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Financial distress of companies in Poland

Marek Gruszczynski
Warsaw School of Economics

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Financial distress of companies in Poland

Marek Gruszczynski
Warsaw School of Economics
marek.gruszczynski@sgh.waw.pl

Abstract

The study examines main determinants of financial distress of companies in Poland during the recent transformation period. The data compose a sample of 1995-97 annual financial statements of 200 unlisted companies in Poland. The sample was collected by the Institute of Economics of the Polish Academy of Sciences. Degree of financial distress is expressed either by the binomial variable with the following states: (1) the company in financial distress, (2) the company financially sound, or by the trinomial ordered variable with the inconclusive state between (1) and (2). The attempted models explain the distress variable (binomial or trinomial) for 1997 by the financial indicators evaluated on the basis of financial statements from previous years (1995 and 1996). The models applied to the data are binomial logit model and trinomial ordered logit model.

The results of the research are presented in a number of estimated binomial and trinomial logit models. The results are sensitive to the choice of explanatory variables. The forecast accuracy of the estimated models lies in the range of 80-90 percent. Paper gives some evidence to the idea that in the second half of the nineties the financial condition of companies in Poland was determined by the degree of liquidity, profitability and the level of financial leverage.

Keywords: financial distress, financial indicators, binomial logit, trinomial ordered logit
JEL codes: C25 and G33

1. Introduction

The degree of financial distress of a company is determined by the ability to service its debts. This ability is routinely assessed by financing banks which may rate the commercial debts on the basis of their own credit rating models, e.g. along the recent Basel accords (see: Principles… [2000]; rule no. 10).

The financial distress of a company may be established:

- comparatively, i.e. contrasting the company's characteristics to some statistical standard (model),
- dynamically, i.e. with the use of the historical data, which evidence the potential deterioration of financial situation of the company.

Comparative analysis of financial distress is possible when the data on a large number of companies from the same industry branch are available. Dynamic approach requires the access to the financial history of a company.

The methodology prevailing in the literature focuses on comparative approach, i.e. makes use of large data sets on companies. Such set possibly includes a substantial number of financially distressed companies as well as the companies financially sound.

In some cases the authors have access to time series of such cross-sectional data (panel data). This means the possibility to investigate the financial distress both comparatively and dynamically. Such situations are not frequent in financial research, especially outside North America and Western Europe.

Financial soundness/financial distress of a company is determined by a plethora of factors. The identification and subsequent quantification of these factors is not always possible. Moreover, the term "financial distress" is also not an easy subject for quantification. Therefore, the task of modelling financial distress always depends on a number of quantifying assumptions.

In this paper we make use of the qualitative variables' models. It means, we assume that the state of company's financial situation may be expressed by means of a qualitative variable, such as the binary one, where "1" denotes financially sound company and "0" represents a company in financial distress. It also means, we assume that such a variable may be reasonably explained by a number of other factors-variables, which are either quantitative or qualitative.

The qualitative variables' models are sometimes referred to as microeconometric models, i.e. models specified and estimated for large data sets, such as sets of individuals, families, firms etc.

2. Models of predicting financial distress and bankruptcy

2.1. Previous studies

Finance and microeconometrics are occupied with bankruptcy and financial distress topics since the Altman seminal article in 1968 (Altman [1968]). Numerous studies and surveys evidence various development paths of the Altman's approach. Major trends include: refinement of the traditional matched-pair mulitivariate linear discrimination model, logit model (like Ohlson [1980]), neural networks and other concepts e.g. gambler's ruin model. The approaches to bankruptcy prediction are surveyed in Morris [1997].

This paper focuses on binomial and multinomial microeconometric models, such as the logit model. Logit models are applied in a large number of recent bankruptcy and financial distress studies. In this regard it is worth to mention papers of Johnsen and Melicher [1994], Lennox [1999], Theodossiou, Kahya, Saidi and Philippatos [1996], Kaiser [2001], Bernhandsen [2001], Neophytou, Charitou and Charambolis [2000], Barniv, Agarwal and Leach [2002] and many other.

