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BASEL II DEFAULT PREDICTION MODELS FOR COMPANIES BASED ON A HUNGARIAN SAMPLE (2002-2006)

PH.D. THESIS

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1. Topic of the research

The thesis is a summary of my researches in the topic of predictive modelling. The reason of choosing this topic is not only my personal interest but also my profession: I have been working in risk monitoring and credit risk management for 8 years.

My starting point was the theory of bankruptcy predictions, which are clearly one of the most widespread financial predictive models. I studied which statistical methodologies, what kinds of data and what types of applied definitions allow the development of these models.

In the first part of the thesis I have summarised altogether 126 bankruptcy models, focusing mainly on the applied methodology. I also introduced the theoretical background of the most common statistical techniques and those measures, which allow quantifying and comparing the efficiency of these models.

In my quantitative researches I aimed to develop a predictive model, which is able to warn earlier than bankruptcy, at the default of 90 days past due. This is also in line with the requirements and definitions of Basel II Capital Accord.

By using a database of 2000 Hungarian companies between 2002 and 2006, I have carried out several analyses, applying three modelling methods: decision trees, logistic regression and neural networks.

During the development I also tried to identify the best performing modelling method and to select the most predictive financial ratios.

I have also tried to justify that the predictive power of the models can be increased by the usage of:

- sectoral indicators, which compare the financial indicators of the companies to those of their sector of activity, and
- dynamic indicators, which show the change of the financial ratios from one year to the other.

2. Theoretical background

Bankruptcy prediction is a quite new topic of research. Although it was introduced in the 1930s, bankruptcy models in the sense that we define them presently appeared only in 1960s. During this period of 40 years that has passed since their first appearance, the applied statistical methodology went through an exciting development.

I have studied altogether 126 bankruptcy models, focusing mainly on the applied modelling techniques. The results of my researches are summarised in the following table.

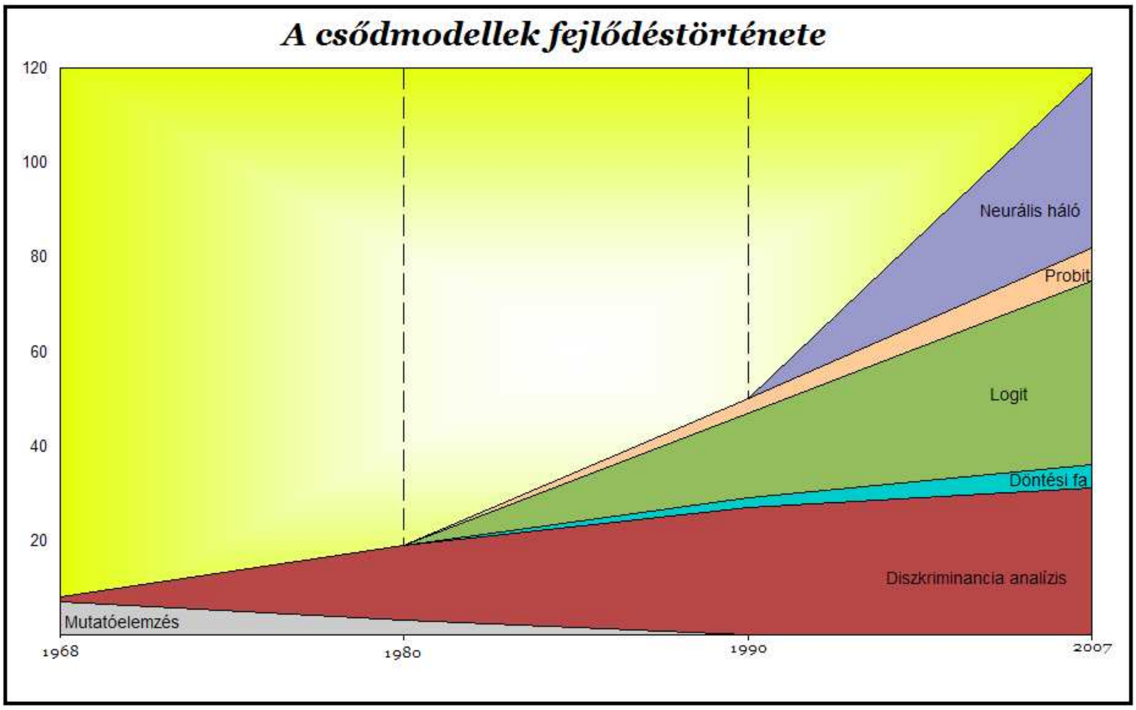
Year	Author	Ratio analysis	Discriminant analysis	Probit	Logit	Decision tree	Neural network
1931	Ramser, Foster	X					
1932	Fitzpatrick	X					
1935	Winakor, Smith	X					
1942	Merwin	X					
1966	Beaver		X				
1966	Mears	X					
1966	Horrigan	X					
1966	Neter	X					
1968	Altman		X				
1971	Wilcox	X					
1972	Deakin		X				
1972	Lane		X				
1972	Bilderbeek		X				
1972	Edmister		X				
1973	Wilcox	X					
1974	Awh, Waters		X				
1974	Blum		X				
1975	Sinkey		X				
1975	Libby	X					
1975	Elam		X				
1976	Altman, Lorris		X				
1977	Altman, Haldeman, Narayan		X				
1977	Taffler, Tisshaw		X				
1978	van Frederikslust		X				
1978	Ketz		X				
1979	Bilderbeek		X				
1979	Norton, Smith		X				
1980	Dambolena, Khoury		X				
1980	Ohlson				X		

