DETERMINING THE FAILURE RATE OF THE BANKING INDUSTRY IN NIGERIA

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Abstract

In this paper, we study the financial status of the banking industry in Nigeria using survival analysis. The study shows that certain Bank with huge capital structure did not live till the end of the monitoring exercise. A contributing factor that aided the survival of banks in Nigeria is the length of time of operation. Our findings show that banks with high profitability ratio, less liquidity ratio and those who have operated for a long time in the industry have low probability of failing.

Survival analysis pertains to a statistical approach designed to take into account the amount of time an experimental unit contributes to a study. It is the study of time between entry into observation and a subsequent event. Originally, the event of interest was death, hence the term "Survival Analysis". The synonyms for survival analysis in the literature include time-to-event analysis, reliability analysis and failure time analysis (Allison, 1995; Smith, 2000). The term survival analysis is used predominantly in biomedical sciences where the interest is in observing time to death of patients or laboratory animals. Time to event analysis has also been widely used in the social sciences where interest is on analyzing time to event such as job changes, marriages, birth of children and so on. In "reliability analysis", the main focus is in modeling time it takes for machines or electronic components to breakdown.

Corporate failure can be seen as the inability of a company to meet its maturing obligations and without enough cash to continue in operation. Corporate failure marks the end of some distinct interrelated events which culminate in liquidation. The usual symptom associated with corporate failure is decline of turnover. It results when the going concern concept ceases to exist i.e when the organization cannot continue in operation into the foreseeable future. Anao and Osaze (1990) asserted that it is a combination of short term liquidity crisis and solvency problem in the organization. Liquidity crises results when the organization cannot meet its short term maturing obligation, while solvency crises will result when the organization fails to meet long term maturing obligations.

From a social perspective, failure can be the result of misallocation of organization resources. The global economic depression has some reverberating effects on corporate performance worldwide. In America and other developed economies, the wave of corporate collapse has seen the demise of traditional corporate giants whose businesses have spanned so many decades. Nigeria and other developing economies are worse hit. In Nigeria for instance, “the banking sector has witnessed a chronic distress syndrome which has culminated in the liquidation of not less than 30 banks. Financial distress as a form of failure is defined as a situation where a firm operating cash-flow are not sufficient to satisfy common obligations (such as trade credits and interest expense) and the firm is forced to take corrective measures.

The purpose of this paper therefore, is on estimating the survival rate of Nigeria Banks, using sensitive financial ratios and specific variables as covariates to predict liquidation in the industry. This study was based on information for 42 banks altogether for a specified period of 10 years.

The rest of the paper is presented as follows: in Section 2, we present literature review of some survival models; in Section 3, we have the data presentation and analysis. In Section 4 we present the interpretation of results and curves while Section 5 concludes the paper.

Literature Review

There exist three different techniques for constructing survival analysis model. They are: parametric, non-parametric and semi parametric techniques. Non-parametric models are useful for preliminary analysis of survival data and for estimating and comparing survival functions. The two main methods are the Kaplan-Meier and the Life-table. Parametric models are referred to as Accelerated Failure Time (AFT) models. The key issue is to specify a probability distribution for the time to event. Common parametric distributions include the exponential, Weibull and Gamma distribution. Semi-parametric models, unlike parametric, do not require to specify the probability distribution of the hazard function over time. This is the reason it is called semi-parametric regression model for survival data in the

Cox proportional hazards model proposed by Cox (1972). The Kaplan-Meier estimator incorporates information from all of the observations available, both censored and uncensored by considering any point in time as a series of steps defined by the observed survival and censored times, see Smith (2005). However, unlike parametric survival analysis models, the Kaplan-Meier technique is not designed to assess the effects of covariates on either function. Thus the Kaplan-Meier is a descriptive procedure for time to event variables and the time is considered as the only salient variable. The Kaplan-Meier model is given as

$$S(\hat{t}) = \prod_{i=1}^{j}(1-\frac{d_j}{n_j})$$

A common research question in medical, biological or engineering (failure time) research is to determine whether or not certain continuous (independent) variables are correlated with the survival or failure times. There are two major reasons why this research issue cannot be addressed via a straight forward multiple regression technique. First, the dependent variable is most likely not normally distributed which is a serious violation of an assumption for ordinary least squares multiple regression. Survival times usually follow an exponential or Weibull distribution (which will be looked at in the next Session). Secondly, there is the problem of censoring, that is, some observation will be incomplete.