Microeconometric studies on financial distress of companies in Poland date back to the late nineties. The application of linear discriminant analysis to analysing bankruptcy in Poland can be found e.g. in the works of Hadasik [1998], Michaluk [2000], Mączyńska and Zawadzki [2001] and Hołda [2001]. The details can be found in Gruszczyński [2001, 2002].

Orłowski, Żółkiewski [2001] also examined questions of business failures in Poland. Their research is based on aggregate data rather than on microdata on companies.

A number of studies on failure and distress were also performed in other Central and East European countries. Papers by Lizal [2002] for the Czech Republic, by Hajdu and Virag [2001] for Hungary, and Hunter and Isachenkova [2000] for Russia are worth mentioning in this regard.

2.2. Predictors of distress

Major predictors of financial distress/bankruptcy as well as the direction of their impact on probability of failure may be structured as follows (see Lennox [1999], Kaiser [2001]):

- unprofitability; the more unprofitable company, the higher probability of failing (sign +),
- debt; bankruptcy is usually beginning with the default on debt servicing; thus, the higher the debt, the higher is the probability of default (+),
- cash flow difficulties; a company with healthy cash flow has relatively easy access to external financing, thus it is less likely to fail (+),
- firm age; firm age has an inverse U-shaped effect on the probability of moving into (out of) financial distress: during the beginning period of growth the chance of failure increases, the medium age is connected with stable probability of default, and afterwards the chance of failure decreases,
- firm size; firm size has also an inverse U-shaped effect on the probability of moving into (out of) financial distress,
- the legal status; e.g. limited liability has a positive effect on the probability that firms move into financial distress (+),
- corporate shareholder; the existence of corporate shareholders has a negative effect on the probability of moving into financial distress (–),
- multiple creditors; Firms with multiple creditors are less likely to run into financial distress than firms with single creditors (–),
- diversification; Diversified firms are less likely of moving into financial distress than nondiversified firms (–),
- industry sector may determine the company's access to finance,
- effect of business cycles; a bad overall industry performance increase the likelihood of moving into financial distress.

In addition to the above it is worth to mention three main reasons for bankruptcy quoted by Lizal [2002]. First, for the transition economies the popular neoclassical explanation of financial distress and bankruptcy is inappropriate allocation of assets within industry. The bankruptcy procedures are therefore the inevitable way to allocate resources efficiently. Second explanation stresses the liquidity constraints in the short run: the company with healthy fundamentals may have liquidity problems and go bankrupt. The third reason is bad management: the company has the proper asset and financial structure but may go bankrupt due to mismanagement and other corporate governance problems. In Lizal's paper the three explanations are verified by means of three separate binomial probit models, each including a number of predictors of the type listed in previous paragraph.

The factors of predicting financial distress are commonly represented by appropriate variables calculated on the basis of financial reports as well as on ownership-specific and industry-specific information. The qualitative factors are expresses by binary variables.

Major types of qualitative variables models discussed in the paper with regard to distress questions include binomial and multinomial models. The first type is of importance when the data set is composed of clearly "bad" as well as clearly "good" companies, as in the case of bankruptcy (yes-no). The latter better fits to the situation where the company's financial health may be expressed in more than two tones, e.g. "bad", "unclear" and "good" company.

The following section quotes three examples of applying multinomial approach to distress and bankruptcy.

2.3. Multinomial models of bankruptcy and distress

The multinomial logit has been applied by Kaiser [2001] to 15 583 German firms from Creditreform database (half-year data from 1994-1999). The firms were categorized into following groups in terms of debt servicing:

a) „no problem" firms: they receive cash discount and pay all their outstanding debts on time,
b) "medium problem" firms: they do not meet obligations within the agreed time schedule,
c) "severe problem" firms: the debt collecting agencies are authorized to collect the outstanding debt or the court procedures are commenced.

Kaiser's study is based on 90 302 time series cross sectional observations. The endogenous variable – firm's financial health – is multinomial, with three states. The explanatory variables include firm age, firm size, variables for limited liability, corporate stockholders, existence of multiple credit relationship and diversification. The research is aimed at modelling the transition probabilities between states of the endogenous variable from the initial state observed in 1994 to the final state in 1999, for each company. Unordered multinomial logit model is applied.

