Entrepreneurship insolvency risk management: a case of Latvia

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Abstract: Financial crisis and its consequences are visible in the capital adequacy of many commercial banks, which indicates that the approach banks took to assess credit risk was not sufficiently sophisticated. This article discusses practical methods of insolvency risk modelling for enterprises. In this paper, the authors analysed the accuracy of ten models developed by foreign authors to assess insolvency risk, which were validated on the database of Latvian companies. The authors have shown that models developed on historical data for foreign companies are less accurate than the model developed on the basis of financial indicators of Latvian companies. The authors developed a three-factor model that estimates probability of default of Latvian enterprises based on historical data for 1,272 enterprises using binary logistic regression analysis.

Keywords: insolvency; probability; default; risk management; logit model; logistic regression analysis; E. Altman model; scoring model; ROC curve; model accuracy; Latvian enterprises; Latvia.

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1 Introduction

From 1991 to 2010 (June) there are 16,675 registered insolvency cases of Latvian enterprises (*Statistics on Insolvency Process*, 2010). Insolvency cases have increased in the time period from 1996 to 2003 and once more from 2006. According to the recent study Creditreform and Incasso firms Verband der Vereine Creditreform (VVC) (2009) out of eight new members of the EU the Baltic states are affected by crisis the most. Last year in this region were registered a comparatively greater number of insolvent enterprises. In 2008 in Lithuania out of 10,000 enterprises 115 became insolvent, Estonia – 108 – and Latvia – 99. According to the data of 2009 (Creditreform, 2009/10) Latvia with 174 insolvencies for every 10,000 companies shows the highest relative insolvency among those countries while 144 insolvency cases were in Lithuania and 92 in Estonia (average number of insolvency cases in Central and Eastern Europe is 97).

Now, when the Basel II Capital Requirements are in force, banks are allowed to use the internal rating-based (IRB) approach relying on their own internal estimates of risk components in determining the capital requirement for a given exposure (Basel Committee on Banking Supervision, 2006). Therefore the credit risk evaluation process in accordance with country specific conditions is very topical for the banks. The credit risk components include the probability of default, which is defined for enterprises as the probability that a company will become insolvent in the next one year. There have been developed many models in the world that have worked very successfully in different countries since Beaver in 1966 and Altman in 1968 proposed to use linear discriminant analysis for insolvency assessment. As examples related to this article we can mention models discussed in Altman (2002) and Altman and Sabato (2006). But financial crisis in the world and specific economic situation in Latvia, and probably in all Baltic countries requires creating appropriate working model in our countries.

The project described in this paper has several goals. The first is to test the preciseness of many well known methods to understand how they are working in Latvia. The second goal is to develop a model, based on Latvian enterprises data, to achieve better accuracy for the probability of default model. Duffie et al. (2007) distinguish three model generations, enabling to estimate solvency/bankruptcy: models based on discriminant analysis, logit/probit models and finally, duration models. In Central and Eastern Europe there increased interest for research method of forecasting enterprise insolvency, e.g., works of Trifan (2009), Andreica et al. (2009), Merkevičius et al. (2007) and Garškienė and Garškaitė (2004).

2 Latest achievements in Latvia

The empirical models to assess insolvency of Latvian enterprises can be found in the works of Šorin and Voronova (1998), Voronova and Romanceviča (2005), Mavļutova (2007), Romanova (2008) and Lace and Koleda (2008). But there is no evaluation of probability of default.

Šorins and Voronova (1998) from Riga Technical University developed forecasts of bankruptcy probabilities in Latvia according to Altman *Z* model. This model does not take into account the peculiarities of the field and already developed models, basing only on small selection of enterprises as the authors themselves have admitted. The study of Voronova and Romanceviča (2005) is devoted to the research of the usage of methods of American scientist D. Duran, enabling to assess the belonging to the one of the five classes of solvency. The authors conducted assessment of the suitability of a given model to a small selection of enterprises in the Baltic region belonging to one branch group.

The works of Mavļutova (2007), Lace and Koleda (2008) deal with selecting the right tool – evaluation of solvency and do not contain practical results of the check of the suitability (validity) of the usage of any models for assessment of enterprise insolvency. Romanova's (2008) work "internal rating for evaluation of the system enterprise credit risk" deals with theoretical basis and methodical provision of the crediting of the systems of internal rating to carry out methods of assessing credit risk of banks. Based on combined approaches the author worked out the techniques of credit risk assessment with its own rating class and credit risk level scale.

The study of Šneidere (2009) is of practical interest, which not only described the most popular models of foreign researchers but also practically studied ten models, relating to the first generation models on the basis of 163 enterprises, belonging to the four branches of Latvia. Only 513 financial statements are used in the above mentioned research and they were analysed during the period of 2000 to 2004. Šneidere's research lacks statistically grounded significance calculations, i.e., ROC curve, Hosmer-Lemeshow test and real bankruptcy of enterprises was considered like insolvency.

