Application of Actuarial Methods For Corporate Financial Distress Prediction in small emerging market – example from Bosnia and Herzegovina

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ABSTRACT

In Bosnia and Herzegovina there is no publicly available credit rating provided by external credit rating agency such are ECAI - External Credit Assessment Institutions in Europe. As long as investor or asset manager has the required expertise, technical means, good organizational setup, documented activities and internal models that compiles with some form of national or supranational level there should not be distinction between external or internal credit risk assessments. Internal rating based approach is methodology often used by banks under the Basel Accords. Although this methodology is mostly used by banks, similar approach is used by insurance companies and other forms of institutional investors. Expected loss under internal rating based approach is calculated with risk parameters PDs, LGDs and EAD. One of the main variables is probability of default (PDs). This parameter can be derived using different actuarial methods. With this paper we will discuss Beaver's Univariate Model, Zmijewski's Financial Distress Prediction Model, Altman EMS Score Model and Logistic Regression models for assessing financial distressed in small emerging markets like Bosnia and Herzegovina. We will test accuracy of models and show how we can apply models with best accuracy power for expected losses calculation in banks and local tax authority books. Also we will suggest application of those models in insurance industry, tax collection and audit profession. Research presented in paper can be used as valuable input for developing new researches in Bosnia and Herzegovina for default risk actuarial pricing and application in insurance economics, improving tax collection etc.

Keywords: Actuarial Pricing, Internal Methodology, Probability of Default, Credit Risk Modeling.

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Introduction

In the next period banks in Bosnia and Herzegovina will implement internal rating methodology for calculating capital needs for their operation. In support of this fact are the latest reports of the International Monetary Fund on financial sector assessment in Bosnia and Herzegovina. According to those reports[2], recommendations were made to the Bosnia and Herzegovina Central Bank. Central bank will help Bosnian banks to improve expected losses calculation from credit operation by modeling of losses from credit risk with risk parameters (PDs , LGDs , EAD). In Bosnia and Herzegovina there are 27 banks with total assets of 24.4 billion BAM (12.2 billion EUR). Internal methodology can be used in insurance industry too, but also can find application in other institutions for calculating expected loss in their books. Insurance companies in Bosnia have much smaller asset compared with banks. Total asset for 27 insurance companies in Bosnia are 630 million EUR worth according to 2015 data. Insurance companies held their asset 40% in deposits, 3% loans, 7% bonds, 4.4% equity, 22% real asset, other instruments 20% etc. Size of domestic insurance in Bosnia compared by global standards are at micro level. In Bosnia and Herzegovina there is also lack of credit rating for companies provided by external credit rating agencies such are ECAI - External Credit Assessment Institutions in Europe. Reason for lack of credit rating provided by ECAI is small financial market, lack of publicly available data and level of knowledge, . ECAI ratings are costly and are not suitable for small countries like Bosnia. As long as investor or asset manager has the required expertise, technical means, good organizational setup, documented activities and internal models that compiles with some form of national or supranational level there should not be distinction between external or internal credit risk assessments. Basel Accord provides two approaches to assessing credit risk. According to Basel there are Standardized approach and an approach based on internal rating (Internal ratings-based - IRB approach). An approach based on internal rating is divided into two groups: the Foundation and Advanced approach. Under the Solvency II insurance companies may calculate Solvency Capital Ratio (SCR) using the standard formula or their own partial of full internal model. If banks use their own internal rating methodology and banks invest in debt instruments so insurance companies as active market participant in debt instrument investments can encompass internal rating produced by banks for the internal credit analysis. Risk parameters (PDs , LGDs , EAD) are parameters that are used in internal rating based methodology. Those

[2] http://www.imf.org/external/country/bih/

parameters can be used not only by banks and insurance companies. It can be used by mutual funds, pension funds to, audits firms when assessing whether the going concern assumption is appropriate. In Bosnian example it can be used by local tax authorities. Reform Agenda for Bosnia and Herzegovina from 2015 – 2018 suggest implementing risk-based approach for audits and inspection by tax authority so why not use this methodology for improving tax collection in Bosnia. Also domestic companies can use this methodology for confirmation of accounts receivables in their accounts and calibrate their business operations in the future.

Objective

The main purposes of this paper are to investigate which prediction model can produce best results in Bosnia and Herzegovina and to see how can we apply those models for internal rating purpose for insurance companies, banks, institutional investor local companies and Bosnia and Herzegovina tax authorities. Problems that are concerned in paper can be summarized as follows:

- Are existing Beaver's Univariate Model (Beaver 1966), Zmijewski's Financial Distress Prediction Model (Zmijewski 1984), Altman EMS score model (Altman 2005) and Logit model applicable in Bosnia?
- Is it possible to design a better model with a better potential of accurately prediction of financial distress in our country?
- Can we use statistical technique for modeling financial distress ?
- What value of expected losses banks and tax authorities will have if we apply models with best accuracy power
- How can insurance companies and local tax authority in Bosnia apply internal rating methodology for better business performance.

Methods

In Bosnia and Herzegovina capital market are totally inefficient. Corporate bonds are very rare and totally illiquid. Dominant way of financing business activity are through commercial bank loans. There is no derivative financial instruments, so for assessing default risk we can not use market price methods. Only possibility that exist is to use actuarial methods. For purpose of this paper we will use Beaver's Univariate Model (Beaver 1966), Zmijewski's Financial Distress

Prediction Model (Zmijewski 1984), Altman EMS score model (Altman 2005) and Logistic regression. We will test their predictive power in Bosnian environment.

We will not treat default event as tested in most papers where default is defined as bankruptcy and liquidation of company. In this paper we will use default as defined by local Law on bankruptcy in Bosnia and Herzegovina in combination with Basel agreement default event definition. Default in Bosnia and Herzegovina Bankruptcy Law is defined as: „Bank account in block status over 60 days“. When account is in block status more than 60 days legal representative of company need, according to Law, start the procedure of bankruptcy. Per Basel A default is considered to have occurred with regard to a particular obligor when either or both of the two following events have taken place.

- The bank considers that the obligor is unlikely to pay its credit obligations to the banking group in full, without recourse by the bank to actions such as realising security (if held).
- The obligor is past due more than 90 days on any material credit obligation to the banking group. Overdrafts will be considered as being past due once the customer has breached an advised limit or been advised of a limit smaller than current outstandings.

So we treat companies in default if companies bank account is in block status more than 90 days. Status od bank account is collected from Bosnia and Herzegovina Central bank database which regularly on monthly level publish status of companies bank account.

First model we will test is Beavre's univariate Model. Beavre's univariate Model use only one variable Cash Flow/Total Liabilities (CF/TL) and his model is a typical example of a univariate models. In our analysis we will used our original sample with 7993 observations.

