, the data suggested that the higher-equity assets were limited to 2008. The authors' findings did suggest that capital played a vital role in shielding banks during times of extreme stress. Thus, high reliance on wholesale funding made banks more vulnerable to shortages during the period of market uncertainty (Chan-Lau et al., 2015). Duffie (2010) and Gorton and Metrick (2012) reiterated this in their separate studies of the Great Economic Recession of 2008.

Thus, one can ask if the Great Economic Recession had any influence on the ROE in the U.S. This study examines the impact of the Great Economic Recession from 1998 to 2018 on stock value investment based on the ROE in the U.S. The focus of this study is institutions that are federally insured by the Federal Deposit Insurance Corporation (FDIC), because of the role that it played during the Great Economic Recession.

## 2 Literature Review

To help maintain public confidence and stability in the U.S. financial system, Congress established an independent agency known as the FDIC. The FDIC insures deposits, examines and supervises financial institutions, makes large and complex financial institutions resolvable, and manages receiverships (Federal Deposit Insurance Corporation, 2019). Created through the Banking Act of 1933, the FDIC provided favorable insurance through the Bank Insurance Fund (Benston & Kaufman, 1997). Following an alarming number of failures in the 1980s, the depletion of the bank insurance fund to a negative net worth in 1991 forced Congress to enact the FDIC Improvement Act of 1991 (FDICIA) (Kuritzkes, Schuermann, & Weiner, 2005). The FDICIA also allowed the FDIC to issue deposit insurance based on risk-based pricing. As a result, the FDIC was able to bail out organizations that had sizable debt by providing liquidity facilities to keep large financial interest institutions solvent, as well as providing capital through the Troubled Asset Relief Program (Hein, Koch, & Nounamo, 2012).

### 2.1 The Great Economic Recession

Throughout the summer of 2008, the U.S. economy continued to experience a slowdown. However, the perceptions of this downturn were relatively similar to the moderate recession that the economy experienced from 1990 to 1991. This particular slowdown also featured a similar banking crisis. During the fall of 2008, the credit markets were virtually frozen. Many banks and holding companies found it extremely difficult to roll over debt at a reasonable cost. This slowdown was compounded in early October of the same year

when the G7 finance managers announced their plan to maintain liquidity and strengthen capital markets to ensure market stability. As a result, the U.S. needed to find a way to guarantee bank debt. The systematic risk exception within the FDICIA provided this mechanism. The Act required that the FDIC resolve failed banks in a less costly manner. Together with the Transition Accounting Guarantee Program and the Debt Guarantee Program, the U.S. was able to preserve and enhance the liquidity of the banking system during times of crisis (Federal Deposit Insurance Corporation, 2017).

In September 2008, Lehman Brothers became exposed to excess mortgage-related risks. As a result, the Federal Reserve was unable to act as a “lender of last resort,” forcing Lehman Brothers to default because it could not offer sufficient collateral (Gertler & Gilchrist, 2018).

Lehman Brothers was not the only bank to experience financial issues. In all, 489 FDIC-insured banks failed from 2008 to 2013. Heightened concentrations of acquisition, development, and construction of real estate loans was one of the typical reasons for these failures. Additionally, rapid asset growth, heightened reliance on funding sources other than stable core deposits, and relatively low capital-to-asset ratios added to the failures (Federal Deposit Insurance Corporation, 2017).

The impact of the failures of investment institutions such as Lehman Brothers was catastrophic. During the final months of 2007, the results of the crisis were the worst in the nation’s history since the 1930s. From peak to trough, the decline of real GDP was 4.25%, compared to that of less than 2.5% during the 1981–82 recession. Payroll unemployment also suffered during this time. The peak-to-trough decline in payroll unemployment reached a staggering 6.3%, compared to 3.1% in 1981–82. Furthermore, in contrast to previous recessions, the recovery has been one of the most anemic in history, with an average growth of 2.2% through 2014 (Blinder, 2015).

## 2.2 The Aftermath of the Great Economic Recession

Studies have categorized the aftermath of the Great Economic Recession as weak or even anemic compared to recessions of the past. Starting in mid-2009, the average growth rate through 2014 was 2.2%. It was not until 2011–12 that the GDP reached 2008 levels. Additionally, it was not until May 2014 that payroll employment rates reached 2008 levels (Blinder, 2015). This prolonged period of slow growth and weakness in the economy concerned many policymakers, who thought it could lead to deflation. This slow down led the Federal Reserve to introduce several quantitative easing techniques that effectively held the federal funds rate at nearly zero (Murphy, 2014).

The recovery has been challenging as it pertains to the unemployment rate. With the slow recovery of the labor markets, researchers have been having a debate on whether this is the result of the Great Economic Recession or something else. While arguing that the damage has already been done, researchers note that many workers remain unemployed or have left the workforce entirely.

However, Federal Reserve chair Janet Yellen suggested that the basis of the aggregation of the sluggish employability of workers rotated on the demand for workers rather than the permanent damage caused by the Great Economic Recession (Daly & Marks, 2014).

As it pertains to 401(k)s, employees observed a boom-to-bust reality during the 1990s and 2000s. This roller coaster effect saw expansion and contraction on a monumental scale. Brezigar-Masten, Masten, and Volk (2015) suggested that 401(k) participation and contribution declined during the Great Economic Recession and that 401(k) assets had dropped as much as 9% at the age of 62. These results tend to coincide with the lower employment rate and sluggish employability suggested by the Federal Reserve chair (Daly & Marks, 2014).