The study by Johnsen i Melicher [1994] classifies the company into one of the three states:

a) bankrupt firm
b) nonbankrupt firm,
c) financially weak firm.

The sample consists of US companies from 1970-83, including 112 bankrupt firms, 293 nonbankrupt and 255 financially weak firms. The fitted multinomial (unordered) models use

Altman's or Beaver's classical explanatory variables (financial ratios). The *ex post* forecasts are more precise for the multinomial model than for the binomial one.

Another study by Barniv, Agarwal and Leach [2002] makes use of ordered multinomial logit. The research subject is the fate of financially distressed firms, following the filing for bankruptcy. Authors demonstrate that the after-filing states may be ordered in the following way:

a) firm is acquired by other firm,
b) firm is emerged as independent entity,
c) firm is liquidated.

Such ordering is founded on the observed cumulative abnormal returns (CARs) for investors in acquired firms (CAR = 155%), emerged firms (CAR = 137%) and liquidated firms (CAR = –11%) for the US market. The date base for the study is composed of 49 acquired firms, 119 emerged and 69 liquidated – of the 237 publicly traded firms which filed for bankruptcy in the period of 1980-1995.

The authors estimate trinomial logit model with 10 explanatory variables, of which 5 are financial variables (some typical financial ratios) and 5 are non-financial, such as the dummies for fraudulent activity and for resignation of top management, index of competition in the industry branch etc. The results of the study are not very encouraging: some of the estimated parameters have the unexpected sign and the forecast precision for the estimated sample is poor (62%). Such outcome may be due to multicollinearity of explanatory variables and the lack of a more statistical approach to specification.

3. Models for Polish companies

3.1. Data

This section demonstrates the models of financial distress specified and fitted to the data on Polish companies from the base collected by the Institute of Economics of the Polish Academy of Sciences. Selected results quoted here are presented also in Gruszczyński [2003].

The database includes financial reports of some 200 unlisted companies on Poland for three years: 1995, 1996 and 1997. The reports were collected directly from companies for the purpose of implementing the Institute's research project on company's restructuring in the nineties.

The 1997 financial reports of the companies were examined by a group of experts (accounting and legal experts). They selected 23 companies in bad financial situation (financially distressed) as well as 23 companies financially sound. These 46 companies constitute major sample for specification of binomial models.

Furthermore, additional 25 companies were sampled from the remaining group of firms. They represent firms in a “medium” financial shape: inconclusive state between “no problem“ and “severe problem”. This third group of companies was added to the major sample for specification of trinomial models.

More complex approach to select the three groups is shown in Wrona [2004] (see below).

3.2. Models and endogenous variables

The endogenous variable y_{it} represents the state of financial distress of i-th the company in the year t.

There are two types of endogenous variables considered:

binomial Y:

$y_{it} = 0$ company is financially distressed (“severe problem” company),

$y_{it} = 1$ company is financially sound (“no problem” company).

ordered trinomial Y:

$y_{it} = 1$ company is financially distressed,

$y_{it} = 2$ financial condition of the company is undetermined,

$y_{it} = 3$ company is financially sound.

Key specifications of the attempted models are as follows:

$$Probability\ (y_{it} = k) = Logit\ (predictor\ variables_{t\text{-}1}),$$

$$Probability\ (y_{it} = k) = Logit\ (predictor\ variables_{t\text{-}2}),$$

where *Logit* denotes either binomial logit or multinomial (trinomial) ordered logit, the term *predictor variables* indicates the list of explanatory variables for the logit models and t=1997. The specification assumes that the financial state of a company in 1997 may be determined by its characteristics for 1995 and/or 1996.

3.3. Predictor variables

The explanatory variables for the logit models originate in financial statements for the companies. There are four groups of financial indicator variables taken into account.