Classificaton Limits for Beaver's Model

CF/TL < 0.1 => 1

CF/TL > 0.1 => 0

Next model we will test is Zmijewski's Financial Distress Prediction Model (Zmijewski 1984). Zmijewski's Financial Distress Prediction Model use three different variable: net income/total asset, total liabilities/total asset, current assets/current liabilities.

Zmijewski model (1984) is as follows:

$$Zmijewski = -4.336 - 4.513x1 + 5.679x2 - 0.004x3$$

x1 - net income/total asset,
x2 - total liabilities/total asset,
x3 - current assets/current liabilities,

We have

P(Z') = Normal standardized Probability for Z' standardized value.

Subject to:

Z' = Zmijewski/ Standard deviation from Z values.

Classificaton Limits Zmijewski's Model

P(Z') > or = 0.5 Failed

P(Z') < 0.5 Non – Failed.

For testing Altman EMS score model with parameters that are used in published paper „An emerging market credit scoring system for corporate bonds" in 2005. The resulting model, is of the form:

$$EM\ Score = 6.56\ (X1) + 3.26\ (X2) + 6.72\ (X3) + 1.05\ (X4) + 3.25$$

X1 – working capital/total asset,

X2 – retained earnings/ total asset

X3 - operating income/ total asset

X4 – book value of equity/total liabilities.

EM Score is than converted in bond equivalent rating (BRE) without any adjustment for industry, competitive position etc. For distress prediction we used EMS Score below 4.5 from Table 12. as cut off point to separate firms as default or not default.

After testing those models we will construct Logistic Regression. Because default or not default are binary outcomes for our dependent variable we use two possible outcome which take values of 0 and 1. For non default companies we use value of 0 and for default firms we use value of 1.

$$y = \begin{cases} 0 \text{ if no} \\ 1 \text{ if yes} \end{cases}$$

Binary outcome models are among the most used in applied economics and estimate the probability that y = 1 as a function of the independent variables.

$$p = pr[y = 1|x] = F(x'\beta)$$

For binary outcome model depending on the functional form of F(x'β) theory identified three different models as follows:

- Regression model (linear probability model)
- Logit model
- Probit model

In regression model F(x'β) = x'β

$$p = pr[y = 1|x] = (x'\beta)$$

Problem with regression model is that the predicted probabilities are not limited between 0 and 1, so it is not used with binary outcome data.

Logit model use F(x'β) as the cumulative distribution function of the logistic distribution while probit model use F(x'β) as the cdf function of the standard normal distribution. In both model predicted probabilities are limited between 0 and 1.

Logit model takes form:

$$F(x'\beta) = \Lambda(x'\beta) = \frac{e^{x'\beta}}{1+ e^{x'\beta}} = \frac{\exp(x'\beta)}{1+ \exp(x'\beta)}$$

While for probit model we have:

$$F(x'\beta) = \Phi(x'\beta) = \int_{-\infty}^{x'\beta} \phi(z)dz$$

Logit and probit models have different functional form but which ever model we use we would get similar results. For this paper we used Logit model only. Those models are estimated by maximum likelihood method.

For OLS regression model, the marginal effects are the coefficients which are not dependent of x.

$$\frac{\partial p}{\partial x} = \beta_j$$

Marginal effects for logit and probit model are calculated as:

$$\frac{\partial p}{\partial x} = F'(x'\beta)\beta_j$$

So we have

$$\frac{\partial p}{\partial x} = \Lambda(x'\beta)\,[1- \Lambda(x'\beta)]\,\beta_j = \frac{e^{x'\beta}}{1+ e^{x'\beta}} = \frac{e^{x'\beta}}{(1+ e^{x'\beta})^2}\beta_j$$

for Logit model, and

$$\frac{\partial p}{\partial x} = \Phi(x'\beta)\,\beta_j$$

for Probit model

After estimating the models we can predict that y=1 for each observation.

$$\hat{p} = pr[y = 1|x] = F(x'\beta)$$

We will use prediction to assess what probability each observation have, and for our sample it will represent probability of default (PD). When we have probability of default we will use average recovery rate for modeling our expected loss and give quantification of loss that different participants in Bosnia Economy will have.

For testing model performance we will use Confusion Matrix, Decile tables, Gain and Lift Charts. Confusion matrix also known as a contingency table or an error matrix is specific table layout that allows visualization of the model performance. Decile tables, Gain and Lift Charts are used to evaluate logistic regression model. They measure how much better one can expect to do with the regression model comparing without a model.

Results

We used financial statement data from local provider APIF (Agency for intermediary and financing services) and got 8393 observations. From sample we extracted companies which total asset is above 5.000 EUR and got 7993 observations. For our independent variable of distress we used data from Bosnia and Herzegovina Central bank which regularly publishing every month data of transaction accounts which are in blocked status. We used data from 2015 and gathered information about accounts status for every month in 2015. If bank account of firm is in block status more than 90 days we treat that company as company in default and our independent variable have value 1 which indicate default company. Otherwise we treat company in the sample as non default company with independent variable value of 0. From our sample of 7993 observed company we have 1111 company in default or 13.9% of entire sample.

First test was conducted with Bevar's model. We used cut off point of 10% as Bevar's suggested. Model accuracy for Bevar's model is 67.18%. Sensitivity of the model is 21.17% while specificity is 74.49%. Positive predictive value is 12.1% while negative is 85.52%. For Bevar's model Type I error is 25.5% while Type II error is 78.12%.

Table1: Confusion Matrix for Beaver's Univariate Model

		Target			
		Positive	Negative		
Model	Positive	243	1755	Positive Predictive Value	0.121621622
	Negative	868	5127	Negative Predictive Value	0.855212677
		Sensitivity	Specificity		
		0.218721872	0.744986922		Accuaracy
					0.671837858

For testing model performance we built Decile Tables and Lift Chart. According to our test we find that Beaver's Univariate Model isn't model we can apply in Bosnia and Herzegovina although model have accuracy of 67.18%. From Cumulative Gain and Lift Chart we can conclude that model isn't good in separating default from non default firms and is far from perfection.

Second test was conducted using Zmijewski model. Our cut off point was 0.5. Accuracy for Zmijewski model is 55.06%. Sensitivity of the model is 79.11% while specificity is 51.17%. Positive predictive value is 20.73% while negative is 93.81%. For Zmijewski model Type I error is 48.8%. while Type II error is 20.88%.

