To what degree is the accuracy of a bankruptcy prediction model affected by the environment? The case of the Baltic States and the Czech Republic

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Abstract

According to some authors, bankruptcy models are less accurate if used in an environment different from the one for which they were designed. This is due to the higher heterogeneity of the data. The accuracy of the prediction model may be improved by reducing this heterogeneity. An alternative solution to the problem of the limited transferability (e.g. robustness) of a model may be to identify the environmental factors that affect the model's prediction accuracy and incorporate them into it. This paper presents research of the prediction accuracy of a bankruptcy model in four countries and the correlation found between the development of selected macroeconomic indicators in these countries. It proved possible in this way to identify those macroeconomic factors that show similar correlation patterns between given environments as investigated by the accuracy of the bankruptcy model. These factors include, first and foremost, the performance of the economy, inflation and unemployment. The incorporation into the model of such factors is very likely to increase model robustness.

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1. Introduction

Interest in research into bankruptcy models has, for many years, been inspired by an effort to avoid the risk of loss from unsuccessful investments. The prediction accuracy of such models, that is how a model can be used to identify the threat of a bankruptcy well in advance, is a much debated issue. The research takes two individual lines:

• Identifying suitable variables of a model. In devising a model, it is rather difficult to collect sufficient data on bankrupt companies, as bankruptcy is relatively rare in business. The first models (Altman, 1968; Ohlson, 1980; Zmijewski, 1984, and others) were designed on the basis of financial ratios calculated using company data on a period of one year prior to bankruptcy (t+1 period). One of the methods of increasing the accuracy of a model is to use indicators covering several years before bankruptcy (e.g. Perry et al., 1984).

• Testing various methods that can improve the prediction accuracy of models. The most commonly used method for designing a model is linear discriminant analysis (see Aziz, Dar, 2006), although attempts to use non-parametric methods are becoming more common (Kim, Kang, 2010; Ding et al., 2008; De Andres et al., 2011, and others).

According to some authors (Niemann et al., 2007; Grice, Dugan, 2001; Wu, Gaunt and Gray, 2010), bankruptcy models are substantially less accurate if applied to an environment, period or industry different to that for which they were originally devised. This may imply that the accuracy of a bankruptcy model is, in addition, affected by factors relating to the environment.

This paper aims to test the prediction accuracy of a bankruptcy prediction model in different environments (i.e. the robustness of the model) and identify the potential reasons for varying prediction accuracies. To this end, the accuracy of a bankruptcy model designed by the authors (Karas, Režňáková, 2013, 2014) was investigated in four countries – Latvia (LV), Lithuania (LT), Estonia (EE) and the Czech Republic (CZ). Its prediction accuracy was examined using data covering the years 2003 to 2013. These countries were selected for the reason that the economies of the Baltic countries were similar to one another during the period in question, while being different from that of the Czech Republic.

2. Method

The aim of the study was investigated using data on companies in the manufacturing industry with the use of the authors' own bankruptcy model and correlation analysis.

1. Research sample: 2,956 manufacturing industry companies (NACE rev. 2, main section C. Manufacturing), these include 2,346 financially healthy companies (further referred to as active) and 610 companies that went bankrupt in the period 2010–2013 (further referred to as bankrupt companies). These companies are based in four countries, Latvia (LV), Lithuania (LT), Estonia (EE) and the Czech Republic (CZ). The period investigated covered the years 2003 to 2013. The company data were obtained from the Amadeus database provided by Bureau Van Dijk; the data on macroeconomic variables came from Eurostat. The data on bankrupt companies are compared with those on the active companies for the same period. Table 1 below shows the numbers of companies investigated by country and character.

Table 1. Numbers of investigated companies

Country	Active	Bankrupt	Total
Lithuania	531	31	562
Latvia	387	154	541
Estonia	255	0	255
Czech Republic	1,173	425	1,598
Total	2,346	610	2,956

As Amadeus, unfortunately, provides no data on Estonia-based bankrupt companies, only active companies in this country were investigated.

2. The bankruptcy model investigated: the model was designed for Czech-based companies. Its accuracy on the original sample (Czech Republic data for the period 2007 to 2010) was 93.91 % on average. It works by combining linear discriminant analysis and Box-Cox transformation of variables (see Box, Cox, 1964). Originally designed for an application in the currency CZK (see Karas, Režňáková, 2013), the model's coefficients were later modified to

include EUR indicators. The currency of the indicators is important because the model uses one absolute variable. The model rates a company as bankrupt if index < 0, otherwise it is rated as active. The model with modified coefficients has the following form (see Karas, Režňáková, 2014):

$$Index = 3.1212 \cdot (X_1 + 1)^{-0.3563} + 4.5477 \cdot (X_2 + 1.12)^{-2.9796} + 62.5978 \cdot (X_3 + 16783.91)^{0.0294} - 87.5857 \qquad (1)$$

where

X1 – is the total assets turnover ratio (ratio of sales to total assets),

X2 – is the ratio of quick assets (current assets minus inventories) to sales,

X3 – is the value of total assets [EUR].