1980	Altman, Levallee		X				
1980	Sharma, Mahajan		X				
1981	Castagna, Matolcsy		X				
1982	Ooghe, Verbaere		X				
1982	Collins, Green		X		X		
1983	Taffler		X				
1983	El-Hennawy, Morris		X				
1983	Hamer		X		X		
1984	Altman, Izan		X				
1984	Zmijewski			X			
1984	Micha		X				
1984	Lincoln		X				
1984	Takahashi, Kurokawa		X				
1985	Zavgren				X		
1985	Barth, Brumbaugh, Sauerhaft, Wang				X		
1985	Gentry, Newbold, Whitford		X		X		
1985	Casey, Bartczak		X		X		
1985	Frydman, Altman, Kao		X			X	
1985	Levitan, Knoblett		X				
1986	Lo		X		X		
1987	Keasey, Watson		X		X		
1987	Pantalone, Platt		X		X		
1987	Betts, Belhoul		X				
1987	Gombola, Haskins, Ketz, Williams		X				
1987	Peel, Peel		X		X		
1987	Lau		X		X		
1988	Rudolph, Hamdan				X		
1988	Gloubos, Grammatikos		X		X		
1988	Aziz, Emanuel, Lawson		X		X		
1988	Dambolena, Shulman				X		
1989	Barniv, Raveh		X	X	X		
1989	Hopwood, McKeown, Mutchler				X		
1990	Odom, Sharda		X				X
1990	H.D. Platt, M. Platt				X		
1990	Keasey, McGuinness				X		
1990	Gilbert, Menon, Schwartz				X		
1990	Skogsvik			X			
1991	Cadden		X				X
1991	Coats, Fant		X				X
1991	Ooghe, Joos, De Vos				X		
1991	Flagg, Giroux				X		
1992	Tam, Kiang		X		X		X
1992	Salchenberger, Cinar, Lash				X		X
1992	Bahnson, Bartley				X		
1993	Coats, Fant		X				X
1993	Fletcher, Goss				X		X
1993	Udo				X		X
1993	Chung, Tam						X
1993	Virág		X		X		