Table 2: Confusion Matrix for Zmijewski model

		Target			
		Positive	Negative		
Model	Positive	879	3360	Positive Predictive Value	0.207360226
	Negative	232	3522	Negative Predictive Value	0.938199254
		Sensitivity	Specificity		
		0.791179118	0.511769834		Accuracy
					0.550606781

After we performed test performance we can conclude that Zmijewski's Financial Distress Prediction Model can be applied in Bosnia and because our lift decile is above 100% till 5th decile Zmijewski's Financial Distress Prediction Model is a good model.

Third model we tested is Altman EMS score model. We used cut off point of EMS Score of 4.15. Accuracy of the model is 68.79%. Sensitivity of the model is 65.43% while specificity is 69.34%. Positive predictive value is 25.62% while negative is 92.55%. For Altman EMS score model Type I error is 30.65% while Type II error is 34.56%.

Table 3: Confusion Matrix for Altman EMS score model

		Target			
		Positive	Negative		
	Positive	727	2110	Positive Predictive Value	0.256257
Model	Negative	384	4772	Negative Predictive Value	0.925524
		Sensitivity	Specificity		
		0.654365437	0.69340308		Accuracy
					0.687977

Because accuracy determined as the proportion of the total number of predictions that were corrected may not be an adequate performance measure when the number of negative cases is much greater than the number of positive cases (Kubat et al., 1998). After testing those models we can conclude for Altman EM Score model from Cumulative Gain Chart which is the graph between Cumulative Right and Cumulative population. The graph tell us how well Altman EM Score segregate default from non default firms. First decile has 10% of population and 21.24% defaulted companies. This means we have 212.42% lift at first decile. From Lift Decile Chart we can conclude that our model does well till 5th decile, so we can conclude that Altman EM Score model is a good model for application in Bosnia and Herzegovina.

After testing models we run logistic regression on our panel data. In our first model we used four independent variable: Sales/Total asset, EBITDA/Total asset, Current liabilities/Total asset, Retained earnings/Total asset. We called our first model, model 1. After we finished test with our first model on model 1 we add one more variable (Working capital/Total asset). In each step we add one variable on previous model and we construct five (5) different models. For testing predictive power of our logistic regression we used Model 5 because model 5 has highest accuracy of all Logit models for different set of variables. Accuracy for Model 5 is 86.03%. Sensitivity of the model is 2.79%% while specificity is 99.47%. Positive predictive value is 46.26% while negative is 86.37%. For Model 5 Type I error is 0% while Type II error is 97.2%. Our cut off point was set on 0.5. With that cut off point we have very high Type II error. Cost of our model 5 Type II error is several times higher for banks, insurance companies, tax authority and different kind of asset manager because it is more expansive to classify company by model as good and be wrong in classification than to classify company as bad and to be wrong Type I error.

Table 4: Confusion Matrix for Logit model 5 at 0.5 cut off point

		Positive	Negative		
Model	Positive	31	36	Positive Predictive Value	0.462687
	Negative	1080	6846	Negative Predictive Value	0.86374
		Sensitivity	Specificity		
		0.02790279	0.994768963		Accuracy
					0.860378

To overcame problems with Type II error we lower our cut off point. Lowering our cut off point to 0.15 we decrease accuracy of the model but also decrease Type II error and future costs for those subject who will apply our model. Accuracy of model 5 with cut off point 0.15 is 73,51%. Sensitivity of the model is 82.35% while specificity is 72.06%. Positive predictive value is 32.26% while negative is 96.19%. Type I error is 27.91% while Type II error is 17.64%.

Table 5: Confusion Matrix for Logit model 5 at 0.15 cut off point

		Positive	Negative		
Model	Positive	915	1921	Positive Predictive Value	0.322638
	Negative	196	4961	Negative Predictive Value	0.961993
		Sensitivity	Specificity		
		0.823582358	0.720866027		Accuracy
					0.735143

After conducting performance test for Logit model 5 at 0.15 cut off point Decile tables Cumulative Gain Charts and Lift Charts suggest good model performance and we can appliy this model in Bosnia and Herzegovina. Our findings for Logit Model 5 with cut off point 0.15 suggest that at first decile of hole population predicted correctly 34.92% companies in default. This means we have 349.23% lift at first decile. From Lift Decile Chart we can conclude that our model does well till 4th decile, so we can conclude that model is a good model for application. However our test also suggest that Logit model are better in prediction because Type II and Type I error are lower than for Altman EM Score, accuracy is higher, and logit model predicted 86.23% of defaulted companies at 4th decile while Altman EM Score predicted 68.79%.

Application of Actuarial Models

For further work we used Logit model 5 with cut off point of 0.15 and applied predicted probability of default to publicly available data from local tax authority which every month publish data about tax liabilities from domestic companies in Bosnia and Herzegovina. With our approach we can use models to calculate expected loss in Tax authority books. For calculating expected loss we need recovery rate parameter for Bosnia and Herzegovina. Average recovery rate according to Doing business report for Bosnia in 2016 is in average 36.3% so we have average LGD of 64.7% (1- recovery rate). Because we used only data from APIF – entity agency for collecting financial statement from Republic of Srpska (one of two entities in Bosnia) we used only data from Republic of Srpska Tax authority. Findings suggest that according to November 2015 data firms in Republic of Srpska (RS) owed 951 million BAM or 500 million EUR from that amount expected loss for firm in RS is 381 million BAM or 194 million EUR or 38% of all claims.

In next step we applied predicted probability of default in banks portfolios. Total asset of all banks in Bosnia in December 2015 was 24.4 billion BAM or 12.2 billion EUR. From total asset we identified three main group of loans: loans given to government, loans given to companies and loans given to households. Total values of credits from different groups of credits we used as exposure of default. For PD for different category of credits we used average PD for Bosnian companies of 13.9%, for credits given to government we used PD derived from price of CDS for country who have similar credit rating as Bosnia. PD for credits given to government is 5.5%. And for households we used percent of NPL's as PD. From IMF FASB report (2015) total NPL in Bosnia for households is 10.6%.

Table 6: Banks portfolio in Bosnia and Herzegovina and expected losses

In million BAM

Parameter	Loans given to government	Loans given to companies	Loans given to households
EAD	2133.4	7953.5	7878
PD	5.50%	13.90%	10.60%
RR	36.30%	36.30%	36.30%
LGD	63.70%	63.70%	63.70%
EL	74.74	704.23	531.94

Total expected loss of Bosnian banks portfolio is 1.3 billion BAM or 670 million EUR. According to aggregate data for Bosnian banks from September 2015 total loan provision for banks in Bosnia is 1.7 billion BAM or 880 million EUR. So initiative from IMF that banks in Bosnia and Herzegovina should use internal methodology on aggregate level will not have negative impact.

