Innovative Predicting Risk Model for Systemically Important Financial Institutions with Artificial Intelligence in the United States

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Abstract

The major objective of this innovative research study was to explore the degree to which national systemically important banks' value investment, in terms of how the price to earnings ratio impacts their return on equity. We used statistical modeling and the artificial intelligence model to find hidden patterns in the input data from a list of systemically important banks. The principle finding of this research is that the financial factor that helps the financial institution, causes a cascading failure with the impact on the World economics. These findings of the new ratios formulas can contribute to improving our understanding of how systemically important banks can predict financial modern risk, using the new feature of artificial intelligence to build an early warning system in real-time. In this research article, we develop an innovative predicting risk model to measure possible contagion bank risk for Systemically Important Financial Institutions, 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.

Keywords: Equity Valuations, Financial Institutions, Price to Earnings, Systemically Important Banks

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In Rabbani et al. (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.

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 systemically important Banking Act of 1933, the FDIC provided favorable insurance through the systemically important Bank Insurance Fund (Benston & Kaufman, 1997). Following an alarming number of failures in the 1980s, the depletion of the systemically important Bank Insurance Fund to a negative net worth in 1991, forced Congress to enact the FDIC Improvement Act of 1991 (FDICIA) (Kuritzkes et al., 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, and capital through the Troubled Asset Relief Program (Hein et al., 2012). We found that the literature review with the topic explored in this study was not researched before this article.

Research Design

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 an artificial intelligence 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 systemically important banks' stock value investments; based on the ROE changed in the sixth-year period from 2009 to 2012, after the beginning of the Great Recession of 2008 in the U.S. The population of interest was comprised of all systemically important financial institutions in the U.S. If these systemically important banks collapse, they can have a significant domino effect on the world.

Research Question and Hypotheses

RQ1: To what extent did national systemically important financial institutions' value investment in terms of reported price to earnings, impact their ROE in the sixth-year period following the economical Great Recession in the U.S.?

H0: There is no statistically significant impact of systemically important financial institutions' stock value investment in terms of reported price to earnings on the ROE in the sixth-year focal period.

H1: There is a statistically significant impact of systemically important financial institutions' stock value investment in terms of reported price to earnings on the ROE in the sixth-year focal period.

The author proposed the hypothesis above based on the visualization of selected financial data points from the open data sources and comparison with the existing literature review. Not one search considers these combination ratios to be an essential element in the risk measurement.

Units of Analysis

DVs: ROE is the amount of net income returned as a percentage of shareholders' equity. Independent variables: 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 considered.

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 sixth-year period after the beginning of the Great Recession, which the study designated as the pretest measurement. The second measurement occurred at the end of the six 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 artificial intelligence 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. Artificial intelligence 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. 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. 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 were 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.

Results

Statistical Data Analysis

The observations for EPS2009 had an average of -7.85 (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). The summary statistics can be found in Table 1.

Table 1:

Summary Statistics Table for Interval and Ratio Variables

Variable	*M*	*SD*	*n*	SE_M	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 the sample size is too small to calculate statistic.

Source: Compiled by 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.

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Table 2: Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Dividend Yield 2009	.04764737	52	.101949482	.014137849
	ROE 2009	.1972	52	15.08770	2.09229
Pair 2	EPS 2009	-7.8627	52	31.71200	4.39766
	ROE 2009	.1972	52	15.08770	2.09229
Pair 3	Dividend Yield 2012	.03422265	52	.073578121	.010203449
	ROE 2012	.0578	52	.05761	.00799
Pair 4	EPS 2012	1.6949	51	2.12897	.29812
	ROE 2012	.0561	51	.05684	.00796
Pair 5	ROE 2009	.1972	52	15.08770	2.09229
	ROE 2012	.0578	52	.05761	.00799

Source: Compiled by 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).

Artificial Intelligence Subset Data Analysis

The researcher selected the unsupervised artificial intelligence 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. Artificial intelligence algorithms find natural patterns in data that generate insight and help us make better decisions and predictions analytics. 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 flat clustering techniques, since the possible data groupings were already known. In flat clustering, we specify the number of clusters we would like the machine to find k-means, where k specifies the number of clusters, we would like to modern algorithm to use.

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 systemically important banks within the target population with a similar level AVG ROE2012, and four systemically important banks with a similar AVE ROE2009.

Table 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.

Table 3: Paired Samples Test

		Paired Differences							
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper	t	df	Sig. (2-tailed)
Pair 1	Dividend Yield 2009 - ROE 2009	-.149585553	15.086323073	2.092096592	-4.349644718	4.050473611	-.072	51	.943
Pair 2	EPS 2009 - ROE 2009	-8.05993	31.80398	4.41042	-16.91421	.79436	-1.827	51	.073
Pair 3	Dividend Yield 2012 - ROE 2012	-.023626273	.084665901	.011741048	-.047197410	-.000055135	-2.012	51	.049
Pair 4	EPS 2012 - ROE 2012	1.63876	2.08686	.29222	1.05182	2.22570	5.608	50	.000
Pair 5	ROE 2009 - ROE 2012	.13938	15.08618	2.09208	-4.06064	4.33940	.067	51	.947

Source: Compiled by Author

Table 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 systemically important 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 systemically important 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. One systemically important bank has the highest proportion of EPS2012 and ROE2012, while another systematically important bank 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 systemically important 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 systemically important bank risk management that could have an impact on the macroeconomic performance.

The most interesting aspect of Table 4 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 Recession, the higher dividend yield ratio may have contributed to the decrease in ROE in 2009. At the end of the Great Recession, the lower dividend yield ratio may have been an important factor in the increase in ROE in 2012.

Table 4:

Two-Tailed Paired Samples t-Test for the Difference Between DividendYield2009 and ROE2009

DividendYield2009		ROE2009				
M	*SD*	*M*	*SD*	*t*	*p*	*d*
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 Author

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

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

EPS2012		ROE2012				
M	*SD*	*M*	*SD*	*t*	*p*	*d*
1.69	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 Author

This study included a research question:

Research Question: To what extent did national systemically important financial institutions' value investment in terms of reported price to earnings, impact their ROE in the sixth-year period following the Great 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).

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 systemically important 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 artificial intelligence model can improve systemically important bank risk measurement and detect the early symptoms of financial instability to prevent future global financial crises. This study cannot be supported or give the real rationale to this discussion since no similar reviews exist on the presented topic. 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 artificial intelligence model. We think that artificial intelligence technology provides new opportunities for systemically important banks and leads to improvements in the efficiency and effectiveness of risk measurement in real-time applications. The financial industry can utilize the findings from this study with the designed and ready-to-use digital interactive tool to their current operational divisions. They need to connect their data sources without paying for the additional storage and use in Tableau within the organization. The executive team can observe the newly discovered ratios in real-time tools with one click. Finally, they can add this tool to their website or other existing analytical tools.

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