1994	Kerling, Poddig		X				X
1994	Altman, Marco, Varetto		X				X
1994	Berg, Hexeberg				X		
1994	Johnsen, Melicher				X		
1994	Platt, Platt, Pedersen				X		
1994	Sheppard, Fraser				X		
1994	Ward				X		
1994	Wilson, Sharda		X				X
1995	Lussier		X		X		
1995	Alici		X		X		X
1995	Boritz, Kennedy, Albuquerque		X	X	X		X
1995	Lacher, Coats, Sharma, Fant		X				X
1996	Back, Laitinen, Sere, Wesel		X		X		X
1996	Leshno, Spector						X
1996	Virág, Hajdu		X				
1996	Hill, Perry				X		
1997	Bardos, Zhu		X		X		X
1997	Pompe, Feelders		X			X	X
1997	Olmeda, Fernandez		X		X	X	X
1998	Kivilioto		X				X
1998	Piramuthu, Raghavan, Shaw						X
1998	McGurr, Devaney		X				
1998	Richardson, Kane, Lobinger				X		
1999	Laitinen, Kankaanpaa		X		X	X	X
1999	Zhang, Hu, Patuwo				X		X
1999	Lennox		X	X	X		
1999	Sjovoll			X			
1999	Tan			X			X
2000	Mckee, Greenstein		X			X	X
2000	Pompe, Bilderbeek		X				X
2000	Yang, Temple				X		X
2000	Bongini, Ferri, Hahm			X			
2000	Gritta, Wang, Davalos, Chow		X				X
2000	Zapranis, Ginoglou		X				X
2001	Hámori				X		
2001	Neophytou, Mar-Molinero				X		X
2001	Atiya						X
2001	Bernhardsen			X			
2001	Hunter, Isachenkova				X		
2001	Yang		X		X		X
2001	Lin, McClean		X		X		X
2002	Ginoglou, Agorastos, Hatzigagios		X	X	X		
2003	Darayseh, Waples, Tsoukalas				X		
2004	Neophytou, Molinero				X		
2004	Charitou, Neophytou, Charalambous				X		X
2005	Virág, Kristóf		X		X		X
2006	Virág, Kristóf		X		X	X	X

Overview of bankruptcy prediction models and authors

In the following chart I have drawn up the historical trends of the methodological evolution of the bankruptcy models, showing the number of studies over time.



Development of bankruptcy prediction – from methodological approach

Based on the results I have stated the following thesis:

T1. Based on my researches I have defined four historical stages of the development of bankruptcy modelling, focusing on the applied methodology:

0. Introduction of bankruptcy studies (1931-67)

1. The era of discriminant analysis (1968-79)

2. The era of logistic regression (1980-1989)

3. Introduction of Artificial Intelligence (1990-present)

Besides the mainstream evolutionary stages I have identified two dead-ends as well: probit and recursive partitioning algorithm.

3. Summary of achievements

In the second part of the thesis I introduced my quantitative researches. I aimed to develop a predictive model, which is able to warn earlier than bankruptcy, at the default of 90 days past due. This is also in line with the requirements and definitions of Basel II Capital Accord.

After listing the main criticism of the bankruptcy models I explained what kinds of solutions could the default models give to these problematic points.

Main criticism of bankruptcy models	Solutions by the applied Basel II default models
legal approach of the definition of bankruptcy	clearly economic definition: predicting 90 days in delay, which is not questionable and objective criterion
hard comparability because of the different legal environments and regulations	easily comparable because of the clear and objective criterion for defining default
application of financial ratios	combined qualification approach: besides the financial indicators (hard factors) I added qualitative (soft) factors to the analysis as well.
year-end financial statements show only a ‘snapshot’ of the main data of the companies	testing with dynamic indicators, which show the change of the financial ratios from one year to the other
limited possibilities for prediction because of the lack of representativity of the sample data	I worked on a sample, which contains data representing the Hungarian economy regarding the net sales and the sector of activity of the companies in the sample

Main criticism of bankruptcy models and the solutions offered by Basel II default models

3.1. Modelling sample

The sample I used for developing the models was organised by Info-Datax Kft. The sample contained data of 1000 defaulted and 1000 control companies. By using the database I was able to develop models for the Hungarian market, analysing 5 years of activity of the enterprises between 2002 and 2006.