1. Liquidity ratios

Ratio	Numerator	Denominator
P1 current ratio	current assets	current liabilities
P2 quick ratio	current assets – inventories	current liabilities
P3 cash ratio	current assets – invent. – receivables (= cash + short term securities)	current liabilities

2. Profitability ratios

Ratio	Numerator	Denominator
ROA return on total assets	net profit after taxes	total assets
ROA1 return on total assets	operating profit	total assets
ROE return on equity	net profit after taxes	stockholders' equity
R1 gross profit margin	gross profit	sales
R2 net profit margin	net profit after taxes	sales

3. Activity ratios

Ratio	Numerator	Denominator
A1 receivables turnover	sales	receivables
A2 liabilities turnover	cost of goods sold	accounts payable
A3 inventory turnover	cost of goods sold	Inventory
A4 total asset turnover	sales	total assets
A5 inventory cycle	inventory	sales

4. Debt management ratios

Ratio	Numerator	Denominator
Z1 debt ratio	total liabilities	total assets
Z2 debt-to-equity ratio	total liabilities	equity
Z3 financial leverage	total assets	equity
Z4 adjusted liabilities/ sales	total liabilities – (cash + + short term securities)	sales

All 17 ratios were calculated for each company for the three annual statements: 1995, 1996 and 1997.

3.4. Models' specification

The financial characteristics of companies in 1995 and/or 1996 are regarded as the only predictors of distress in 1997. This simplifying assumption is due to lack of other data on companies in the sample.

The models assume one or two-year lag for explaining the 1997-stand of the company. The lag length is due to the financial data format. The financial statements before 1995 were significantly different from those in 1995 and after, because of major changes in the law on accounting in Poland which were introduced in 1995.

The four classes of models considered in the research are:

BLM 95: binomial logit model with predictor variables from 1995,

BLM 96: binomial logit model with predictor variables from 1996,

TLM 95: trinomial ordered logit model with predictor variables from 1995,

TLM 96: trinomial ordered logit model with predictor variables from 1996.

Table 1. Description of logit models for financial distress

Logit model Y_{97}	Predictor (explanatory) variables from X_{95}	X_{96}
Binomial logit Y=0 or Y=1	BLM 95	BLM 96
Trinomial ordered logit Y=1 or Y=2 or Y=3	TLM 95	TLM 96

The explanatory variables for the model in each class are selected in a sequence of following steps:

1. The financial ratio X explaining Y is significantly correlated with Y.

   For the binomial Y the ordinary correlation coefficient with X variable is adequate to demonstrate the degree of correlation.

   For the ordered trinomial Y the correlation is replaced by the chi-square test of independence: the model may only accept the ratios, for which the hypothesis of independence (with Y) is rejected. The direction (sign) of this association is then determined by a simple XY-correlation coefficient where the Y variable is treated as dichotomous (with $y_i = 2$ rejected).
2. The ratios-predictors of distress are accepted to the model as explanatory variables only if they are rather weakly correlated between themselves. For this purpose the examination of an interdependence matrix was the major method of selecting variables.

3. The model is accepted only if the sign of *YX*-correlation is the same as the sign of relevant *X* parameter estimate in the logit model. In such application this rule is very practical and intuitive. In Polish econometric literature we call it *the principle of coincidence*. It means that once we are sure that the increasing values of *X* are associated with increasing values of *Y* (from 0 to 1 in binomial model or from 1 to 2 to 3 in trinomial model), the models we may reasonably accept shall have positive sign of the parameter's estimate for the *X* variable. The decreasing values of *X* associated with increasing values of *Y* shall result in accepting the model with the negative sign of the parameter's estimate for the *X* variable.
   For the trinomial models the principle of coincidence is verified by using the *XY*-correlation coefficient where the *Y* variable is treated as dichotomous (with $y_i = 2$ rejected)
4. From each predictors group (see 3.3 above) the model shall include only one or two predictors. This rule is the necessity: the predictors are highly correlated inside one group and therefore there is no use in including more than 1-2 predictors from each group. In such situation the selected predictor conveys majority of information from the entire group.
5. The explanatory variables (predictors) included into a model are significant. This condition is not applied rigorously. The incorrect indication of significance test is here possible due to multicollinearity of explanatory variables as well as to the small sample.
6. The model has a good *ex post* predictive capacity. The forecast accuracy is calculated as the share of correct forecasts of *Y* in the sample. The forecast of *Y* is the state (0 or 1 for the binomial model and 1 or 2 or 3 for the trinomial model) with the largest probability predicted from the estimated model.