The Cox’s proportional regression model is the most general of the regression models because it is not based on any assumption concerning the nature or shape of the underlying survival distribution. The model assumes that the underlying hazard rate (rather than survival times), is a function of the independent variables (covariates) and no assumptions are made about the nature or shape of the hazard function. Hence, the Cox’s regression model may be considered to be a non-parametric method, see Statsoft (2008).

In Cox (1972), there are two significant innovations which include the proportional hazard model and maximum partial likelihood. The proportional hazard model is given by:

$$h(t) = h_o(t)\exp^{(X'\beta)} \qquad (1)$$

where $h_o(t)$ is an arbitrary unspecified baseline hazard rate which measures the effect of time on the hazard rate for an individual whose covariates values are all zero. x represents the vector of covariates that influence the hazard and β is the vector of their coefficients. In estimating covariate co-efficient, we simply take the log of equation (1) to linearize the model and then use the least square approach to estimate the parameters.

Cox (1972) used the method of partial likelihood to estimate the parameter β in equation (1). A general

expression for the partial likelihood function is given by the following:

$$L_p(\beta) = \prod_{i=1}^{n}\left[\frac{\text{[redacted]}\text{xp}^{(x',\beta)}}{\sum_{i\varepsilon R(t_i)}^{n} Y_{ij}\exp^{(x',\beta)}}\right]^{c_i}$$

$$Y_{ij} = \begin{cases} 1 & if \quad t_j \geq t_i \\ 0 & if \quad t_j < t_i \end{cases} \quad , \quad c_i = \begin{cases} 1 & event \quad occured \\ 0 & event \quad censored \end{cases}$$

The main reason for the popularity of Cox proportional hazards model is that it uses semi-parametric approach which does not require the particular probability distribution to represent survival times.

Data Presentation and Analysis

Survival analysis is an appropriate method in this study as this method allows for time-varying covariates and censored observation which are two key advantages of survival analysis compared to the traditional methods which makes use of Logit model, Probit model and some others.

Censored observations are observations that have never experienced the event during the observation time. Censoring occur when the duration of the study is limited in time. In this study, censored observations are the active banks that have not entered into financial distressed state during the study time. However, survival analysis makes it possible to use the information from these observations by including them as censored observation. Maximum or partial likelihood method helps to provide consistent parameter estimates. This is an improvement over the traditional methods which cannot incorporate information from censored observations, Allison (1995).

The Cox proportional hazard form of survival analysis is applied to the population of banks listed on the Nigerian Stock Exchange (NSE) using annual financial ratios, banks specific variable of age and size for the period of 1998-2008. During these period of study, 42 banks are listed. Among these 42 banks, 21 banks experienced the event (liquidation) while 21 Banks were censored (lost to continuous observation). The independent variables used in this study are age (which is date of incorporation as listed in the stock exchange), size (which is the total asset of the bank), profitability ratio (which is given by ratio of profit after tax to shareholder’s fund or net asset), and liquidity ratio (which is given by ratio of current asset to current liability). However the dummy in the Table 1 below reflect the outcome of an event (i.e liquidity indicated by 1) and withdrawal or censored subject (as indicated by 0). Duration (which reflect the duration of the subject in the study). Since the dependent variable is time to events, the time the bank entered into financial distress is constructed in this study.

Table1: Banks Listed on the Stock Exchange With Some Selected Financial Ratios.