The accuracy of the model was tested for the 8 periods preceding a bankruptcy.

3. Methodology used to identify the external factors affecting model robustness: The method for identifying the external factors that degrade model robustness is based on the following idea. If companies exist in different environments, then in environments that are more similar, the models will also have a similar accuracy, whereas with more differences between the models, the accuracies will differ more. This degree of similarity was judged by the correlation between the development of variables over time. Spearman's rank correlation coefficient was chosen to measure correlation because of its non-parametric assumptions.

4. The macroeconomic variables investigated: the variables include the GDP growth rate for the performance of the economy, harmonised indices of consumer prices (HICP) for rate of inflation, money market interest rates – 3 month rates (IR3M), total unemployment according to ILO definition, and gross value added at current prices (GVA) for degree of industrialisation..

3. Results

First the accuracy of the model was tested for the above countries over the eight years preceding a bankruptcy starting one year before it. In this way, eight model accuracy values were obtained. Accuracy was rated as the percentage of correctly predicted active or bankrupt companies and, further, as the total accuracy. Total accuracy is a weighted average of active and bankrupt accuracy, the weighting being the observation numbers in the given period. Table 2 below shows the total model accuracy by country.

Table 2. Total model accuracy by country

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8
Lithuania	79.04	78.12	81.28	87.64	84.16	81.83	74.84	72.68
Latvia	77.21	74.16	77.87	83.92	77.97	78.67	73.71	75.60
Estonia*	71.60	68.80	64.29	68.10	68.84	62.69	62.09	60.84
Czech Republic	92.43	90.56	89.98	88.87	88.30	84.98	83.00	80.96

*accuracy of a sample of active companies

Subsequently, the similarities of the environments were analysed in terms of the existence of correlation between the macroeconomic indicators investigated, see Table 3.

Table 3. Correlation of macroeconomic indicators

	GDP	IR3M	Inflation	Unemployment	GVA
CZ/LT	0.696979	0.844186	0.610694	0.284434	0.935495
CZ/LV	0.841823	0.871665	0.737351	0.365806	0.843239
CZ/EE	0.742372	n.a.	0.792449	0.373819	0.895388
Average	0.760391	0.857926	0.713498	0.341353	0.891374
LT/LV	0.879970	0.962078	0.701113	0.955087	0.919786
LT/EE	0.863734	n.a.	0.840016	0.965736	0.963904
LV/EE	0.879428	n.a.	0.707842	0.955991	0.959559
Average	0.874377	0.962078	0.749657	0.958938	0.947750

All the above correlations were obtained at a five-percent level of significance. On average, there are stronger similarities between the Baltic countries than between any one of them and the Czech Republic. The greatest differences existed in unemployment and GDP, as well as in interest rates. There was less difference in inflation and GVA.

Next, the similarities were analysed between the model accuracies in individual countries, that is the correlation between total accuracies. Table 4 displays the resulting Spearman's rank coefficient. The correlations established at a five-percent significance level are highlighted in bold face.

Table 4. Model accuracy correlations

	Spearman	t(N-2)	p-value
LT & LV	**0.904762**	**5.203364**	**0.002008**
CZ & LV	0.095238	0.234350	0.822505
EE & LV*	0.238095	0.600481	0.570156
CZ & LT	0.285714	0.730297	0.492726
EE & LT*	0.476190	1.326473	0.232936
CZ & EE*	**0.833333**	**3.692745**	**0.010176**

*only for active companies

The total prediction accuracy of the model was determined between samples of companies from Latvia (LV) and Lithuania (LT), then between accuracies using samples of active Czech and Estonian companies. In Estonia, however, only active companies were involved. No statistically significant correlation was found between the model prediction accuracies in the Czech Republic and Latvia or Lithuania. This, as well as the correlation between the behaviours of macroeconomic figures, corroborates the similarities of the Baltic environments.

On the other hand, the differences in the history of macroeconomic quantities between the Czech Republic and the Baltic States could account for the differences of the prediction models thus reducing the bankruptcy model robustness.

4. Discussion/Conclusions

According to Horrigan (1966), model robustness can be improved by collecting data from more industries or environments. Horrigan proposed correcting the different industry indicators by dividing each industry indicator by the overall average. Niemann et al. (2008) defined the heterogeneity of a financial ratio as the difference of the same ratio between companies in different environments or industries. According to Niemann et al. (2008), it is mainly "different interest rate environments, tax regimes, wage levels, and access to capital markets" that account for environment heterogeneity.

Our research has shown that different economic environments affect bankruptcy model prediction accuracy for industrial companies. The highest accuracy was achieved by a model in its native environment (CZ), even if used for different periods. Different GDPs and interest and unemployment rates seem to be significant factors. On the other hand, inflation represented by HICP and degree of industrialisation expressed by GVA do not appear to be of such importance. In further research, we will focus on the possibility of incorporating these factors into the model and evaluating their contribution to model robustness. It is probable that the inclusion of these environmental factors will also improve model robustness over time.

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