Despite the massive programs introduced during the Great Economic Recession, banks still face an upward climb as it pertains to being repeatedly downgraded and having declining equity prices. According to Chan-Lau et al. (2015), weak growth prospects and heightened solvent risk are driving the returns on equity within the banking sector after the Great Economic Recession and the European sovereign debt crisis. However, even with dismal ROE performance, the banking sector is showing evidence that it has outperformed its peers during these times.

While researchers have addressed several aspects of the Great Economic Recession of 2008, including unemployment inequity within the banking sector, they have been silent on how the Great Economic Recession influenced financial institutions' stock value investment based on the ROE in the U.S. This would include financial institutions insured by the FDIC. This study will try to answer this question by examining the impact that the price-to-earnings ratio has on the ROE and if the dividend yield rate influences the ROE of financial institutions insured by the FDIC.

### 3 Research Design

This study elected to utilize a causal-comparative research design for several different reasons. The researcher noticed that objective performance metrics that show the impact of the dividend yield and price-to-earnings ratio on the dependent variables (DVs) remain largely absent from other sources. The researcher collected the primary data needed for this study using public data sources with available financial statements. The research methodology used for the study was quantitative with a casual-comparative research design and a machine learning model using the Lloyd's algorithm with squared Euclidean distance. The goal of this quantitative nonexperimental causal comparative study was to examine the extent to which national banks' stock value investments based on the ROE changed in the four-year period from 2009 to 2012 after the beginning of the Great Economic Recession of 2008 in the U.S. The population of interest was comprised of all national banks with over \$10 million dollars in total assets in the United States.

The researcher utilized the G\*Power software to compute the a priori sample size needed for the planned paired t-test. The input included the following: expected medium effect size,  $f_2 = 0.15$  (Cohen, 1992); standard level of statistical significance,  $\alpha = 0.05$ ; and minimum power, 0.80 (preferably 0.95). The G\*Power output showed a minimum sample size of 34 participants. For a preferable power of 0.95, the necessary sample size was 54. The population for this study consisted of national banks located in the U.S. The sample consisted of 54 national banks with over \$10 million dollars of total assets in the U.S.

#### 3.1 Research Questions and Hypotheses

**RQ1:** To what extent did national banks' value investment in terms of reported price to earnings impact their ROE in the four-year period following the Great Economic Recession in the U.S.?

**H0:** There is no statistically significant impact of national banks' stock value investment in terms of reported price to earnings on the ROE in the four-year focal period.

**H1:** There is a statistically significant impact of national banks' stock value investment in terms of reported price to earnings on the ROE in the four-year focal period.

**RQ2:** To what extent did national banks' stock value investment in terms of dividend yield impact their ROE in the four-year focal period?

**H0:** There is no statistically significant impact of the national banks' stock value investment in terms of dividend yield on their ROE in the four-year focal period.

**H1:** There is a statistically significant impact of the national banks' stock value investment in terms of dividend yield on their ROE in the four-year focal period.

#### 3.2 Units of Analysis

DVs: ROE is the amount of net income returned as a percentage of shareholders' equity. Independent variables: Dividend yield and reported price to earnings. The dividend yield is the yield a company pays out to its shareholders in the form of dividends. It is calculated by taking the number of dividends paid per share over the course of a year and dividing it by the stock price. The reported price to earnings is the most common measure of how expensive a stock is.

## 4 Data Analysis

This study examined the research questions utilizing a paired t-test and the two-tailed Wilcoxon test design analysis of mean difference between paired observations for ROE. The first measurement of ROE that the study took occurred at the end of the four-year period after the beginning of the Great Economic Recession, which the study designated as the pretest measurement. The second measurement occurred at the end of the four years subsequent to the pretest, which the study labeled the posttest. The researcher defined outliers as data points within a study's data that did not follow the usual pattern and distorted the findings of the analysis. The second subset data analysis covered the machine learning model with Lloyd's algorithm with squared Euclidean distances to compute the k-means clustering for each k. Combined with the splitting procedure to determine the initial centers for each  $k > 1$ , the resulting clustering was deterministic, with the result dependent only on the number of clusters.

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### Algorithm 1 Lloyd's algorithm for k-means

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Input: Data  $X = \{x_1, \dots, x_n\} \subset \mathbb{R}^d$ , no. of clusters  $k \in \mathbb{N}$

Initialization: random centers  $c_1 \dots c_k \subset \mathbb{R}^d$

Repeat

Find closest cluster centers:

$V_j \subset X : b(x) = \operatorname{argmin}_{j=1, \dots, k} \{d(x, c_j)\}$  Update cluster center  $c_1 \dots c_k$ :

$V_j \subset \{1 \dots k\} : c_j = \operatorname{mean}(\{x \in X \mid b(x) = j\})$  Until cluster centers stop changing

Output: cluster centers  $c_1, \dots, c_k$

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**Figure 1:** Algorithm 1 Lloyd's Algorithm for k-Means. **Source:** Compiled by author