Our research is based on empirical models like Šorin and Voronova (1998), Voronova and Romanceviča (2005) and Šneidere (2009) but authors have added logit/probit model to assess probability of default.

3 Data

Our population consists of active Latvian enterprises, which made it possible to get balance sheet data from Latvian entrepreneurship register during three years in time period from 2003 to 2007. The total number of balance sheets was 2,860, that represent 1,272 unique enterprises and out of which 54 were qualified as insolvent during the research period. In addition, an enterprise is considered to be insolvent in case an enterprise delays its payment obligations for more than 90 days (Basel II default definition).

In total, the authors calculated 34 different financial ratios showing the following financial information: profitability, leverage, solvency, liquidity and some other ones. The list of those and symbols used are shown in Appendix 1.

The traditional approach in statistical model building involves seeking the most parsimonious model that still explains the observed data. The rationale for minimising the number of variables in the model is that the resultant model is more likely to be numerically stable, and is more generalised.

Sample size determination is often an important step in planning a statistical study and it is usually a difficult one. Whitemore research results provide some guidance for a logistic model containing a single dichotomous covariate (cited from Hosmer and Lemeshow, 2000). On the probability of default model example we illustrate one of the Whitemore (1981) approaches. We use it to evaluate what sample size we would take to test statistical reliability of 50% increase in the default frequency. In terms of the logistic regression model the null and alternative hypotheses are H_0: β_1 = ln(1) = 0 versus H_0: β_1 = ln(1.5) = 0. To determine the sample size we need an estimate of the response of probability $P_0 = (Y = 1| x = 0)$. Cross classifying the outcome variable (PD) by the covariate (for example: capital ratio) shows that 20% of observations with capital ratio > 0.5 are default. In this case the formula is

$$n = (1 + 2P_0) \times \frac{\left(z_{1-\alpha} \sqrt{\frac{1}{1-\pi} + \frac{1}{\pi}} + z_{1-\theta} \sqrt{\frac{1}{1-\pi} + \frac{1}{\pi e^{\beta_1}}} \right)^2}{P_0 \beta_1^2}$$

where $z_{1-\alpha}$ and $z_{1-\theta}$ denote the upper α and θ percent point respectively of the standard normal distribution. This number we would need for a 5% level test to have 80% power.

π Denotes the fraction of subjects in the study expected to have $x = 0$. In our case we have unequal numbers of events in covariate. Let the value $\pi = 0.9$. The sample size is

$$n = (1 + 2 \times 0.2) \times \frac{\left(1.645 \sqrt{\frac{1}{1-0.9} + \frac{1}{0.9}} + 0.842 \sqrt{\frac{1}{1-0.9} + \frac{1}{0.9 e^{[\ln(1.5)]}}} \right)^2}{0.2 \times [\ln(1.5)]^2} = 2892$$

Therefore rounding up, we would need 2,892 subjects, from which 10% are default cases.

A second consideration, and one relevant to any model being fit, is the issue of events per covariate. Peduzzi et al. (1996) examine the issue of how many events per covariate are needed to obtain reliable estimates of regression coefficients when fitting a logistic regression model. In general the relevant quantity is the frequency of the least frequent outcome, $m = \min(n_1, n_0)$. In our case this is usually the number with the event present ($y = 1$) but it could just as well be the number with the event absent ($y = 0$). Peduzzi et al. show that a minimum of ten events per covariate are needed to avoid problems of over estimated and under estimated variances and thus poor coverage of Wald-based confidence intervals and Wald tests of coefficients.

Thus the simplest answer to the 'do we have enough data' question is to suggest that the model contains no more than $p + 1 \leq \min(n_1, n_0)/10$ covariates.

In our case, we have 54 defaults and 2,806 non-defaults. The rule suggests that the models should contain no more than four covariates.

$$p+1 \leq \frac{\min(54; 2{,}806)}{10} = 5$$

4 Well known models and their test results

There are many models in the world on how to evaluate solvency but every model is created for a concrete region. The authors checked the possibility of using ten very well known models: Altman Z. discussed in Altman (1968), Altman Z' and Altman Z" in Altman (1993) and in Altman an Hotchkiss (2005), Zmijewski (1984), Lisa from Taffler (1984), Taffler and Tisshaw (1997), Springate (1978), Irkutsk in Davidova and Belikov (1999), Savicka (1999) and one of the Latvian models which is adopted from above Altman model by Šorin and Voronova (1998).

Table 1 Accuracy and error rates of different Altman models in Latvia

Model		*Accuracy*		*Error*	*Total*
		Amount	*%*	*%*	*N*
Altman Z	M_1	1,886	67	33	2,804
	M_2	31	57	43	54
	Total	1,917	62.33	38	2,858
Altman Z'	M_1	2,137	76	24	2,804
	M_2	24	44	56	54
	Total	2,161	60.33	40	2,858
Altman Z"	M_1	2,011	72	28	2,804
	M_2	26	48	52	54
	Total	2,037	59.93	40	2,858
Altman-LV	M_1	903	32	68	2,804
	M_2	48	89	11	54
	Total	951	60.55	39	2,858

To evaluate how the above mentioned models are working in Latvia calculations for each enterprise from data sample were done using each model. After that the result of model was compared with existing situation. All balance sheets were divided into two groups: enterprises are solvent – M_1 – and insolvent – M_2. The preciseness in each group was considered if real situation coincided with situation given by model, but the error is in opposite situation. The results of several Altman models including their modification in Latvia are shown in Table 1.