In 2015 total asset of Insurance industry in Bosnia is 630 million EUR worth, with capital of 178 million EUR. On the insurance market of Bosnia and Herzegovina the business operation is performed by 24 insurance companies and one reinsurance company. Total premium is 287 million EUR. In total premium credit and financial loss insurance premium is 1.87% or 5.6 million EUR. Results can be used as good foundation for developing models for predicting probability of default of firms and calculating insurance premium. According to Logit Model 5 we can group firms in Republic of Srpska in several categories according to their PD.

Table 7: PD categorization of Republic of Srpska Firms

PD	No Firms	Percent of all firms
below 1%	1231	15.40%
1.01% - 5%	1854	23.20%
5.01% - 20%	2753	34.44%
Above 20%	2155	26.96%

From previous table we identified 3085 firms that have PD below 5%. Those firms can be very good starting point for insurance companies to write premiums for their credit obligation or financial loss and with other mitigation risk technique good start for new business opportunity.

Conclusion

Internal rating methodology for calculating capital needs for banks operation are recommend under Basel II guidelines. This methodology is used for the purpose of calculating regulatory capital. Under the recommendation given by IMF to Bosnian authorities in 2015, Central bank with local regulatory bodies will help Bosnian banks to improve expected losses from credit operation to model loss from credit risk. Risk parameters that are used are PDs, LGDs , EAD. PDs is parameter that banks calculate with their own methodology while LGDs and EAD are given by regulator in foundation internal rating based approach. For calculating PD parameters banks used different scoring techniques and models. Small financial markets, small firms, political instability, lack of interest from foreign investor, lack of interest from domestic institutions, failure to promote need for good credit ratings are some of main reason why external credit assessment institution from Europe don’t give credit ratings to domestic firms. However we can use different model to assess probability of default. Three models are applicable in Bosnia and Herzegovina but with different accuracy prediction power. We have tested Beaver's Univariate Model (Beaver 1966), Zmijewski's Financial Distress Prediction Model (Zmijewski 1984), Altman EMS score model (Altman 2005) and Logit model. While Zmijewski's Financial Distress Prediction Model are statistically significant this model have lower accuracy, then Altman EMS score and Logit model 5. Best prediction power have Altman EMS score model (68.79%) and Logit model 5 (86.03%). While predictive power of Logit model 5 is very good this model have highest Type II error. For Logit model 5 with cut off point 0.5 Type II error is 97.2%. To overcome this problem we lowered our cut off point to 0.15 and while this step lower accuracy of our model from 86.03% to 73.51% we have very high trade off in Type II error. Type II error for Logit Model 5 with cut off point 0.15 is 17.64% from 97.2%. Logit model 5 suggest that firms with greater sales, EBITDA, retained earnings, higher working capital and firms that export are less likely to default, while firms who have greater leverage and higher current liabilities are likely to default. This model is best model from models we have tested in Republic of Srpska and can be applied in Bosnia and Herzegovina. From performance test that we have performed, we can conclude that Beaver's Univariate Model isn't model we can apply in Bosnia and Herzegovina while all other tested models are good model in predicting financial distress. When we apply those models in Bosnia environment and use internal rating approach to assess expected loss on aggregate level our findings suggest that Bosnian banks have enough provisions for their credit operation. Very good application those models can be find in tax collection. If local tax authority wish to decide for which firm to reschedule tax payment obligation those models can be applied. Also our local domestic insurance industry can use presented models for new business ventures and increasing their revenue. Credit insurance can help banks and domestic firms to assess to new loans and help domestic firms to increase their market potential.

Table 8: Definition of Variable

Variable	Definition
SALES/TA	Net Sales/Total assets
EBITDA/TA	Earnings before intrest, tax and depreciation/Total assets
CURRENTLIABILITES/TA	Current liabilites/Total assets
RETAINDED EARNINGS/TA	Retained Earnings/Total Assets
WORKINGCAPITAL/TA	Working capital/Total Assets
EXPORT	Dummy variable that equals one if firm export; otherwise zero
OWNERSHIP	Dummy variable that equals one if firm is private; otherwise zero
DEBT/TA	Total Liabilites /Total assets

Note: This table defines the variables used in Logit Model. The accounting data and other firm-specific variables are obtained from the APIF database

Table 9: Descriptive Statistics: Full Sample

Variable	Min	1st Quartile	Median	Mean	3rd Quartile	Max	Stdev
SALES/TA	0.000	0.296	0.864	1.274	1.668	42.800	1.715
EBITDA/TA	-3.000	0.000	0.060	0.090	0.160	10.900	0.282
CURRENTLIABILITES/TA	0.000	0.304	0.604	0.575	0.878	1.000	0.318
RET. EARNINGS/TA	0.000	0.011	0.143	0.255	0.428	2.990	0.288
WORKINGCAPITAL/TA	-1.000	-0.181	0.061	0.046	0.326	1.000	0.434
EXPORT	0.000	0.000	0.000	0.098	0.000	1.000	0.297
OWNERSHIP	0.000	1.000	1.000	0.953	1.000	1.000	0.211
Debt/TA	0.000	0.332	0.661	0.614	0.937	1.000	0.324

This table presents the minimum, 1st quartile, median, mean, 3rd quartile, maximum and standard deviation, for the variables based on the entire sample of firms. SALES/TA is the ratio of net sales to total assets. EBITDA/TA is measured as profit before tax divided by total asset; RET. EARNINGS/TA is the ratio of retained earnings to total asset, WORKINGCAPITAL/TA is the ratio of working capital to total assets, Export is a dummy variable obtained from APIF database that takes the value one if the firm exports, zero otherwise. Ownership is a dummy variable which equals to one if a firm is in private ownership otherwise zero. Debt/TA is the ratio of Total debt to total asset.

Table 10: Descriptive Statistics for Default Firms

Variable	Min	1st Quartile	Median	Mean	3rd Quartile	Max	Stdev
SALES/TA	0.000	0.463	1.013	1.419	1.813	42.801	1.769
EBITDA/TA	-3.007	0.014	0.074	0.107	0.177	10.907	0.290
CURRENTLIABILITES/TA	0.000	0.332	0.628	0.591	0.890	1.000	0.314
RETAINDED EARNINGS/TA	0.000	0.025	0.185	0.280	0.472	2.995	0.293
WORKINGCAPITAL/TA	-1.000	-0.130	0.096	0.086	0.363	1.000	0.424
EXPORT	0.000	0.000	0.000	0.106	0.000	1.000	0.309
OWNERSHIP	0.000	1.000	1.000	0.953	1.000	1.000	0.323
Debt/TA	0.000	0.302	0.619	0.585	0.900	1.000	0.212

This table presents the minimum, 1st quartile, median, mean, 3rd quartile, maximum and standard deviation, for the variables based on the sample of firms that are in default. SALES/TA is the ratio of net sales to total assets. EBITDA/TA is measured as profit before tax divided by total asset; RET. EARNINGS/TA is the ratio of retained earnings to total asset, WORKINGCAPITAL/TA is the ratio of working capital to total assets, Export is a dummy variable obtained from APIF database that takes the value one if the firm exports, zero otherwise. Ownership is a dummy variable which equals to one if a firm is in private ownership otherwise zero. Debt/TA is the ratio of Total debt to total asset.