3.5. Significant ratios

Out of the 17 financial ratios, the potential predictors selected in the first step of the procedure indicated in 3.4 include:

8 ratios for the models BLM 95 and TLM 95

and 12 ratios for the models BLM 96 and TLM 96.

Number of ratios significantly correlated/ associated with *Y* is larger for 1996 than for 1995. Evidently, symptoms of financial distress increase in number by approaching the year 1997 (year of companies' classification).

Table 2. Significant correlations/associations of predictors X_{95} and X_{96} with Y_{97}

Ratio \ Model	BLM 95 (X_{95})	TLM 95 (X_{95})	BLM 96 (X_{96})	TLM 96 (X_{96})
P1 current ratio	+	+	+	+
P2 quick ratio	+	+	+	+
P3 cash ratio	+	+	+	+
ROA return on total assets		+	+	+
ROA1 return on total assets	+	+	+	+
ROE return on equity			+	+
R1 gross profit margin			+	+
R2 net profit margin			+	+
A1 receivables turnover				
A2 liabilities turnover	+	+	+	+
A3 inventory turnover				
A4 total asset turnover				
A5 inventory cycle	–		–	–
Z1 debt ratio	–	–	–	–
Z2 debt-to-equity ratio				
Z3 financial leverage				
Z4 adjusted liabilities/ sales	–	–	–	–

The ratios for all models include the liquidity ratios P1, P2 and P3. They are positively correlated with Y. This means that the companies with higher liquidity have better chances to be financially sound after 1-2 years than the companies with liquidity problems.

The profitability ratio most frequently chosen to the models is ROA1: "operating" ROA (return on assets defined with the operating profit in numerator). All five profitability ratios are selected to TLM 96. The profitability is also positively correlated with Y: the higher profits of the company, the higher probability to stay in a good financial shape.

The activity or asset management ratios selected to the models are A2: liabilities turnover and A5: inventory cycle. Obviously, the sign of correlation between A2 and Y is positive and between A5 and Y is negative: the higher "activity" of a company (numerator in A2 and denominator in A5), the lower possible financial distress.

Debt ratios significantly correlated with Y are Z1: debt ratio and Z4: ratio of liabilities (adjusted for most liquid assets) to sales. Z4 measures the size of real debt with respect to company's capacity expressed by annual sales. Both correlations are negative: increasing debt is inevitably associated with company's decreasing ability to survive.

3.6. Logit models

According to the specification procedure outlined above in 3.3 the models estimated in each class (BLM 95, BLM 96, TLM 95 and TLM 96) include financial ratios which:

– are possibly weakly intercorrelated,
– represent various groups of predictors (liquidity, profitability, activity and leverage),
– produce the model's coefficient with the expected sign,
– are possibly significant in the model,
– generate (as a group) correct forecasts for the sample.

From the entire variety of logit models fitting to the specification procedure we present a collection of six models in each class.

Tables A1 to A4 in the Appendix show the estimation results for these models in an abbreviated form. Each column represents one estimated model. The ratios-predictors included into the model as explanatory variables are indicated by "x". Number of significant variables $m(n)$ denotes m variables significant at the level of 0,1 while n of them are significant at 0,05. For the trinomial ordered logit model additionally the significance of limit points is indicated (level of 0,05).

In this section we present the detailed estimation results for one model from each class.

3.6.1. Binomial models

For binomial Y the model no.7 from BLM 95 and model no.15 from BLM 96 are presented in Tables 3-4.