It is possible to see from Table 1 that the most accurate in the insolvent group M_2 is Altman-LV (Šorin and Voronova, 1998) model. This model can forecast insolvent enterprises with 89% probability. The wide range of errors is in group M_1: from 24% to 68%. The lowest error has Altman Z' model but the largest Altman-LV model. The results of other models are shown in Table 2.

Table 2 Accuracy and error rates of different models worked out by different scientists

Model		*Accuracy*		*Error*	*Total*
		Amount	*%*	*%*	*N*
Springate	M_1	1,595	57	43	2,790
	M_2	35	65	35	54
	Total	1,630	60.99	39	2,844
Zmijewski	M_1	1,402	50	50%	2,790
	M_2	38	70	30%	54
	Total	1,440	60.31	40%	2,844
Savicka	M_1	2,512	90	10%	2,806
	M_2	13	24	76%	54
	Total	2,525	56.80	43%	2,860
Lis	M_1	2,077	74	26%	2,804
	M_2	27	50	50	54
	Total	2,104	62.04	38	2,858
Taffler/Tisshaw	M_1	2,389	86	14	2,790
	M_2	20	37	63	54
	Total	2,409	61.33	39	2,844
Irkutsk	M_1	2,655	97	3	2,738
	M_2	8	16	84	50
	Total	2,663	56.48	44	2,788

Table 3 Area under ROC curve of considered models

Model	*Altman Z*	*Altman Z'*	*Altman Z''*	*Altman-LV*	*Springate*	*Zmijewski*	*Savicka*	*Lisa*	*Taffler/Tisshaw*	*Irkutsk*
ROC (%)	67.3	67.4	61.9	66.0	65.6	64.3	65.4	66.9	67.3	58.5

Error in group M_1 is in the range from 3% till 50% but in group M_2 from 30% till 84%. The models of Springate and Zmijewski show average accuracy in both groups. The largest average accuracy has been achieved in Lis model. Model of Taffler/Tisshow has shown little smaller accuracy to compare with others but the smallest accuracy is reached with Savicka and Irkutsk models. Additionally, the authors, to be able to define which model more accurately forecasts insolvency, have used ROC curve. Results are shown in Table 3.

Analysing foreign models it is possible to see that the largest value of ROC is given by Altman Z, Altman Z' and Taffler/Tisshaw models, which shows that these models can better forecast insolvent entrepreneurships to compare with other ones.

5 Input data analysis

Input data analysis was started with standardising ratios by using distribution function of standardised normal distribution. The next step before starting scoring model was worked out to estimate importance of each input variable. The authors considered relationship between each of 34 financial ratios and default frequency by ordering each financial ratio into increasing order and to calculate default frequency for each decile. Graphical results of some selected ratios are shown in Figures 1, 2 and 3. But results for all ratios and their correlation with default frequency analysis are shown in Appendix 1. Relation between financial ratio and default frequency can be understood from economic point of view. For example, ratio gross profit over net turnover (GP) and default frequency must have negative correlation. Therefore we are seeing from Figure 3 that the relation between ratio GP and default frequency does not fulfil.

Using univariate analysis authors omit 17 ratios. The above ratios are shown in Appendix 1 in grey colour. As further step correlation analysis was done to see which ratios are highly correlated to avoid multicollinearity problem. The explanatory variables of regression should be not correlated between themselves, because inclusion of highly correlated variables for estimation of the optimal weights for a model can result in unstable estimates of those models. Obtained correlation matrix is shown in Appendix 2.

Figure 1 Ratio profit before tax over equity (PBTE) and default frequency relationship (see online version for colours)

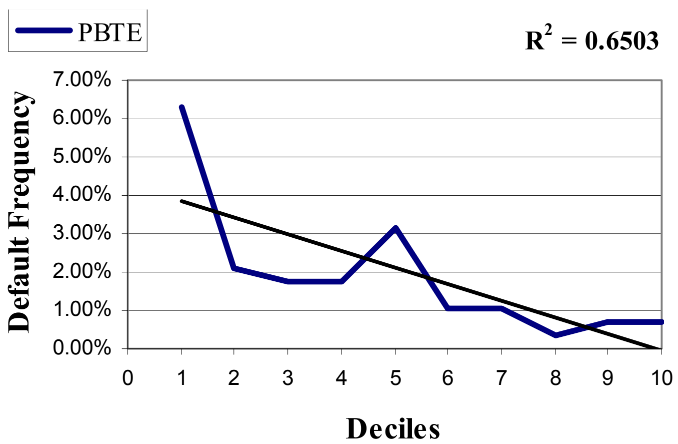


Figure 2 Ratio long term liability over total assets (LTLA) and default frequency relationship (see online version for colours)