Table 11: Descriptive Statistics for Non Default Firms

Variable	Min	1st Quartile	Median	Mean	3rd Quartile	Max	Stdev
SALES/TA	0.000	0.000	0.088	0.374	0.425	19.847	0.908
EBITDA/TA	-2.911	-0.048	-0.002	-0.002	0.031	1.350	0.191
CURRENTLIABILITES/TA	0.000	0.170	0.448	0.468	0.765	1.000	0.325
RETAINDED EARNINGS/TA	0.000	0.000	0.010	0.098	0.107	1.265	0.184
WORKINGCAPITAL/TA	-1.000	-0.050	-0.016	-0.020	0.060	0.944	0.412
EXPORT	0.000	0.000	0.000	0.044	0.000	1.000	0.205
OWNERSHIP	0.000	1.000	1.000	0.957	1.000	1.000	0.201
Debt/TA	0.000	0.634	0.927	0.786	1.000	1.000	0.275

This table presents the minimum, 1st quartile, median, mean, 3rd quartile, maximum and standard deviation, for the variables based on the sample of Non Default Firms. SALES/TA is the ratio of net sales to total assets. EBITDA/TA is measured as profit before tax divided by total asset; RET. EARNINGS/TA is the ratio of retained earnings to total asset, WORKINGCAPITAL/TA is the ratio of working capital to total assets, Export is a dummy variable obtained from APIF database that takes the value one if the firm exports, zero otherwise. Ownership is a dummy variable which equals to one if a firm is in private ownership otherwise zero. Debt/TA is the ratio of Total debt to total asset.

Table 12. Results For Logit Models

	Model1	Model2	Model3	Model4	Model5
Constant	-0.69149***	-1.2262***	-1.2187***	-1.5874***	-1.8677***
	(-10.758)	(-13.382)	(-13.294)	(-9.209)	(-10.202)
SALES.TA	-1.47123***	-1.5052***	-1.4843***	-1.4804***	-1.4902***
	(-18.813)	(-19.24)	(-18.995)	(-18.94)	(-19.025)
EBITDA.TA	-0.53339**	-0.1652	-0.1606***	-0.1699	-0.1724
	(-2.775)	(-0.835)	(-0.815)	(-0.863)	(-0.873)
CURRENTLIABILITES/TA	0.55674***	1.27639***	1.28843***	1.21497***	0.5121**
	(4.861)	(8.955)	(9.035)	(8.371)	(2.735)
RETAINED.EARNINGS.TA	-2.13787***	-1.5185***	-1.5066***	-1.5629***	-1.1897***
	(-10.626)	(-7.156)	(-7.109)	(-7.318)	(-5.33)
WORKINGCAPITAL.TA		-1.0266***	-1.0216***	-0.9759***	-0.2552
		(-8.848)	(-8.809)	(-8.329)	(-1.511)
EXPORT			-0.3881*	-0.4033*	-0.4425**
			(-2.42)	(-2.513)	(-2.75)
OWNERSHIP				0.4399**	0.30235.
				(2.586)	(1.753)
DEBT.TA					1.11247***
					(5.651)
Accuarcy	0.8607532	0.85988	0.861	0.86063	0.86038
McFadden R^2	0.1880289	0.20086	0.2017	0.20279	0.2078
Number of observation	7993	7993	7993	7993	7993

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Note: This table contains results derived from the Logit Models. The dependent variable is an indicator variable that equals zero if the firm is not financially distressed. If the firm is financially distressed, then the dependent variable equals one. Distressed firm are firms with transaction account in blockade more than 90 days. Table contains parameter estimates and test of their significance for each model. Model1 column contains results for a model that uses 4 accounting ratios, i.e., profitability, leverage and retained earnings divided by total assets. Model2 column shows the results from a model that incorporates an retained earnings, along with the four accounting ratios. Model3 column contains results from a logit model that additionally includes export dummy variable. Model4 column contains results from a model that combines that combines the variables used in the Model3 with ownership parameter. Model5 use all variable from Model4 and Debt/TA ratio.

Table 1: Confusion Matrix for Zmijewski model

		Target			
		Positive	Negative		
Model	Positive	879	3360	Positive Predictive Value	0.207360226
	Negative	232	3522	Negative Predictive Value	0.938199254
		Sensitivity	Specificity		
		0.791179118	0.511769834		Accuracy
					0.550606781

Table 2: Confusion Matrix for Beaver's Univariate Model

		Target			
		Positive	Negative		
Model	Positive	243	1755	Positive Predictive Value	0.121621622
	Negative	868	5127	Negative Predictive Value	0.855212677
		Sensitivity	Specificity		
		0.21872187	0.744986922		Accuracy
					0.671837858

Table 3: Confusion Matrix for Altman EMS score model

		Target			
		Positive	Negative		
Model	Positive	727	2110	Positive Predictive Value	0.256257
	Negative	384	4772	Negative Predictive Value	0.925524
		Sensitivity	Specificity		
		0.654365437	0.69340308		Accuracy
					0.687977

Table 4: Confusion Matrix for Logit model at 0.5 cut off point

		Positive	Negative		
Model	Positive	31	36	Positive Predictive Value	0.462687
	Negative	1080	6846	Negative Predictive Value	0.86374
		Sensitivity	Specificity		
		0.02790279	0.994768963		Accuracy
					0.860378

Table 5: Confusion Matrix for Logit model 5 at 0.15 cut off point

		Positive	Negative		
Model	Positive	915	1921	Positive Predictive Value	0.322638
	Negative	196	4961	Negative Predictive Value	0.961993
		Sensitivity	Specificity		Accuracy
		0.823582358	0.720866027		0.735143

Table 12: Average Z'' Score by rating from in Depth Data Corporation financial statement

Zone	EM Score		Rating	Zone	EM Score		Rating
Safe zone	8,15	>8,15	AAA	Grey zone	5,65	5,85	BBB-
	7,6	8,15	AA+		5,25	5,65	BB+
	7,3	7,6	AA		4,95	5,25	BB
	7	7,3	AA-		4,75	4,95	BB-
	6,85	7	A+		4,5	4,75	B+
	6,65	6,85	A		4,15	4,5	B
	6,4	6,65	A-	Distress zone	3,75	4,15	B-
	6,25	6,4	BBB+		3,2	3,75	CCC+
	5,85	6,25	BBB		2,5	3,2	CCC
					<1,75	2,5	CCC-
					<1,75	1,75	D