S/N	Subject(Banks)	Age	Size	Profitability Ratio	Liquidity Ratio	Dummy	Duration

1	EKO INTERNATIONAL BANK PLC	22	8648784	0.1478	0.4214	1	2
2	REGENT BANK PLC	8	3563569	0.4767	0.7171	1	5
3	FIRST CITY MONUMENT BANK PLC	26	182368765	0.0724	0.097	0	5
4	STANBIC BANK PLC	19	130077341	0.1044	0.0673	0	5
5	STERLING BANK PLC	16	106832372	0.496	0.3696	0	5
6	OCEANIC BANK PLC	18	313444702	0.1704	0.1749	0	6
7	DIAMOND BANK PLC	9	121748031	0.064	0.2102	0	6
8	FIDELITY BANK PLC	21	160092402	0.1856	0.1732	0	6
9	ZENITH BANK PLC	18	653547025	0.1491	0.703	0	6
10	ECO BANK PLC	22	168093723	0.5044	0.2845	0	6
11	FIRSTINLAND BANK PLC	20	134704873	0.4921	0.3365	0	6
12	PLANTINUM HABIB BANK PLC	19	279343451	0.1378	0.4221	0	6
13	AFRICAN EXPRESS BANK PLC	24	888230	0.1738	0.003	1	7
14	CHARTERED BANK PLC	20	31495722	0.3517	0.5798	1	7
15	CO-OPERATIVE DEVELOPMENT BANK PLC	55	6462898.3	0.1351	0.6304	1	7
16	FSB INTERNATIONAL BANK PLC	16	25707732	0.2424	0.4961	1	7
17	HALLMARK BANK PLC	18	34003670	0.2412	0.4515	1	7
18	IMB INTERNATIONAL BANK PLC	34	4893903.3	0.3261	0.5245	1	7
19	INLAND BANK (NIG)PLC	20	16540763	0.1627	0.4514	1	7
20	LIBERTY BANK PLC	18	5176339.7	0.589	0.3176	1	7
21	MANNY BANK PLC	19	6841864.2	0.2116	0.6846	1	7
22	TRADE BANK PLC	23	9878745	0.1745	0.041	1	7
23	EIB INTERNATIONAL BANK PLC	22	9337585.8	0.2412	0.3743	1	7
24	UNITY BANK PLC	21	73149333	0.1451	0.6047	1	7
25	LION BANK PLC	26	10395849	0.1922	0.4277	1	7
26	FIRST ATLANTIC BANK PLC	18	8235197.5	0.2453	0.6926	1	7
27	GULF BANK OF NIGERIA PLC	18	11812414	0.4606	0.6858	0	7
28	STANDARD TRUST BANK PLC	11	56737188	0.3938	0.2091	0	7
29	SKYE BANK PLC	9	213820556	0.1688	0.1015	0	7
30	CO-OPERATIVE BANK PLC	29	9706052	0.1301	0.3084	1	8
31	NAL MERCHANT BANK PLC	48	18172988	0.1156	0.3434	1	8

32	OMEGA BANK PLC	27	13661400	0.2322	0.3645	1	8
33	TRANS INTERNATIONAL BANK PLC	21	13313993	0.1706	0.4398	1	8
34	UNIVERSAL TRUST BANK PLC	23	26787765	0.381	0.5315	1	8
35	ACCESS BANK PLC	19	141015902	0.1102	0.3884	0	10
36	AFRIBANK NIGERIA PLC	39	124925400	0.1628	0.2406	0	10
37	FIRST BANK OF (NIG) PLC	39	416783100	0.2727	0.4683	0	10
38	GUARANTY TRUST BANK PLC	18	144921334	0.275	0.3207	0	10

39	UNITED BANK OF AFRICA PLC	47	502455700	0.2176	0.3241	0	10
40	UNION BANK (NIG) PLC	39	450954600	0.2212	0.4347	0	10
41	INTERCONTINENTAL BANK PLC	19	326749415	0.1836	0.1759	0	10
42	WEMA BANK PLC	63	63943524	0.1962	0.404	0	10

Interpretation of Results and Curves

In order to estimate the parameters of the Cox hazard function, we make use of a statistical software package known as Statistical Package for Scientific Solutions (SPSS). The results of the estimated covariate coefficients are presented in Table 2 below while figures 1 and 2 give the survival function and hazard function at mean covariates respectively.

Table 2: Variables in the Equation and the Estimated Coefficient

Covariates	β	**Se**	**Wald**	**Df**	**Sig.**	$\exp(\beta)$
Age	-.047	.036	1.675	1	.196	.954
Size	.000	.000	4.666	1	.031	1.000
Profitability ratio	-1.115	2.126	.275	1	.600	.328
Liquidity ratio	.692	1.285	.290	1	.590	1.998

From the results in Table 2, it can be observed that the covariate **Age** has a coefficient of $\beta_1 = -0.047$. $\beta_1 < 0$ indicates that an increase in age decreases the hazard of entering into financial distress. Furthermore, the hazard ratio of **Age** is 0.954 means that a unit increase in age would result to a 95% decrease in risk of banks being financially distressed.

The covariate **Size** has a coefficient of $\beta_2 = 0$ which implies that there is no effect of the covariate on survival time. This result is true as the hazard ratio equals 1 which indicates that there is no effect of size on survival. Note that if hazard ratio is greater than or less than 1, it indicates the more rapid or slower hazard timing, respectively.

The covariate profitability has a coefficient of $\beta_3 = -1.115$ which is negative indicating that an increase in profitability reduces the hazard of entering into financial distress. The hazard ratio for profitability is positive (i.e $\exp(\beta) = 0.600$) means an increase of one unit of profitability implies about 60% decrease in risk of financial distressed.