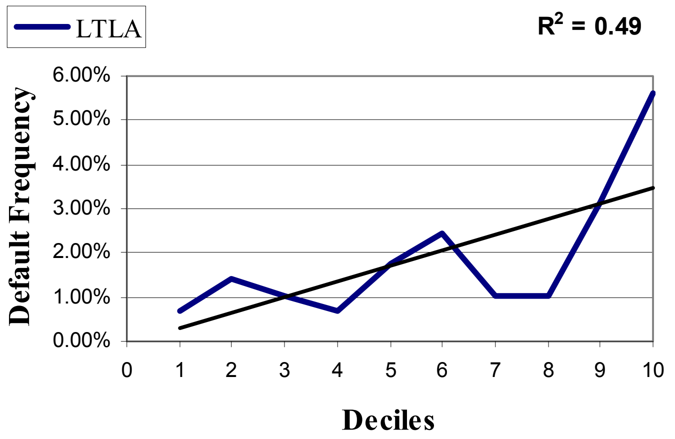
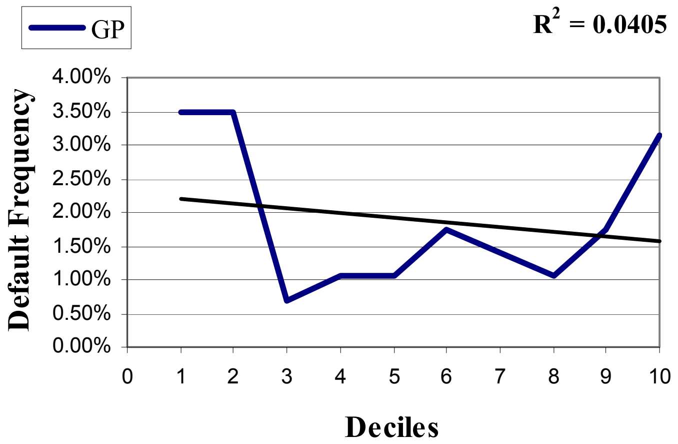


Figure 3 Ratio gross profit over net turnover (GP) and default frequency relationship (see online version for colours)



6 Creating a scoring model

The variables selected in the previous stage were used to create a model which could be simply used, with high precision, statistically significant and easily understandable. The authors have chosen the binomial logistic regression following Fernandes (2005) or in Gelman and Hill (2007).

Binomial logistic regression is a type of regression useful to model relationship where the dependent variable is dichotomous (only assumes two values) and independent variables are of any type. Logistic regression estimates the probability of a certain event accruing, since it applies maximum likelihood estimation after transforming the dependent variable into a logit variable (the natural log of the odds of the dependent occurring or not).

Let y_i be a binary discrete variable that indicates whether enterprise (borrower) *i* has defaulted (1) or not (0) in a period of a one year, and let x_i^k represent the values of the *k* explanatory variables for borrower *i*. The conditional probability that borrower *i* defaults is given by $P\left(y_i = 1 \middle| x_i^k\right) = \pi\left(x_i^k\right)$, while the conditional probability that the borrower *i* does not default is given by $P\left(y_i = 0 \middle| x_i^k\right) = 1 - \pi\left(x_i^k\right)$.

Thus, the odds that the borrower defaults are simply:

$$odds_i = \frac{\pi\left(x_i^k\right)}{1 - \pi\left(x_i^k\right)} \tag{1}$$

The estimated regression relates a combination of the independent variables to the natural log of the odds of the dependent outcome occurring:

$$L(x;\beta) = \ln\left[\frac{\pi\left(x_i^k\right)}{1 - \pi\left(x_i^k\right)}\right] = \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k \tag{2}$$

or,

$$\pi(x) = \frac{\exp\left(\beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k\right)}{1 + \exp\left(\beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k\right)} = \frac{1}{1 + \exp\left(\beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k\right)} \tag{3}$$

The authors used function for transforming each of 17 ratios:

$$PD_{ki} = L\left(x_{ki}, a_k, b_k\right) = \frac{1}{1 + e^{-\left(a_k + b_k x_{ki}\right)}} \tag{4}$$

where a_k and b_k are constants later found maximising log of likelihood function:

$$\ln l_k\left(a_k, b_k\right) = \sum_{i=1}^{2860}\left[y_i \cdot \ln PD_{ki} + \left(1 - y_i\right) \cdot \ln\left(1 - PD_{ki}\right],\right. k \in \{1, 2, \ldots, 17\} \tag{5}$$

The last step to variable selection is to use a stepwise method (SPSS) in which variables are selected either for inclusion or exclusion from the model in a sequential fashion-based solely on statistical criteria. For the final three models the selected variables and their estimated parameters are presented in Tables 4–6.