Table 13: Decile tables for Beaver's Univariate Model

Row labels	0	1	Grand Totals	Rights%	Wrongs%	Population%	CumRight	Cumulative Population	CumWrong	K-S	Lift Decile
1	727	72	799	6.48%	10.56%	10%	6.48%	10%	10.56%	-4.08%	64.81%
2	685	114	799	10.26%	9.95%	10%	16.74%	20%	20.52%	-3.78%	102.61%
3	681	118	799	10.62%	9.90%	10%	27.36%	30%	30.41%	-3.05%	106.21%
4	699	100	799	9.00%	10.16%	10%	36.36%	40%	40.57%	-4.21%	90.01%
5	682	117	799	10.53%	9.91%	10%	46.89%	50%	50.48%	-3.58%	105.31%
6	680	119	799	10.71%	9.88%	10%	57.61%	60%	60.36%	-2.75%	107.11%
7	679	120	799	10.80%	9.87%	10%	68.41%	70%	70.23%	-1.82%	108.01%
8	670	129	799	11.61%	9.74%	10%	80.02%	80%	79.96%	0.06%	116.11%
9	695	104	799	9.36%	10.10%	10%	89.38%	90%	90.06%	-0.68%	93.61%
10	684	118	802	10.62%	9.94%	10%	100.00%	100%	100.00%	0.00%	106.21%

Chart 1: Cumulative Gain Chart for Beaver's Univariate Model

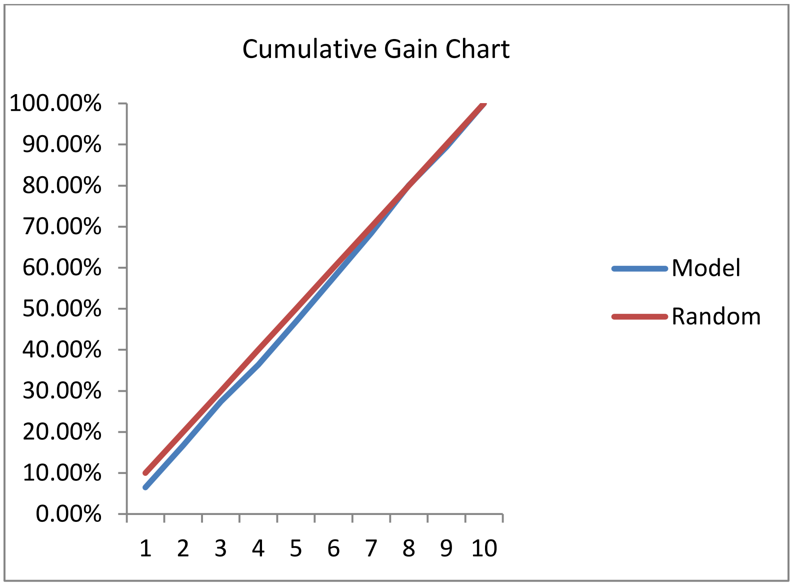


Chart 2: Lift chart for Beaver's Univariate Model

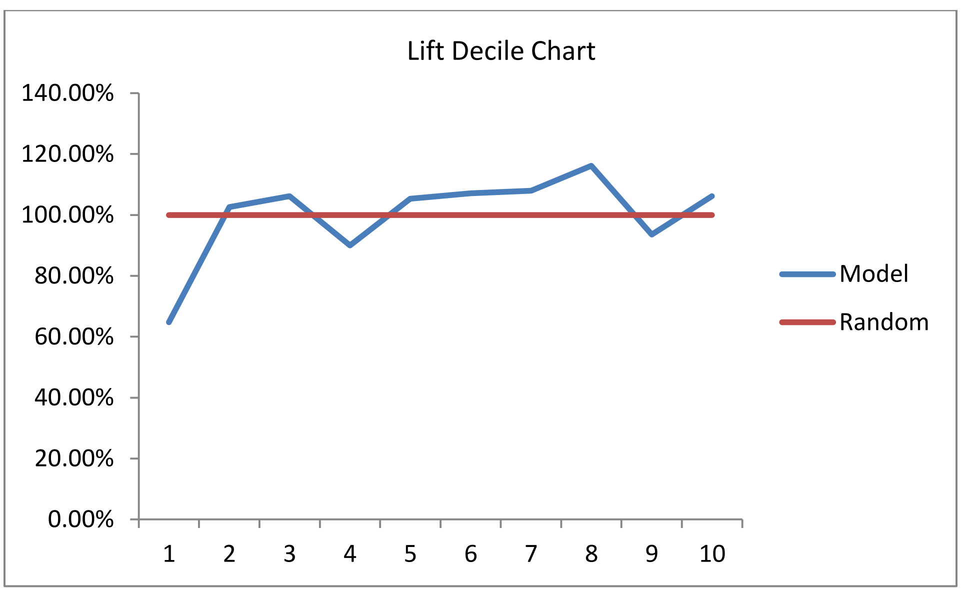


Table 13: Decile tables for Zmijewski model

Row labels	0	1	Grand Totals	Rights%	Wrongs%	Population%	CumRight	Cumulative Population	CumWrong	K-S	Lift Decile
1	574	225	799	20.25%	8.34%	10%	20.25%	10%	8.34%	11.91%	202.52%
2	530	269	799	24.21%	7.70%	10%	44.46%	20%	16.04%	28.42%	242.12%
3	661	138	799	12.42%	9.60%	10%	56.89%	30%	25.65%	31.24%	124.21%
4	686	113	799	10.17%	9.97%	10%	67.06%	40%	35.61%	31.44%	101.71%
5	698	101	799	9.09%	10.14%	10%	76.15%	50%	45.76%	30.39%	90.91%
6	710	89	799	8.01%	10.32%	10%	84.16%	60%	56.07%	28.08%	80.11%
7	728	71	799	6.39%	10.58%	10%	90.55%	70%	66.65%	23.90%	63.91%
8	752	47	799	4.23%	10.93%	10%	94.78%	80%	77.58%	17.20%	42.30%
9	756	43	799	3.87%	10.99%	10%	98.65%	90%	88.56%	10.09%	38.70%
10	787	15	802	1.35%	11.44%	10%	100.00%	100%	100.00%	0.00%	13.50%