Machine learning teaches computers to do what comes naturally to humans and learn from visual experience. The algorithms used the computational method to learn information directly from the input data without relying on a predetermined equation as a model. The selected algorithms adaptively improved their performance as the number of samples available for learning increased. Unsupervised learning found hidden patterns in the data, which were used to draw inferences from the available datasets consisting of input data without labeled responses. Clustering with Lloyd's algorithm was used for the exploratory data analysis to find hidden patterns and groupings in the input data. For a given number of clusters  $k$ , the algorithm partitioned the data into  $k$  clusters. Each cluster had a center (centroid) that was the mean value of all points in that cluster. K-means located the centers through an iterative procedure that minimized the distances between individual points in a cluster and the cluster center. The researcher specified a desired number of clusters and suggested an optimal number of clusters. K-means required an initial specification of cluster centers. Starting with one cluster, the method chose a variable whose mean was used as a threshold for splitting the data in two. The centroids of these two parts were then used to initialize k-means to optimize the membership of the five clusters. Next, one of the two clusters was chosen for splitting and a variable within that cluster was chosen whose mean was used as a threshold for splitting that cluster into five. K-means was then used to partition the data into five clusters, initialized with the centroids of the two parts of the split cluster and the centroid of the remaining cluster. This process was repeated until a set number of clusters was reached. Lloyd's algorithm with squared Euclidean distances was used to compute the k-means clustering for each  $k$ . Combined with the splitting procedure to determine the initial centers for each  $k > 1$ , the resulting clustering was deterministic, with the result dependent only on the number of clusters. Tableau, R, and Python were used to accomplish the machine learning training data. The statistical data analysis was prepared using SPSS software.

## 5 Results

### 5.1 Statistical Data Analysis

Summary statistics were calculated for DividendYield2009, EPS2012, DividendYield2012, ROE2009, EPS2009, and ROE2012. The observations for DividendYield2009 had an average of 0.05 ( $SD = 0.10$ ,  $SEM = 0.01$ ,  $Min = 0.00$ ,  $Max = 0.63$ ,  $Skewness = 4.28$ ,  $Kurtosis = 20.03$ ). The observations for DividendYield2012 had an average of 0.03 ( $SD = 0.07$ ,  $SEM = 0.01$ ,  $Min = 0.00$ ,  $Max = 0.42$ ,  $Skewness = 4.13$ ,  $Kurtosis = 17.33$ ). The summary statistics can be found in Table 1.

**Table 1.** Summary Statistics for the Interval and Ratio Variables

Variable	<i>M</i>	<i>SD</i>	<i>n</i>	<i>SEM</i>	Min	Max	Skewness	Kurtosis
DividendYield2009	0.05	0.10	52	0.01	0.00	0.63	4.28	20.03
DividendYield2012	0.03	0.07	52	0.01	0.00	0.42	4.13	17.33
EPS2009	-7.86	31.71	52	4.40	-162.00	4.40	-4.18	16.42
EPS2012	1.69	2.13	51	0.30	-2.95	7.57	0.71	0.70
ROE2009	0.20	15.09	52	2.09	-70.21	81.72	1.11	23.53
ROE2012	0.06	0.06	52	0.01	-0.11	0.23	-0.10	1.57

*Note.* '-' denotes that the sample size was too small to calculate the statistic. **Source:** Compiled by the author

The observations for EPS2009 had an average of -7.86 ( $SD = 31.71$ ,  $SEM = 4.40$ ,  $Min = -162.00$ ,  $Max = 4.40$ ,  $Skewness = -4.18$ ,  $Kurtosis = 16.42$ ). The observations for EPS2012 had an average of 1.69 ( $SD = 2.13$ ,  $SEM = 0.30$ ,  $Min = -2.95$ ,  $Max = 7.57$ ,  $Skewness = 0.71$ ,  $Kurtosis = 0.70$ ).

The observations for ROE2009 had an average of 0.20 ( $SD = 15.09$ ,  $SEM = 2.09$ ,  $Min = -70.21$ ,  $Max = 81.72$ ,  $Skewness = 1.11$ ,  $Kurtosis = 23.53$ ). The observations for ROE2012 had an average of 0.06 ( $SD = 0.06$ ,  $SEM = 0.01$ ,  $Min = -0.11$ ,  $Max = 0.23$ ,  $Skewness = -0.10$ ,  $Kurtosis = 1.57$ ). When the skewness is greater than 2 in absolute value, the variable is considered to be asymmetrical about its mean. When the kurtosis is greater than or equal to 3, then the variable's distribution is markedly different from a normal distribution in its tendency to produce outliers (Westfall & Henning, 2013).

**Table 2.** Paired Samples Statistics

Mean		<i>N</i>	Std. Deviation	Std. Error Mean
Pair 1	Dividend Yield 2009	52	.101949482	.014137849
	ROE2009	52	15.08770	2.09229
Pair 2	EPS2009	52	31.71200	4.39766
	ROE2009	52	15.08770	2.09229
Pair 3	Dividend Yield 2012	52	.073578121	.010203449
	ROE2012	52	.05761	.00799
Pair 4	EPS2012	51	2.12897	.29812
	ROE2012	51	.05684	.00796
Pair 5	ROE2009	52	15.08770	2.09229
	ROE2012	52	.05761	.00799

**Source:** Compiled by the author

A two-tailed paired samples *t*-test was conducted to examine whether the mean difference of ROE2009 and ROE2012 was significantly different from zero. A Shapiro-Wilk test was conducted to determine whether the differences in ROE2009 and ROE2012 could have been produced by a normal distribution (Razali & Wah, 2011). The results of the Shapiro-Wilk test were significant based on an alpha value of 0.05 ( $W = 0.25$ ,  $p < .001$ ). This result suggests the differences in ROE2009 and ROE2012 are unlikely to have been produced by a normal distribution, indicating the normality assumption was violated. A Levene's test was conducted to assess whether the variances of ROE2009 and ROE2012 were significantly different.