Table 4 Variables in the equation Model 1

Name	*Ratio*	*β*	*S.E.*	*Wald*	*df*	*Wald test p-value*
SA	Net turnover/total assets	35.128	9.145	14.756	1	.000
PBTE	Profit before tax/equity	31.423	9.065	12.015	1	.001
Constant		–5.469	.325	282.417	1	.000

Table 5 Variables in the equation Model 2

Name	*Ratio*	*β*	*S.E.*	*Wald*	*df*	*Wald test p-value*
SA	Net turnover/total assets	33.358	9.164	13.251	1	.000
PBTE	Profit before tax/equity	25.998	9.752	7.107	1	.008
LTLA	Long term liability/total assets	16.208	9.985	2.635	1	.105
Constant		–5.662	.352	258.539	1	.000

Table 6 Variables in the equation Model 3

Name	*Ratio*	*β*	*S.E.*	*Wald*	*df*	*Wald test p-value*
SA	Net turnover/total assets	35.737	9.596	13.868	1	.000
PBTE	Profit before tax/equity	29.319	10.558	7.711	1	.005
LTLA	Long term liability/total assets	15.853	10.039	2.494	1	.114
NPM	Net profit/net turnover	–7.871	10.784	.533	1	.465
Constant		–5.625	.362	242.122	1	.000

Additionally the authors checked areas under ROC curve for all three models. Results are shown in Table 7.

Table 7 Areas under curve for all three models

Test result variable(s)	*Area*	*Std. error*	*Asymptotic sig.*	*Asymptotic 95% confidence interval*	
				Lower bound	*Upper bound*
1 model	.719	.034	.000	.652	.786
2 model	.723	.035	.000	.655	.791
3 model	.724	.035	.000	.656	.791

One can see in Table 7 that Model 2 and Model 3 have approximately the same area under ROC curve but Wald test *p*-values for coefficients *β* are better in Model 2, based on this fact the authors have finally chosen Model 2 for credit risk evaluation.

Transformation coefficients for ratios used in Model 2 are shown in Table 8.

Table 8 Transformation coefficients of ratios used in Model 2

Name	*Ratio*	*a*	*b*
PBTE	Profit before tax/equity	–3.03080	–2.06326
SA	Net turnover/total assets	–1.07324	–3.59669
LTLA	Long term liability/total assets	–6.80139	4.35983

Finally, using logistic regression it is possible to find coefficients for each of three variables and to check if the model is statistically significant with Hosmer and Lemeshow test (Hosmer and Lemeshow, 2000). The results of the test are shown in Table 9.

Table 9 Hosmer and Lemeshow test for Model 2

Hosmer and Lemeshow test			
Step	Chi-square	df	Sig.
1	14.141	8	.078

Hosmer and Lemeshow test is used to understand whether using an appropriate statistical technique (in this case the logistic regression) is statistically significant. As it is possible to see from the Table 9 *p*-value of test is 7.8%. It is not very high but to take into account that test can be used only to the wide range of values of the original predictors and our sample is not large at all we have to be satisfied with results because the area under the ROC curve is 0.723 which means that our model can evaluate solvency with probability of 72.3%.

Finally, the authors have to end with formula for Z-score calculation taking into account that every financial ratio used in the formula has to be standardised and transformed [equation(4), Table 8]:

$$Z - score = 25,998K_1 + 33,358K_2 + 16.208K_3 - 5.662,$$

$$PD_i = \frac{1}{\left(1 + e^{-Z}\right)}$$

where

K_1 standardised and transformed ratio profit before tax/equity

K_2 standardised and transformed ratio net turnover/total assets

K_3 standardised and transformed ratio long term liability/total assets.

To compare our model accuracy with the accuracy of other models shown in Table 1 and Table 2 one can see that there is higher accuracy.

Further we tried to evaluate model fitting for different economic sectors. Table 10 shows the size of sample in each category but Table 11 shows areas under ROC curve for each sector, according to the model.

Table 10 Sample size distribution by economic sectors

Status/sector	*Manufacturing industry*	*Trade*	*Public services*
M_2 – insolvent cases	4	10	6
M_1 – solvent cases	365	772	363

Table 11 Area under ROC curve for different economic sectors

	Area	*Std. error*[a]	*Asymptotic sig.*[b]	*Asymptotic 95% confidence interval*	
				Lower bound	*Upper bound*
Manufacturing	.759	.105	.075	.554	.964
Trade	.724	.077	020	.563	.864
Public services	.805	.079	.010	651	.960

Based on ROC curve calculations range after dividing all enterprises into the branches it is possible to conclude that the worked out model is the best to fit public services as well as manufacturing industry.