Table 3. Estimation results for BLM 95 model no.7

Variable	Parameter estimate	Standard error	t statistic	Probability
Const	0,3133	0,8286	0,3781	0,7053
ROA1	8,7592	3,2861	2,6656	0,0077
A5	-8,0069	4,5512	-1,7593	0,0785
Akaike criterion	1,1276	Hannan-Quinn criterion		1,1723
Schwarz criterion	1,2469	McFadden R-squared		0,2807
Prediction accuracy	y_i	number of companies	predicted number	% correct
	0	23	19	82,61
	1	23	20	86,96

Table 4. Estimation results for BLM 96 model no.15

Variable	Parameter estimate	Standard error	t statistic	Probability
Const	-4,7238	1,5925	-2,9663	0,0030
R1	16,1075	6,5392	2,4632	0,0138
A2	0,5761	0,2025	2,8447	0,0044
Akaike criterion	0,6134	Hannan-Quinn criterion		0,6580
Schwarz criterion	0,7326	McFadden R-squared		0,6516
Prediction accuracy	y_i	number of companies	predicted number	% correct
	0	23	20	86,96
	1	23	20	86,96

3.6.2. Trinomial models

The trinomial ordered logit model is used to describe Y defined as:

$y_{it} = 1$ company is financially distressed,

$y_{it} = 2$ financial condition of the company is undetermined,

$y_{it} = 3$ company is financially sound.

It is assumed that the states of Y correspond to the values of an unobserved latent variable y^*. The values of y^* represent the level of financial distress of the company. Accordingly, we assume that

$y_i = 1$ for $y_i^* < \tau_1$,

$y_i = 2$ for $\tau_1 \leq y_i^* < \tau_2$,

$y_i = 3$ for $\tau_2 \leq y_i^*$.

Parameters τ (also identified as *limit points*) are unknown and subject to estimation. The latent variable y^* is explained in terms of explanatory variables X as follows:

$$y_i^* = \mathbf{x}_i^T \boldsymbol{\beta} + \varepsilon_i \tag{1}$$

Vector $\mathbf{x}_i$ represents the financial ratios for the i-th company, $\boldsymbol{\beta}$ is the parameter vector and ε_i is the disturbance.

Table 5. Estimation results for TLM 95 model no.8

Variable	Parameter estimate	Standard error	t statistic	Probability
P2	1,2654	0,4804	2,6340	0,0084
ROA	1,4402	1,6272	0,8851	0,3761
Z1	-2,6851	1,4980	-1,7925	0,0731
Limit points				
τ_1	-0,6002	0,9092	-0,6602	0,5091
τ_2	1,5527	0,9198	1,6880	0,0914
Akaike criterion	1,8490	Hannan-Quinn criterion		1,9124
Schwarz criterion	2,0084	McFadden R-squared		0,2220
Prediction accuracy y_i	number of companies	predicted number	sum of all probabilities	error
1	23	25	23,4263	-0,4263
2	25	25	24,5721	0,4279
3	23	21	23,0015	-0,0015

If the distribution of ε_i is logistic, then the model is ordered logit. In this case the probabilities of Y for each state are:

$$P(y_i = 1 \mid \mathbf{x}_i) = \mathrm{A}, \qquad P(y_i = 2 \mid \mathbf{x}_i) = \mathrm{B} - \mathrm{A}, \qquad P(y_i = 3 \mid \mathbf{x}_i) = 1 - \mathrm{B} \tag{2}$$

where

$$\mathrm{A} = \frac{e^{\tau_1 - \mathbf{x}_i^T \boldsymbol{\beta}}}{1 + e^{\tau_1 - \mathbf{x}_i^T \boldsymbol{\beta}}} \qquad \text{and} \qquad \mathrm{B} = \frac{e^{\tau_2 - \mathbf{x}_i^T \boldsymbol{\beta}}}{1 + e^{\tau_2 - \mathbf{x}_i^T \boldsymbol{\beta}}}$$

Elements of $\boldsymbol{\beta}$ as well as the limit points τ_1 and τ_2 are estimated by maximum likelihood.

The estimates of two trinomial ordered logit models from each group (TLM 95 and TLM 96) are as presented in Tables 5-6.