**Table 3.** Paired Samples Test

	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference		t	df	Sig. (2-tailed)
				Lower	Upper			
				Pair 1 Dividend Yield 2009 - ROE2009	.1495855 53			
Pair 2 EPS2009 - ROE2009	-8.05993	31.80398	4.41042	-16.91421	.79436	-1.827	51	.073
Pair 3 Dividend Yield 2012 - ROE2012	- .0236262 73	.08466590 1	.01174104 8	- .04719741 0	- .00005513 5	-2.012	51	.049
Pair 4 EPS2012 - ROE2012	1.63876	2.08686	.29222	1.05182	2.22570	5.608	50	.000
Pair 5 ROE2009 - ROE2012	.13938	15.08618	2.09208	-4.06064	4.33940	.067	51	.947

Source: Compiled by the author

A two-tailed paired samples *t*-test was conducted to examine whether the mean difference of DividendYield2009 and ROE2009 was significantly different from zero. A Shapiro-Wilk test was conducted to determine whether the differences in DividendYield2009 and ROE2009 could have been produced by a normal distribution (Razali & Wah, 2011). The results of the Shapiro-Wilk test were significant based on an alpha value of 0.05 ( $W = 0.25$ ,  $p < .001$ ). This result suggests that the differences in DividendYield2009 and ROE2009 are unlikely to have been produced by a normal distribution, indicating the normality assumption was violated. A Levene's test was conducted to assess whether the variances of DividendYield2009 and ROE2009 were significantly different. The result of the Levene's test was not significant based on an alpha value of 0.05 ( $F(1, 102) = 2.12$ ,  $p = .149$ ). This result suggests it is possible that DividendYield2009 and ROE2009 were produced by distributions with equal variances, indicating that the assumption of homogeneity of variance was met.

The results of the two-tailed paired samples *t*-test were not significant based on an alpha value of 0.05 ( $t(51) = -0.07$ ,  $p = .943$ ), indicating the null hypothesis cannot be rejected. This finding suggests that the difference in the means of DividendYield2009 and ROE2009 was not significantly different from zero. The results are presented in Table 4.

**Table 4.** Two-Tailed Paired Samples *t*-Test for the Difference Between DividendYield2009 and ROE2009

DividendYield2009		ROE2009		t	p	d
M	SD	M	SD			
0.05	0.10	0.20	15.09	-0.07	.943	0.01

Note.  $N = 52$ . Degrees of freedom for the *t*-statistic = 51. *d* represents Cohen's *d*. Source: Compiled by the author



A two-tailed Wilcoxon signed-rank test was conducted to examine whether there was a significant difference between DividendYield2009 and ROE2009. The two-tailed Wilcoxon signed-rank test is a non-parametric alternative to the paired samples  $t$ -test and does not share its distributional assumptions (Conover & Iman, 1981). The results of the two-tailed Wilcoxon signed-rank test were significant based on an alpha value of 0.05 ( $V = 629.00$ ,  $z = -2.22$ ,  $p = .026$ ). This indicates that the differences between DividendYield2009 and ROE2009 were not likely due to random variation. The median of DividendYield2009 ( $Mdn = 0.02$ ) was significantly larger than that of ROE2009 ( $Mdn = 0.00$ ).

A two-tailed paired samples  $t$ -test was conducted to examine whether the mean difference of EPS2012 and ROE2012 was significantly different from zero. A Shapiro-Wilk test was conducted to determine whether the differences in EPS2012 and ROE2012 could have been produced by a normal distribution (Razali & Wah, 2011). The results of the Shapiro-Wilk test were significant based on an alpha value of 0.05 ( $W = 0.92$ ,  $p = .002$ ). This result suggests that the differences in EPS2012 and ROE2012 were unlikely to have been produced by a normal distribution, indicating that the normality assumption was violated. A Levene's test was conducted to assess whether the variances of EPS2012 and ROE2012 were significantly different. The result was significant based on an alpha value of 0.05 ( $F(1, 100) = 49.58$ ,  $p < .001$ ). This result suggests it is unlikely that EPS2012 and ROE2012 were produced by distributions with equal variances, indicating that the assumption of homogeneity of variance was violated. The results of the two-tailed paired samples  $t$ -test were significant based on an alpha value of 0.05 ( $t(50) = 5.61$ ,  $p < .001$ ), indicating that the null hypothesis can be rejected. This finding suggests that the difference in the means of EPS2012 and ROE2012 was significantly different from zero. The mean of EPS2012 was significantly higher than that of ROE2012. The results are presented in Table 5.

**Table 5.** Two-Tailed Paired Samples  $t$ -Test for the Difference Between EPS2012 and ROE2012

EPS2012		ROE2012		t	p	d
M	SD	M	SD			
69	2.13	0.06	0.06	5.61	< .001	0.79

*Note.*  $N = 51$ . Degrees of freedom for the  $t$ -statistic = 50.  $d$  represents Cohen's  $d$ . **Source:** Compiled by the author

A two-tailed Wilcoxon signed-rank test was conducted to examine whether there was a significant difference between EPS2012 and ROE2012. This test is a non-parametric alternative to the paired samples  $t$ -test and does not share its distributional assumptions (Conover & Iman, 1981). The results of the two-tailed Wilcoxon signed-rank test were significant based on an alpha value of 0.05 ( $V = 968.00$ ,  $z = -5.09$ ,  $p < .001$ ). This indicates that the differences between EPS2012 and ROE2012 were not likely due to random variation. The median of EPS2012 ( $Mdn = 1.13$ ) was significantly larger than that of ROE2012 ( $Mdn = 0.06$ ). Figure 11 presents a boxplot of the ranked values of EPS2012 and ROE2012.