In order for the models to be representative for the Hungarian market and therefore be applicable for prediction purposes, the data were representative for the economy regarding two factors: the net sales and the sector of activity of the companies.

The data relative to default, meaning 90 days in delay are also coming from a national database. The source is KHR (Központi Hitelinformációs Rendszer, Central Credit Information System), owned by BISZ Rt. This central database is obligatory filled by Hungarian banks and contains data of all credit transactions by banks and credit institutions. The database registers unpaid statuses of customers as well. A client is considered to be problematic in case the delay in payments is over 30 days. This implies that default can be defined as being at least 60 days in the system as a problematic client.

Because it is normal for banks to define a minimum limit for net sales to be fulfilled by their customers, the sample contained firms with net sales of at least 50 million HUF, to be reached in one of the two last observation years.

3.2. Factors taken into account in the analysis

During the work of model development I used both qualitative (soft) and quantitative (hard) factors.

The analysed qualitative factors:

- *geographical location*: on the levels of counties and regions;
- *activity* (based on TEÁOR code): agriculture, industry, commerce, services;
- *legal form*: kft, bt, rt, etc.

Within hard factors, I analysed altogether 52 financial ratios, which represented 7 groups of indicators:

- liquidity,
- capital structure,
- debt service,
- working capital,
- asset turnover,
- productivity,
- profitability.

3.3. The final models

I have used Enterprise Miner 5.2. software to develop the predictive models, provided by SAS Institute Kft.

I compared three different modelling techniques: decision tree, logistic regression and neural network. For the partition of the sample I have applied the most common 75-25% proportions, in order to separate a development sample and a test sample out of the original database.

During the model development I have run several tests and trial steps, using different parameterisation for the calculations and comparing the results. Finally I took the best performing version for all types of models.

T2. By using the data sample available, I have proven that following the patterns of bankruptcy prediction it is possible to build up a model, which predicts the default of companies, meaning 90 days past due payments according to Basel II definitions. The precision of these models was observed around 83%.

By analysing the decision factors used by each model, I could derive the following achievement:

T3. It was proven that the usage of qualitative factors in the models was successful. Two factors (namely the legal form of the companies and the county of activity) were appearing in all the three types of models.

and:

T4. The most important financial indicators in default prediction models were the followings:

1. long-term indebtedness,

2. cash-flow coverage,

3. short-term liabilities / tangible fixed assets,

4. Return on Assets (ROA).

These ratios were appearing in all the final default prediction models.

The following table lists all those decision factors, which appeared in at least two models.

Indicators	*Decision tree*	*Logit regression*	*Neural network*
Qualitative factors			
legal form	X	X	X
county	X	X	X
Liquidity			
dynamic liquidity (m_4)		X	X
Capital structure			
capital adequacy (m_6)		X	X
long-term indebtedness (m_9)	X	X	X
liabilities / tangible assets (m_{10})		X	X
liabilities / tangible fixed assets (m_{11})	X		X
Debt service			
cash-flow coverage (m_{16})	X	X	X
debt service ability (m_{17})		X	X
Working capital			
short-term liabilities / tangible fixed assets (m_{21})	X	X	X
Asset turnover			
total assets turnover (m_{22})	X		X
trade creditors turnover (m_{27})		X	X
Profitability			
Return on assets - ROA (m_{34})	X	X	X

The most important decision factors used by the final default-models

The developed models were evaluated with the measurement methods described in the previous chapters about theoretical background.

T5. The predictive power of the default models were below the ones of the bankruptcy prediction models. The possible explanation is most probably that the profiles of the financially healthy and problematic companies do not differ as much as the profiles of a bankrupted and a survival company, therefore the prediction is more difficult and less effective.

Hereby I present the results of the different model types in the most commonly used classification matrix.