Chart 3: Cumulative Gain Chart for Zmijewski model

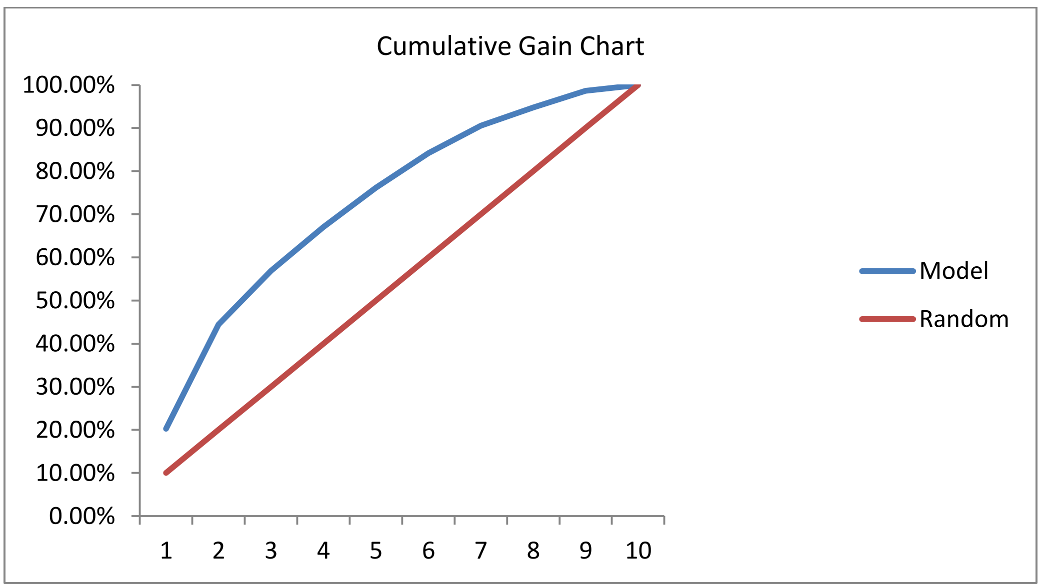


Chart 4: Lift chart for Zmijewski model

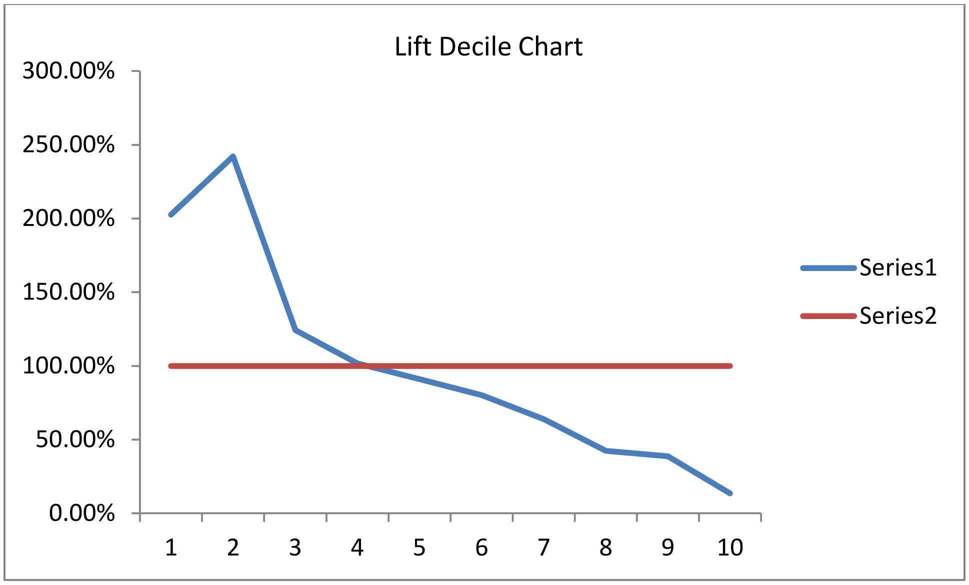


Table 14: Decile tables for Altman EMS Score model

Row labels	0	1	Grand Totals	Rights%	Wrongs%	Population%	CumRight	Cumulative Population	CumWrong	K-S	Lift Decile
1	563	236	799	21.24%	8.18%	10%	21.24%	10%	8.18%	13.06%	212.42%
2	568	231	799	20.79%	8.25%	10%	42.03%	20%	16.43%	25.60%	207.92%
3	608	191	799	17.19%	8.83%	10%	59.23%	30%	25.27%	33.96%	171.92%
4	675	124	799	11.16%	9.81%	10%	70.39%	40%	35.08%	35.31%	111.61%
5	693	106	799	9.54%	10.07%	10%	79.93%	50%	45.15%	34.78%	95.41%
6	724	75	799	6.75%	10.52%	10%	86.68%	60%	55.67%	31.01%	67.51%
7	740	59	799	5.31%	10.75%	10%	91.99%	70%	66.42%	25.57%	53.11%
8	762	37	799	3.33%	11.07%	10%	95.32%	80%	77.49%	17.83%	33.30%
9	771	28	799	2.52%	11.20%	10%	97.84%	90%	88.70%	9.14%	25.20%
10	778	24	802	2.16%	11.30%	10%	100.00%	100%	100.00%	0.00%	21.60%