## 5.2 Machine Learning Subset Data Analysis

The researcher selected the unsupervised machine learning model since they needed to explore the data and wanted to train a model to find a good internal representation, such as splitting data up into clusters. Machine learning algorithms find natural patterns in data that generate insight and help us make better decisions and predictions. They are used every day to make critical decisions in economic diagnosis, stock trading, energy load forecasting, and more.

In cluster analysis, data are partitioned into groups based on some measure of similarity or shared characteristics. Clusters are formed so that objects in the same cluster are very similar and objects in different clusters are very distinct. Clustering algorithms fall into two broad groups: a) hard clustering, where each data point belongs to only one cluster, and b) soft clustering, where each data point can belong to more than one cluster. This study used soft clustering techniques, since the possible data groupings were already known.

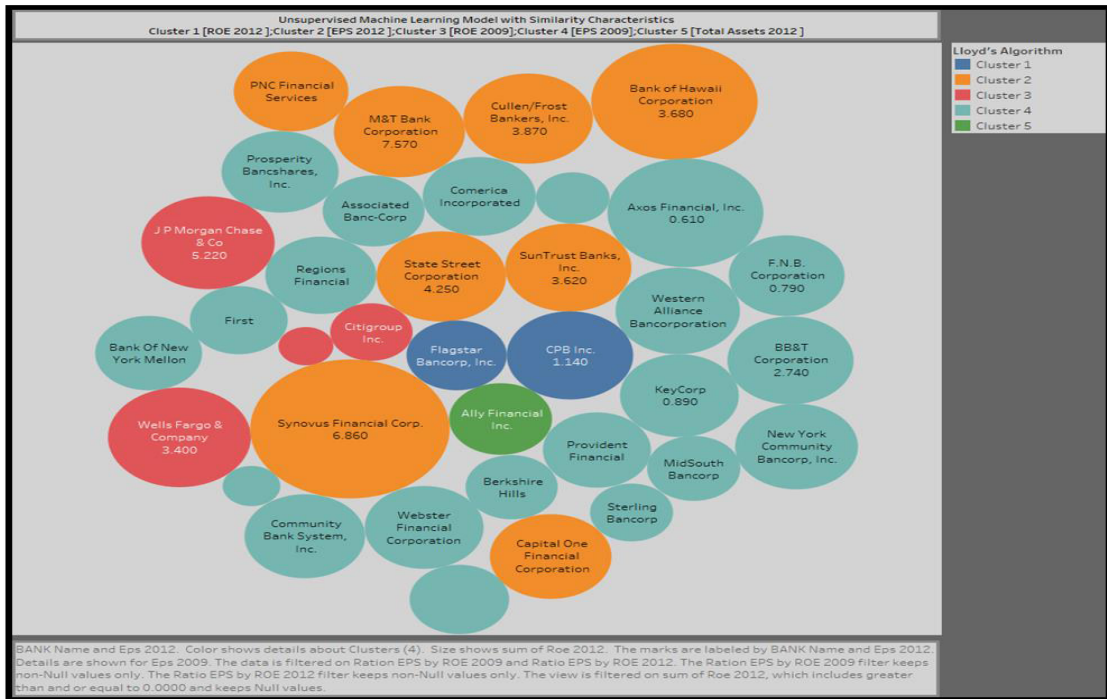


Figure 2: Target Population Characteristics of National Banks in the U.S. Source: Compiled by the author

Table 6. Description of All Clusters

Centers						
Clusters	Number of Items	Avg. ROE2012	Avg. EPS2012	Avg. ROE2009	Avg. EPS2009	Avg. Total Assets
Cluster 1	2	0.076457	2.455	-0.86048	-155.74	9.2262e+06
Cluster 2	8	0.11892	5.1775	10.169	-2.645	1.4496e+08
Cluster 3	4	0.07045	2.8625	0.039749	-1.1125	1.9642e+09
Cluster 4	21	0.070359	1.3486	0.028994	-0.090952	4.7743e+07
Cluster 5	1	0.061992	3.01	-70.214	-70.21	1.8239e+08
Not Clustered	0					