		Decision tree	Logit regression	Neural network
Accuracy	*Development*	82,9%	83,5%	83,5%
	Test	78,0%	81,8%	81,4%
Type I error	*Development*	11,8%	8,6%	8,3%
	Test	12,8%	9,4%	10,4%
Type II error	*Development*	5,3%	7,9%	8,1%
	Test	9,2%	8,8%	8,2%

The precision and the error rates of the default models

T6. The comparison of the different modelling techniques showed that the least efficient was the decision tree. Logistic regression and neural network had about the same power, however the aspects of easier implementation and applicability are for the logistic regression.

3.4. Further tests, analytics

Application of sectoral ratios

More different studies[1] have proven that the usage of sectoral ratios can improve the predictive power the bankruptcy models. I tried to verify this hypothesis by using the available default database.

The goal was to prove that applying the same definitions and modelling techniques, it is possible to measure an improvement in predictive power in case of adding sectoral ratios to the input factors.

The testing was done in two ways. First I have run the same models as before, but adding 52 new sectoral ratios, which compared the financial indicators of the companies to the median of that ratio of the given economic sector. Secondly I used only these new 52 sectoral ratios, leaving the original ones out of the analysis.

[1] lásd pl. Platt-Platt (1990), Virág (1996), Virág-Kristóf (2006)

The tests – surprisingly – were not positive at all. In the first version I observed that the new indicators did not get into the models, and the levels of predictive power were in fact the same as before.

I found a very small improvement only in case of the neural network, an increase of 1.5 point in the prediction power on the development sample. But on the test sample, which indicates the assumption of the applicability on unknown data, it stayed on the same level as before, or even showed a small decrease of accuracy. In case of the other two models I did not experience even such a small change.

In the second test I observed a big decrease in the predictive power of the models: it dropped down to a level of 70% for all types.

Despite of the contradictory findings of other studies, I have to disapprove the statements of this hypothesis.

T7. More studies have proven that the usage of sectoral ratios can improve the predictive power the bankruptcy models, but this fact was not provable by the applied definition background and the available database. The usage of sectoral ratios did not improve any of the models.

Testing the models with dynamic ratios

My other hypothesis was to verify the effect of using the so-called dynamic indicators, which show the yearly evolution, dynamism of the different financial ratios. In other words, these new ratios compare indicators $m_1 ... m_{52}$ of the given financial year to the same ones of the previous year.

The testing was similar to the previous case: I have run the same models with the same parameters but with additional 52 new ratios in the input factors, containing the yearly evolution of the original indicators $m_1 ... m_{52}$.

The results of this test were positive. The efficiency of the different models increased by 1-2 points, the accuracies grew to a level around 85% on the development sample, and to a level around 83% on the test sample.

T8. By using the available database I have proven that the usage of dynamic indicators, which show the yearly evolution, dynamics of the different financial ratios, can improve the accuracy of the default prediction models.

		Decision tree	*Logit regression*	*Neural network*
Accuracy	*Development*	85,7%	84,5%	85,7%
	Test	79,6%	82,2%	83,6%
Type I error	*Development*	7,6%	8,3%	8,0%
	Test	9,0%	9,8%	9,8%
Type II error	*Development*	6,7%	7,2%	6,3%
	Test	11,4%	8,0%	6,6%

The precision and the error rates of the dynamic models

Comparing the different modelling techniques it was still valid that decision tree was on the third place, but neural network this time performed slightly over logistic regression. However, it is also still remarkable that applicability and structural simplicity are still besides the logit model.

T9. Among the dynamic indicators the most predictive was the yearly evolution of ROIC, which appeared in all the three models as new variable.

The following table shows those indicators, which appeared in at least two of the models as decision factors.