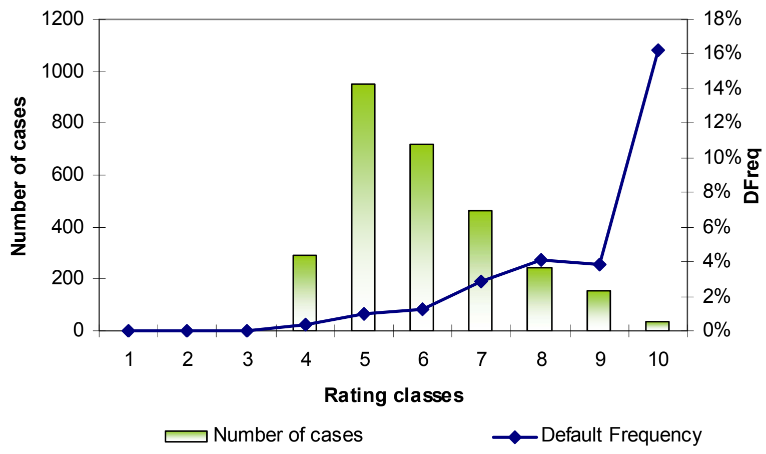
Using the model, the rating categories are found. The limits of rating classes (Table 12) are assumed to show more sensitive distribution of probability of default.

Table 12 Rating categories

Rating classes	*Probability of default*		*Scores*	
	Lower border	*Upper border*	*Lower border*	*Upper border*
1	0.01%	0.10%	–9.31	–6.95
2	0.10%	0.25%	–6.95	–6.01
3	0.25%	0.50%	–6.01	–5.30
4	0.50%	0.75%	–5.30	–4.89
5	0.75%	1.00%	–4.89	–4.59
6	1.00%	1.75%	–4.59	–4.02
7	1.75%	3.00%	–4.02	–3.47
8	3.00%	5.00%	–3.47	–2.95
9	5.00%	10.00%	–2.95	–2.24
10	10.00%	25.00%	–2.24	–1.30

The model output was calibrated to the PD level of 2.5% that corresponds to the relative indicator in year 2007 when 252 of 10,000 Latvian enterprises were insolvent (that is 2.5%) (Creditreform, 2007/08).

Figure 4 Financials and insolvency (default) frequency by rating classes (see online version for colours)



We can see from Figure 4 that the largest empirical default frequency is in the 10th rating. This leads to the conclusion that the model is intuitively economically correct.

Let us outline the fact that for practical application in certain commercial banks the best model is the model which has been developed basing on the range of clients and may change every year. Therefore in Basel II documents there is a recommendation to review internal rating determining models.

7 Conclusions

The model developed out by the authors shows 72.3% accuracy evaluation probability which has 95% confidence interval between 66% and 80%. The model for the branch of public service shows 80.5% accuracy probability, which has 95% confidence interval between 65% and 96%. In addition, accuracy of evaluation of the branch of manufacturing industry reaches 76% with confidence interval (55%; 96%). The model worked out for trade shows lower accuracy (72.4%) than all other branches, but this may be explained by a small number of data of insolvent enterprises. It is enough when there are two enterprises in the set of data which had some other reason for insolvency rather than financial problems and thus it did not appear in the annual financial statement and accordingly in the developed model.

As for economic effects, the authors consider that the developed model may serve as an instrument of risk management in a certain Latvian commercial bank. It can also be used as an instrument for managing structure of assets portfolio. Using the model as an instrument of making decisions for granting loans, it is possible, to influence portfolio structure, to lessen (lower) capital risk requirements as well with the same revenues and up with larger equity profitability and make this enterprise successful.

The disadvantages of the model are that there are no high results of statistical tests because of small statistical default sample. Further model has to be adopted more seriously in Latvia.

References

Altman, E.I. (1993) *Corporate Financial Distress and Bankruptcy*, 3rd ed., John Wiley & Sons, Inc, New York.

Altman, I.E. (1968) 'Financial ratios, discriminant analysis and the prediction of corporate bankruptcy', *Journal of Finance*, Vol. 23, No. 4, pp.589–609.

Altman, I.E. (2002) 'Corporate distress prediction models in a turbulent economic and Basel II environment', available at http://pages.stern.nyu.edu/~ealtman/Corp-Distress.pdf (accessed on 20/12/2007).

Altman, I.E. and Hotchkiss, E. (2005) *Corporate Financial Distress and Bankruptcy*, 3rd ed., John Wiley & Sons, New York.

Altman, I.E. and Sabato, G. (2006) 'Modeling credit risk for SMEs: evidence from the US market', available at http://pages.stern.nyu.edu/~ealtman/ModelingCreditRiskforMEs%20.pdf (accessed 20/12/2007).

Andreica, M.E., Andreica, M.I. and Andeica, M. (2009) 'Using financial ratios to identify Romanian distressed companies', *The Ninth International Conference Investment and Economic Recovery*, 22–23 May, available at http://www.management.ase.ro/reveconomia/2009-1s/10.pdf (accessed 11/5/2010).

Basel Committee on Banking Supervision (2006) *International Convergence of Capital Measurement and Capital Standards*, available at http://www.big.org.

Beaver, W. (1966) 'Financial ratios as predictors of bankruptcy', *Journal of Accounting Research*, Vol. 4, pp.71–102.