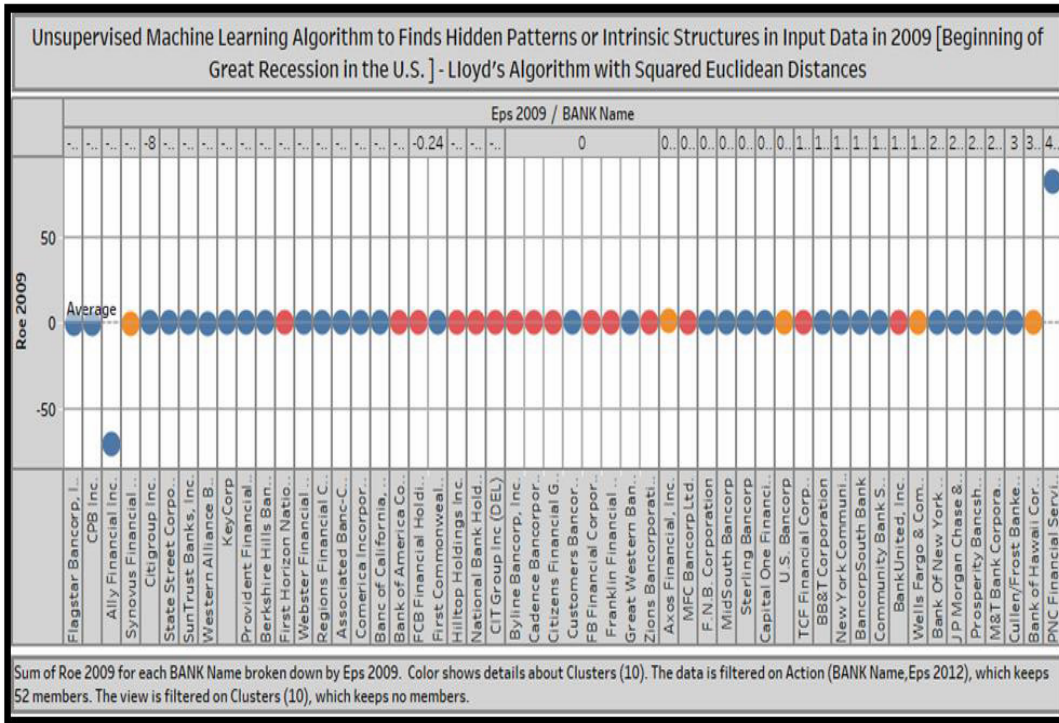
Source: Compiled by the author

The bubble chart displays quantitative values for different major categories such as EPS2009, ROE2009, EPS2012, ROE2012, and Total Assets 2012 included for further breakdown. It is based on the use of circles, one for each category, sized in proportion to the quantities they represent. Sometimes, several separated clusters are used to display further categorical dimensions; otherwise, the coloring of each circle can achieve this. It is similar in concept to the proportional shape chart but differs through the typical layout being based on clustering, which also enables it to show part-to-whole relationships.

The author found eight banks within the target population with a similar level AVG ROE2012, and four banks with a similar AVE ROE2009.

Figure 3 illustrates the impact of EPS2009 on ROE2009; the results were close to the axis, with an average of 0.2. Statistical significance was not found in the statistical data analysis of both variables. There was no increase in EPS2009 associated with an increase in ROE2009. There was evidence that EPS2009 did not have an impact on ROE2009. Much of the instability in the proportion of earnings per share (EPS) vs.

ROE close to zero on the axis can be attributed to the economic effects of financial stability.

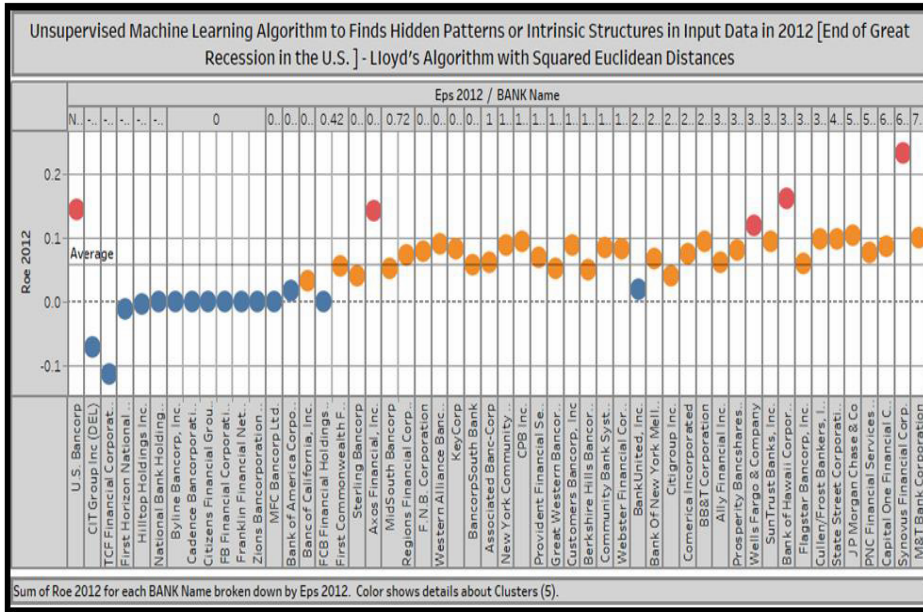


**Figure 3:** Unsupervised Machine Learning Algorithm to Find Hidden Patterns in the Input Data from 2009 (Lloyd's Algorithms with Squared Euclidean Distances) **Source:** Compiled by the author