Indicators	*Decision tree*	*Logit regression*	*Neural network*
Qualitative factors			
legal form	X	X	X
county	X	X	X
Liquidity			
dynamic liquidity (m_4)		X	X
Capital structure			
long-term indebtedness (m_9)		X	X
liabilities / tangible assets (m_{10})	X		X
liabilities / tangible fixed assets (m_{11})	X		X
Debt service			
cash-flow coverage (m_{16})	X	X	X
Working capital			
short-term liabilities / dologi nettó érték (m_{21})	X	X	X
Asset turnover			
trade creditors turnover (m_{27})		X	X
Profitability			
EBT on assets (m_{39})		X	X
Dynamic liquidity indicators			
cash ratio (d_3)		X	X
Dynamic working capital indicators			
short-term liabilities / tangible fixed assets (d_{21})		X	X
Dynamic asset turnover indicators			
trade creditors turnover (d_{27})		X	X
Dynamic productivity indicators			
net sales on one employee (d_{28})	X		X
Dynamic profitability indicators			
return on invested capital - ROIC (d_{50})	X	X	X

The most important decision factors used by the dynamic default models

4. Applicability of the results of the research

The results of the thesis can be used directly in credit activities in banking. Banks apply prediction models, however those can be developed and tested on their own customer database.

My researches whereas used a national database, and my models were developed on a wide range of companies acting on the Hungarian market. The Basel II Capital Accord itself also enforces that banks should use external data and sources of information in their decision in risk management.

The results of my researches have added values to the theoretical background of the topic of predictive modelling as well.

At first, the achievements of the quantitative tests add new inputs to the endless “competition” of the different modelling techniques: the analyses on the available database showed that logit was the best performing model, however strictly statistically speaking, it did not perform much over the neural network.

Secondly, the overview of the historical evolution of bankruptcy modelling from methodological point of view has also added values, and can inspire the further researches in this topic.

During my researches I did not find any studies in Hungarian about the methods of measuring the efficiency of predictive models. Hopefully the summary I prepared in the frame of this thesis would lay down the basics for such studies.

5. Indicative directions for the further researches

Although the modelling project and the testing of the hypotheses fulfilled the goals set up in advance, there are still some questions remaining to be answered by carrying out further analytics and researches.

In my opinion the most important would be to try to change the binary output variable to another with more possible options. The financial situation of the companies in reality can be described with a much wider range of statuses, than what can be expressed by these two extreme points. It is especially true for the bankrupted and survival companies, but also valid in case of applying the definition of default.

At least three output categories should be differentiated by defining an intermediary "grey zone": for example those companies, which had unpaid debts with less than 90 days but over 30 days past due. Of course it requires another database in convenient quality and with the same national sampling method, but according my opinion it would be feasible even with KHR data, if the availability would be granted.

Of course this approach would require the adaptation of the applied modelling techniques as well, hence not all models can be used for a non-binary target variable.

This methodological problem could be solved by taking the grey zone companies out of the sample. By this, we could apply the same methods with binary output, but the analysis would be fine-tuned because of the stricter separation of the two output groups, containing firms with more different profile.

It would be also worth to carry out further tests about the limits of this grey zone. The definition of non-defaulting at 30 days past due is given in the system by nature: only those debtors are registered in KHR as problematic, which have at least 30 days past due. It could be analysed if instead of the above mentioned 30-90 days past due category it would be more efficient to define other limits (e.g. 45, 60 days past due) for these grey zone companies.

Of course even in frame of this new definition background, we could also verify the validity of using the sectoral ratios and the dynamic indicators in order to improve the predictive power of the new models, just like I have tested in my thesis.

The predictions on more than two output categories provide further facilities as well: later on they would be capable to model the movements from one category to the other.

Another interesting test could be run by changing the presently used partition method: instead of the separation of a development and a test sample on the commonly used method, a time-based partition could be applied. This would mean to define the data of 2002-2004 as development sample, and then to test the results on the data of 2005-2006.

These above described researches of course require another more detailed data sample.

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University study-aid

„Statistical modelling methodolgies" – for subjects of Banking and Bank Management.
University of Miskolc, Faculty of Finance
http://www.gtk.uni-miskolc.hu/gtk/ui/uipz/