Duffie, D., Saita, L. and Wang, K. (2007) 'Multi-period corporate default prediction with stochastic covariates', *Journal of Financial Economics,* Vol. 83, pp.635–665.

Fernandes, J.E. (2005) 'Corporate credit risk modelling: quantitative rating system and probability of default estimation', available at http://www.jstatsoft.org/v30/b03/paper (accessed 20/12/2007).

Garškienė, A. and Garškaitė, K. (2004) 'Enterprise bankruptcy in Lithuania', *Journal of Business Economics and Management*, Technika, Vilnius, Vol. V, No 1, pp.51–58.

Gelman, A. and Hill, J. (2007) *Data Analysis Using Regression and Multilevel/Hierarchical Models*, Cambridge University Press, London.

Hosmer, D.W. and Lemeshow, S. (2000) *Applied Logistic Regression*, 2nd ed., John Wiley & Sons, New York.

Insolvencies in Europe (2007/08) 'Creditreform', available at: http://www.infohub.moneyadvicetrust.org/content_files/files/insolvencies_in_europe_2007_2008.pdf (accessed on 20/12/2007).

Insolvencies in Europe (2009/10) 'Creditreform', available at http://www.creditreform.de/Deutsch/Creditreform/Presse/Archiv/Insolvenzen_Europa/2009-10/Insolvencies_in_ Europe_ 2009-10.pdf (accessed 6/6/2010).

Lace, N. and Koleda, N. (2008) 'Selecting the right tool for evaluating of solvency: the case of Latvian enterprises', *Business and Management*, Selected Papers, Vilnius, Lithuania, pp.162–168.

Mavļutova, I. (2007) 'Uzņēmumu maksātnespējas prognozēšanas', *Bilance*, Nr.1, Vol. 157, pp.13–15.

Merkevičius, E., Garšva, G. and Simutis, R. (2007) 'Neuro-discriminate model for the forecasting of changes of companies financial standings on the basis of self-organizing maps', *Paper Presented at the 7th International Conference*, Proceedings, Part II, Beijing, China, 27–30 May.

Peduzzi, P. et al. (1996) 'A simulation study of the number of events per variable in logistic regression analysis', *Journal of Clinical Epidemiology*, Vol. 49, pp.1372–1379.

Romanova, I. (2008) *Iekšējo reitingu sistēma aizņēmēju kredītriska novērtēšanai*, Latvijas Universitāte, Rīga.

Šneidere, R. (2009) 'Finanšu analīzes metodes uzņēmuma maksātnespējas prognozēšanai', (Methods of financial analysis for predicting enterprise bankruptcy), Rīga, Latvijas Informacijas dienests.

Šorins, R. and Voronova, I. (1998) 'Uzņēmuma maksātnespējas novērtējums', in *Ekonomiskās problēmas uzņēmējdarbībā*, pp.125–131, RTU, Rīga.

Springate, G.L.V. (1978) 'Predicting the possibility of failure in Canadian firm', Unpublished MBA Research Project, Simon Fraser University, pp.69–72.

Taffler, R.J. (1984) 'Empirical models for the monitoring of UK corporations', *Journal of Banking and Finance,* No 8, pp.199–227.

Taffler, R.J. and Tisshaw, H. (1977) 'Going, going, gone – four factors which predict', *Accountancy,* Vol. 88, pp.50–54.

Trifan, A. (2009) 'Considerations on the methods of prediction of an entity's bankruptcy', available at http://but.unitbv.ro/BU2009/BULETIN2009Series%20V/ BULETIN%20V%20PDF/181%20trifan%20BUT%202009% 20BUN%20pg.pdf (accessed on 11/5/2010).

Voronova, I. and Romanceviča, J. (2005) 'Uzņēmumu ekonomiskās stabilitātes novērtēšana', in Sabiedriskās attiecības: kvalitāte, ieguvumi un riski, pp.134–142, Rīga, Augstskola Turība.

Zmijewski, M. (1984) 'Methodological issues related to the estimation of financial distress prediction models', *Journal of Accounting Research*, Vol. 22, pp.59–82.

Appendix 1

Used financial ratios, its effect of probability of default and linear correlation with default frequency