Chart 5: Cumulative Gain Chart for Altman EMS Score model

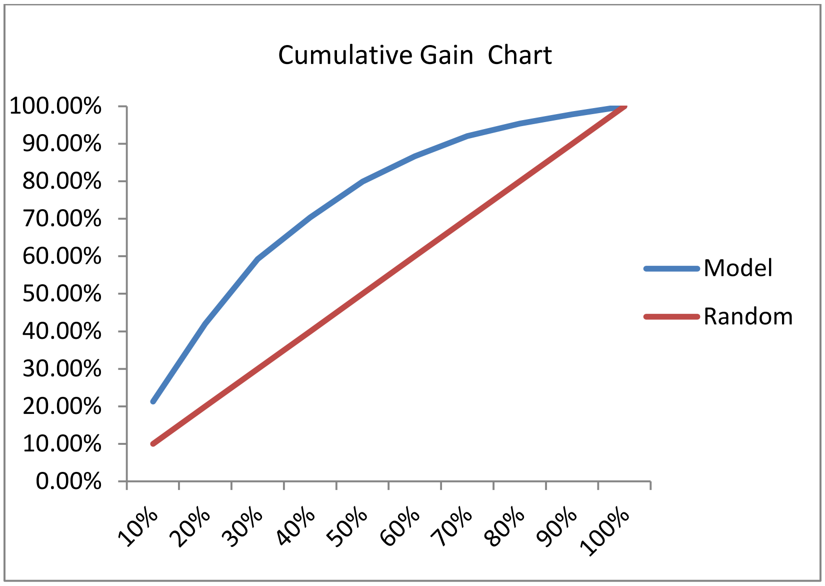


Chart 6: Lift chart for Altman EMS Score model

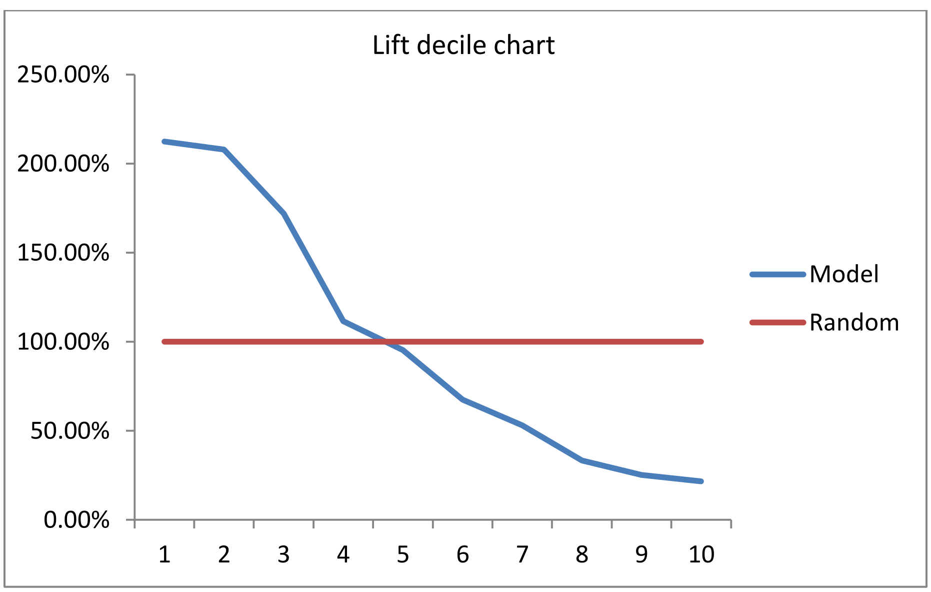


Table 15: Decile tables for Logit models 5

Row labels	0	1	Grand Totals	Rights%	Wrongs%	Population%	CumRight	Cumulative Population	CumWrong	K-S	Lift Decile
1	411	388	799	34.92%	5.97%	10%	34.92%	10%	5.97%	28.95%	349.23%
2	511	288	799	25.92%	7.43%	10%	60.85%	20%	13.40%	47.45%	259.23%
3	621	178	799	16.02%	9.02%	10%	76.87%	30%	22.42%	54.45%	160.22%
4	695	104	799	9.36%	10.10%	10%	86.23%	40%	32.52%	53.71%	93.61%
5	747	52	799	4.68%	10.85%	10%	90.91%	50%	43.37%	47.54%	46.80%
6	765	34	799	3.06%	11.12%	10%	93.97%	60%	54.49%	39.48%	30.60%
7	772	27	799	2.43%	11.22%	10%	96.40%	70%	65.71%	30.69%	24.30%
8	787	12	799	1.08%	11.44%	10%	97.48%	80%	77.14%	20.34%	10.80%
9	784	15	799	1.35%	11.39%	10%	98.83%	90%	88.54%	10.29%	13.50%
10	789	13	802	1.17%	11.46%	10%	100.00%	100%	100.00%	0.00%	11.70%

Chart 6: Cumulative Gain Chart for Logit models 5

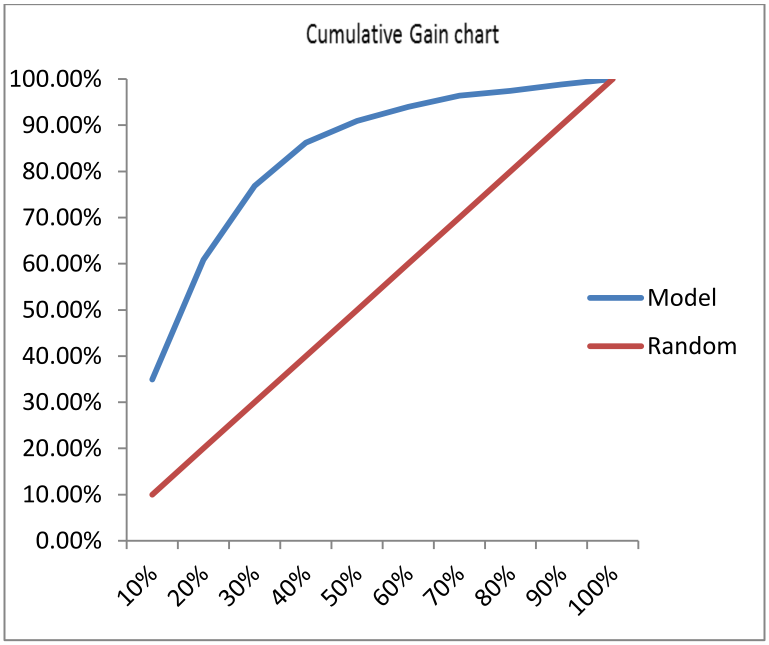
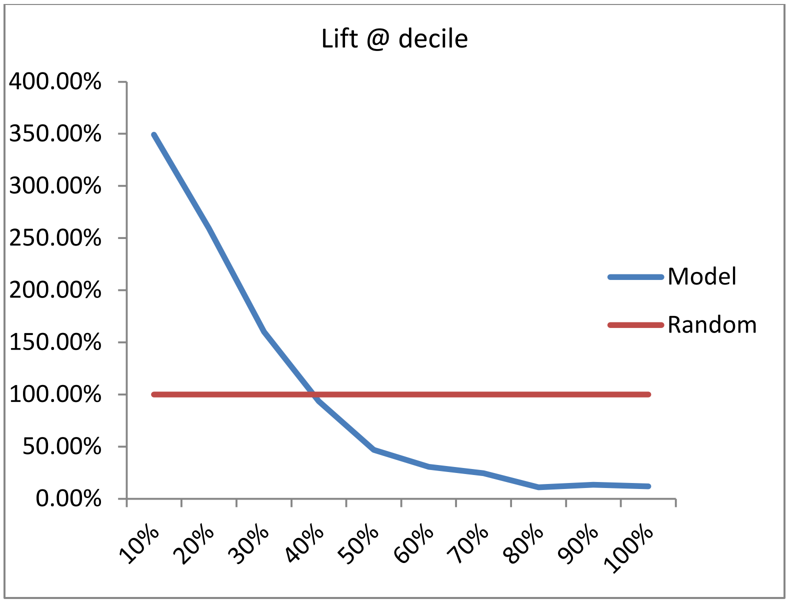


Chart 7: Lift chart for chart for Logit models 5



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