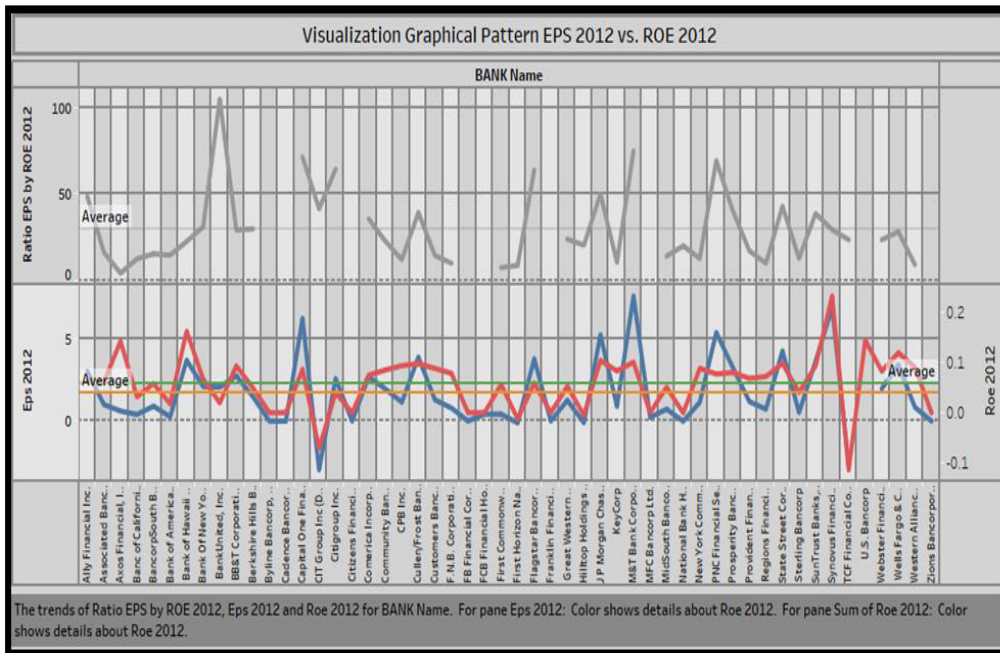
Figure 4 illustrates the impact of EPS2012 on ROE2012 and the results were found away from the axis with an average of 0.0578. Statistical significance was found in the statistical data analysis of both variables. There was an increase in EPS2012 associated with an increase in ROE2012. There was evidence that EPS2012 had an impact on ROE2012. There was evidence that EPS2009 did not have an impact on ROE2009. The visual and digital dashboard presentation could assist national banks or the FDIC in discovering early symptoms of failure on a daily basis for the sake of supervised management. In summary, we found that the EPS ratio may have contributed to the increase in the ROE ratio and thus may constitute a new future mandatory ratio for continuing the observation of bank risk measurement in liquidity prediction.

The additional visualization of the graphical pattern of EPS2012 vs. ROE2012 highlights other variability in the data. The line chart illustrates the average number of EPS and ROE in 2012. BankUnited Inc. has the highest proportion of EPS2012 and ROE2012, while Axios Financial Inc. has the lowest proportion. The line graph represents how EPS2012 and ROE2012 have changed over time. Overall, we can see a clear upward trend in the numbers of EPS and ROE and the new proposed ratio of EPS/ROE can be used to measure liquidity risk in financial institutions. The EPS shows the growth in value excluding five banks. The ROE captures both the EPS and ROE. In contrast, a statistical data analysis provides a detailed report like this that can inform wise financial business decisions and ensure proper supervision of all bank risk management that could have an impact on the macroeconomic performance.

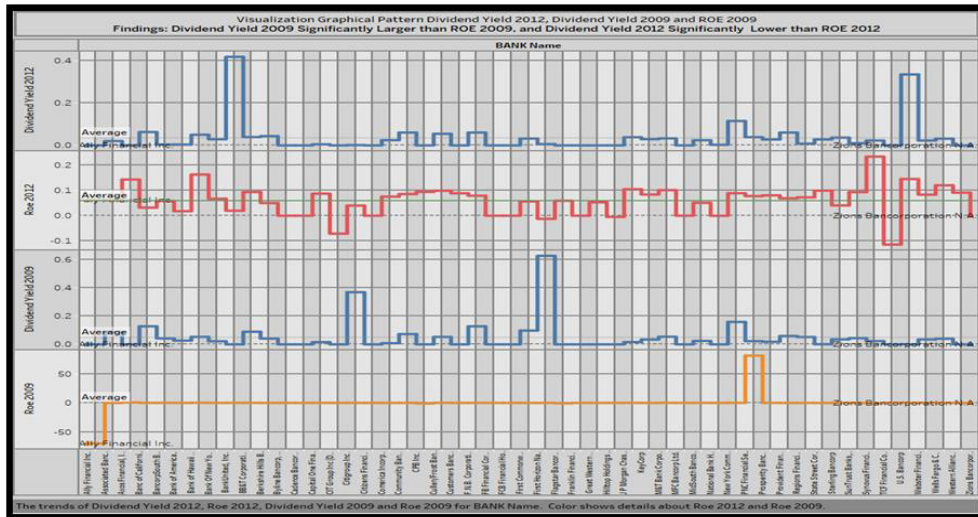
The most interesting aspect of Figure 6 is that it shows the dividend yield ratio and ROE in 2009 and 2012 for the sake of comparison. The difference between the dividend yield and ROE was significant. At the beginning of the Great Economic Recession, the higher dividend yield ratio may have contributed to the decrease in ROE in 2009. At the end of the Great Economic Recession, the lower dividend yield ratio may have been an important factor in the increase in ROE in 2012.