Type	*Name*	*Ratio*	*Expected effect of PD*	R^2	*Correlation coefficient*
Profitability	GP	Gross profit/net turnover	–	0.041	0.017
	PM	Profit before tax/net turnover	–	0.452	0.063**
	NPM	Net profit/net turnover	–	0.485	0.063**
	PBTE	Profit before tax/equity	–	0.650	0.087**
	GPE	Gross profit/equity	–	0.390	0.043*
	ROE	Net profit/equity	–	0.599	0.089*
	PBTA	Profit before tax/total assets	–	0.727	0.076**
	GPA	Gross profit/total assets	–	0.735	0.069**
	ROA	Net profit/total assets	–	0.743	0.075**
Leverage	DR	Liability/total assets	+	0.594	0.063**
	CRA	Equity/total assets	–	0.594	0.063**
	STLCA	(Short term liability – cash)/total assets	+	0.193	0.020
	STLA	Short term liability/total assets	+	0.347	0.033
	STLE	Short term liability/equity	+	0.082	0.035
	FACR	(Equity + long term liability)/long term assets	–	0.189	0.010
	LTLA	Long term liability/total assets	+	0.490	0.075**
	LTLE	Long term liability/equity	+	0.263	0.081**
Solvency	PBTL	Profit before tax/liability	–	0.563	0.069**
	NPL	Net profit/liability	–	0.551	0.068**
	STAL	Short term assets/liability	–	0.557	0.068**
	WCL	Working capital/liability	–	0.085	0.018
	EL	Equity/liability	–	0.594	0.062**
Liquidity	CR	Short term assets/short term liability	–	0.047	0.015
	STAA	Short term assets/total assets	–	0.303	0.050**
	CA	Cash/total assets	–	0.499	0.064**
	WCA	Working capital/total assets	–	0.064	0.015
	WCS	Working capital/net turnover	–	0.081	0.016
Another	STLS	Short term liability/net turnover	+	0.121	0.026
	LTAA	Long term assets/total assets	+	0.303	0.050**
	WCSTA	Working capital/short term assets	–	0.050	0.018
	LS	Liability/net turnover	+	0.493	0.065**
	ES	Equity/net turnover	–	0.307	0.035
	TLE	Liability/equity	+	0.068	0.064**
	SA	Net turnover/total assets	–	0.454	0.076**

Note: **correlation coefficient is significant at 0.01 level.

Appendix 2

Correlation matrix

	PM	NPM	LS	ROA	GPA	PBTA	DR	CRA	LTLA	CA	SA	ROE	PBTE	STAL	EL	PBTL	NPL
PM	1.000	.965**	.104**	.849**	.318**	.870**	.462**	.462**	.079**	.116**	–.068**	.711**	.718**	.158**	.456**	.851**	.833**
NPM	.965**	1.000	109**	.881**	.322**	.850**	.451**	.451**	.084**	.18**	–.053**	.736**	.696**	.166**	.446**	.828**	.863**
LS	.104**	.109**	1.000	.90**	.536**	.406**	.507**	.507**	.489**	.63**	.851**	.267**	.265**	.538**	.485**	.424**	.403**
ROA	.849**	.881**	.390**	1.000	.509**	.974**	.519**	.519**	.211**	.02**	.256**	.797**	.759**	.303**	.512**	.940**	.970**
GPA	.318**	.322**	.536**	.509**	1.000	.521**	.314**	.314**	.262**	.12**	.528**	.414**	.415**	.302**	.307**	.499**	.492**
PBTA	.870**	.850**	.406**	.974**	.521**	1.000	.531**	.531**	.216**	.03**	.268**	.777**	.785**	.306**	.523**	.967**	.946**
DR	.462**	.451**	.507**	.519**	.314**	.531**	1.000	1.000**	.388**	.74**	.149**	.349**	.326**	.480**	.978**	.594**	.572**
CRA	.462**	.451**	.507**	.519**	.314**	.531**	1.000**	1.000	.388**	.74**	.149**	.349**	.326**	.480**	.978**	.594**	.572**
LTLA	.079**	.084**	.489**	.211**	.262**	.216**	.388**	.388**	1.000	.58**	.351**	.155**	.146**	.534**	.367**	.233**	.221**
CA	.116**	.118**	.263**	.202**	.212**	.203**	.174**	.174**	.158**	1.000	.220**	.145**	.135**	.310**	.167**	.199**	.197**
SA	–.068**	–.053**	.851**	.256**	.528**	.268**	.149**	.149**	.351**	.20**	1.000	.205**	.210**	.355**	.137**	.246**	.239**
ROE	.711**	.736**	.267**	.797**	.414**	.777**	.349**	.349**	.155**	.145**	.205**	1.000	.966**	.213**	.346**	.726**	.751**
PBTE	.718**	.696**	.265**	.759**	.415**	.785**	.326**	.326**	.146**	.135**	.210**	.966**	1.000	.197**	.323**	.732**	.714**
STAL	.158**	.166**	.538**	.303**	.302**	.306**	.480**	.480**	.534**	.310**	.355**	.213**	.197**	1.000	.503**	.363**	.354**
EL	.456**	.446**	.485**	.512**	.307**	.523**	.978**	.978**	.367**	.167**	.137**	.346**	.323**	.503**	1.000	.615**	.593**
PBTL	.851**	.828**	.424**	.940**	.499**	.967**	.594**	.594**	.233**	.199**	.246**	.726**	.732**	.363**	.615**	.1000	.972**
NPL	.833**	.863**	.403**	.970**	.492**	.946**	.572**	.572**	.221**	.197**	.239**	.751**	.714**	.354**	.593**	.972**	1.000

Note: **correlation coefficient is significant at 0.01 level.