The covariate liquidity has a coefficient of $\beta_4 = 0.692$ which has a positive sign means that an increase in liquidity increases the hazard of entering into financial distress. Hazard ratio for liquidity is $\exp(\beta) = 1.998$ means that a unit increases in liquidity, the risk of becoming financially distressed changes by a multiple of 1.998.

Interpretation of Curves

The basic survival curve is a visual display of the model. The horizontal axis shows the time to event (i.e duration). While the vertical axis shows the cumulative probability of survival. Any point in the curve shows the probability that an average company will remain in success past the event time.

The Survival Curve

The survival curve displayed in Figure 1 shows a slight decline in the survival rate of banks after 5 years of being included in the study and respectively slight declines in the sixth and seventh years but on getting to the eighth year, there is a rapid decline in the survival rate. But the banks that remain after the eighth year begin to experience a steady probability of survival and hence are not likely to be liquidated.

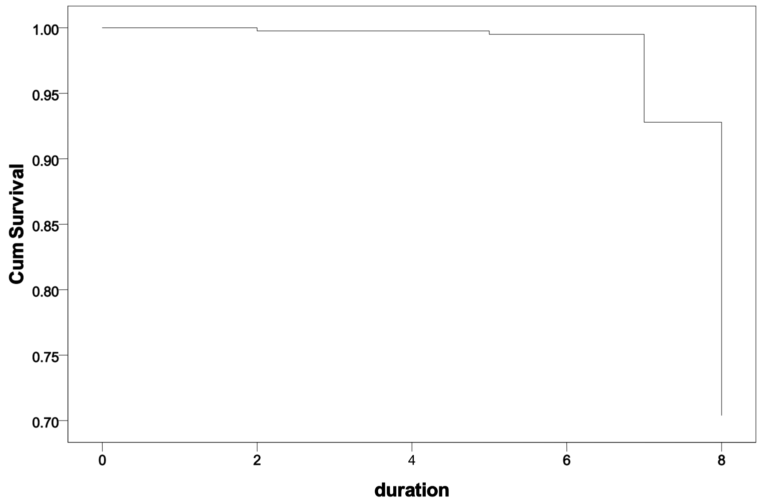

Figure 1: Survival function at mean of covariates

The Hazard Curve

From the hazard curve in Figure 2, the cumulative hazard function is shown to be steady in the ~~first six years and increases in the sixth year but after the eighth year, it remains constant~~. This means that for a bank that has survived for eight years or more during the study period, the likelihood it may liquidate in the near future is low.

These seem intuitively logical as established banks that have historically been considered much less likely to fail than relatively new generation.

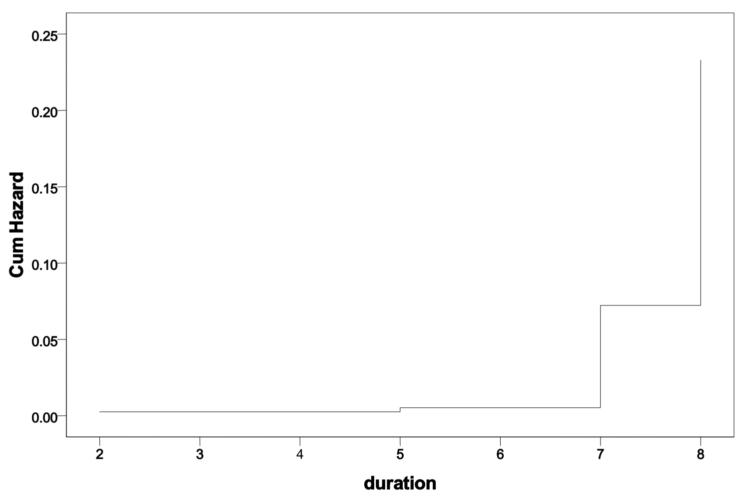

Figure 2: Hazard function at mean of covariates

Conclusion

In this paper, we were able to see how survival analysis could be used to analyze the data given table 1 and predict liquidation using Cox proportional hazard model. Data from the Nigeria Stock Exchange encompassing forty-two (42) banks listed on the floor of the Nigeria Stock Exchange between the period of 1999 to 2008 and their ten years financial summary of each of the banks. A statistical software package known as SPSS was used to analyze, estimate survival function and estimate parameters of the Cox proportional hazard model of the data set, and gives a graphical display and interpretation of results.

This work is very crucial to investors, Managers, Government, Corporate bodies, Business men, individuals, customers, etc, as this will enable them to ascertain the state of these banks even with the advent of consolidation of the banking sector in Nigeria.

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