**Figure 4:** Unsupervised Machine Learning Algorithm to Find Hidden Patterns in the Input Data from 2012 (Lloyd's Algorithms with Squared Euclidean Distances) **Source:** Compiled by the author



**Figure 5:** Visualization Graphical Pattern: EPS2012 vs. ROE2012 **Source:** Compiled by the author



**Figure 6:** Findings: Dividend Yield 2009 Significantly Larger than ROE2009 and Dividend Yield 2012 Significantly Lower than ROE2012 **Source:** Compiled by the author

## 6 Discussion

The results of this causal comparative study were based on descriptive statistics, paired *t*-tests, and two-tailed Wilcoxon tests. The study was able to find differences between EPS2012 and ROE2012 that were not likely due to random variation. The median of EPS2012 ( $Mdn = 1.13$ ) was significantly larger than that of ROE2012 ( $Mdn = 0.06$ ). The practical implications suggest that this new potential ratio (EPS/ROE) could become a new risk indicator for predicting bank failures for the central bank in the U.S. The findings also showed that the median of DividendYield2009 ( $Mdn = 0.02$ ) was significantly larger than that of ROE2009 ( $Mdn = 0.00$ ). The results of the two-tailed paired samples *t*-test were significant based on an alpha value of 0.05, ( $t(51) = -2.01, p = .049$ ), indicating that the null hypothesis can be rejected. This finding suggests that the difference in the mean of DividendYield2012 and the mean of ROE2012 was significantly different from zero. The mean of DividendYield2012 was significantly lower than that of ROE2012. The practical implications suggest that this new potential ratio (dividend yield/ROE) could also become another risk indicator for predicting bank failures for the central bank in the U.S. The dividend yield was significantly larger than the ROE at the beginning of the Great Economic Recession, while it was significantly lower than the ROE at the end of the recession.

However, real financial decisions should be made based on the implementation of the machine learning model as an extension of statistical research data analysis. Artificial intelligence applications can support the daily discovery of individual bank branches for audit or investigation before there are any financial implications for the macroeconomic market.

This study included two research questions:

**Research Question 1:** To what extent did national banks' value investment in terms of reported price to earnings impact their ROE in the four-year period following the Great Economic Recession in the U.S.? The results of the two-tailed paired samples *t*-test were not significant based on an alpha value of 0.05 ( $t(51) = -1.83, p = .073$ ), indicating that the null hypothesis cannot be rejected. This finding suggests that the difference in the mean of EPS2009 and that of ROE2009 was not significantly different from zero. The results of the two-tailed Wilcoxon signed-rank test were not significant based on an alpha value of 0.05 ( $V = 415.00, z = -0.93, p = .351$ ). This indicates that the differences between EPS2009 ( $Mdn = 0.00$ ) and ROE2009 ( $Mdn = 0.00$ ) were explainable by random variation. The results of the two-tailed paired samples *t*-test were

significant based on an alpha value of 0.05 ( $t(50) = 5.61, p < .001$ ), indicating that the null hypothesis can be rejected. This finding suggests that the difference in the mean of EPS2012 and the mean of ROE2012 was significantly different from zero. The mean of EPS2012 was significantly higher than that of ROE2012. The results of the two-tailed Wilcoxon signed-rank test were significant based on an alpha value of 0.05 ( $V = 968.00, z = -5.09, p < .001$ ). This indicates that the differences between EPS2012 and ROE2012 were not likely due to random variation. The median of EPS2012 ( $Mdn = 1.13$ ) was significantly larger than that of ROE2012 ( $Mdn = 0.06$ ).

**Research Question 2:** To what extent did national banks' stock value investment in terms of dividend yield impact their ROE in the four-year focal period? The results of the two-tailed paired samples  $t$ -test were not significant based on an alpha value of 0.05 ( $t(51) = -0.07, p = .943$ ), indicating that the null hypothesis cannot be rejected. This finding suggests that the difference in the mean of DividendYield2009 and the mean of ROE2009 was not significantly different from zero. The results of the two-tailed Wilcoxon signed-rank test were significant based on an alpha value of 0.05 ( $V = 629.00, z = -2.22, p = .026$ ). This indicates that the differences between DividendYield2009 and ROE2009 were not likely due to random variation. The median of DividendYield2009 ( $Mdn = 0.02$ ) was significantly larger than that of ROE2009 ( $Mdn = 0.00$ ). The results of the two-tailed paired samples  $t$ -test were significant based on an alpha value of 0.05 ( $t(51) = -2.01, p = .049$ ), indicating that the null hypothesis can be rejected. This finding suggests the difference in the mean of DividendYield2012 and the mean of ROE2012 was significantly different from zero. The mean of DividendYield2012 was significantly lower than the mean of ROE2012. The results of the two-tailed Wilcoxon signed-rank test were significant based on an alpha value of 0.05 ( $V = 194.00, z = -3.51, p < .001$ ). This indicates that the differences between DividendYield2012 and ROE2012 were not likely due to random variation. The median of DividendYield2012 ( $Mdn = 0.02$ ) was significantly lower than the median of ROE2012 ( $Mdn = 0.06$ ).

## 7 Conclusion

This study set out to investigate the impact of dividend yield on the ROE, and the impact of EPS on the ROE at the beginning of the global financial economic disaster and at the end of the recession in the U.S. The results indicated that there exist new methods of risk assessment for national banks, and they are game changers that use statistics and an innovative subset artificial intelligence application of data analysis to support scientific and business decisions at the same time. The following conclusions can be drawn from the present study: observing the impact of dividend yield and EPS on the ROE using the machine learning model can improve bank risk measurement and detect the early symptoms of financial instability to prevent future global financial crises. The interactive dashboard will become a daily observational tool that helps the management understand the current financial situation and support wise business decisions. This paper contributes to the recent historiographical debates concerning potential future global financial crises and how countries can protect themselves using new innovative statistical data analysis of subset data using the selected machine learning model. This research was limited by its use of public data that was not current or not updated in the Yahoo! financial portal used for this study. A possible direction for future research would be to investigate the same variables and their impact on other industries in the U.S.

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