Table 6. Estimation results for TLM 96 model no.12

Variable	Parameter estimate	Standard error	t statistic	Probability
P3	1,5917	0,7087	2,2459	0,0247
R2	4,0927	2,0412	2,0051	0,0450
A2	0,1747	0,0606	2,8848	0,0039
Limit points				
τ_1	0,6926	0,4229	1,6376	0,1015
τ_2	2,9942	0,5825	5,1402	0,0000
Akaike criterion	1,7635	Hannan-Quinn criterion		1,8269
Schwarz criterion	1,9228	McFadden R-squared		0,2610
Prediction accuracy y_i	number of companies	predicted number	sum of all probabilities	error
1	23	20	23,3184	-0,3184
2	25	32	25,3139	-0,3139
3	23	19	22,3677	0,6323

The estimated models allow for calculation of the probabilities defined in (2) for each company in the sample. The *ex post* forecast of the state of Y (1 or 2 or 3) is then determined as the one with highest probability.

3.7. Review of the results

The binomial and trinomial models explaining financial distress of Polish companies by means of their previous financial data give an insight to several key determining factors.

As in other economies, financial distress of companies in Poland is determined mainly by the degree of liquidity, profitability and by the size of debt.

The best predictors of financial distress of Polish companies in the second half of ninieties were:

- the loss of liquidity (liquidity ratio),
- diminishing profitability (return on assets),
- increasing debt (debt ratio),
- decreasing turnover of liabilities.

The models containing the reasonable collection of 2-3 financial ratios are able to predict the state of the company's financial distress after one or two years. The precision of such forecast lies in the area of 70-80%.

Selection of variables according to several quite universal rules, resulted in obtaining a good number of prediction models with acceptable statistical and economic properties.

It is worth to note that models with predictors from 1995 (two-year lag) perform better than models with predictors from 1996 (one-year lag). The average prediction accuracy for BLM and TLM models is as follows:

BLM 95 84,60%

BLM 96 90,70%

TLM 95 86,85%

TLM 96 87,33%.

The difference in forecast precision between 1995 and 1996 is much higher for the binomial models than for the trinomial ones.

4. Extensions

The attempt of applying logit models to prediction of financial distress gives satisfactory and promising results, despite the small sample size and the limitation in the data only to financial variables.

One major flaw in this research lies in the soft, imprecise way to assess the last (1997) financial standing of a company. Of course, much obvious classification of companies is possible in the research on bankruptcy: bankrupt vs. non-bankrupt.

To this end Wrona [2004] uses various non-soft approaches, such as:

– the going-concern opinion by the auditor: this qualifies the company to the group of financially distressed,
– indication of other models: if the model estimated for the same economy and for the similar period gives strong prediction of distress, then the company shall be classified accordingly as distressed,
– use of rating models: the banks exploit such models in credit risk assessment and they also may be used for determining the degree of distress.

The research by Wrona [2004] is aimed at finding distress predictors for Polish companies in 2002. The database is composed from the financial reports of companies published in *Monitor Polski B*. This research may be considered as the natural extension of the study presented here.

Other extensions may include examination of corporate governance variables and their influence on financial distress in Poland. The preliminary attempt in this regard can be found in Gruszczyński [2003a].

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APPENDIX

Table I. Estimation results for binomial logit models BLM 95

Ratio \ Model no.	1	2	4	7	8	10
P1 current ratio					x	
P2 quick ratio		x				
P3 cash ratio	x					
ROA1 return on total assets	x	x	x	x		x
A2 liabilities turnover						
A5 inventory cycle				x	x	x
Z1 debt ratio	x	x	x			x
Z4 adjusted liabilities/ sales					x	
Pseudo R-squared	0,453	0,440	0,429	0,281	0,498	0,443
No. of significant variables	1(1)	1(0)	2(2)	2(1)	1(0)	2(2)
Forecast accuracy (%)	84,78	86,96	86,96	84,78	82,61	84,78

Table II. Estimation results for binomial logit models BLM 96

Ratio \ Model no.	2	5	8	12	15	18
P1 current ratio		x				
P2 quick ratio	x					
P3 cash ratio				x		
ROA return on assets			x	x		
ROA1 return on total assets	x					
ROE return on equity		x				
R1 gross profit margin		x			x	
R2 net profit margin						x
A2 liabilities turnover					x	x
A5 inventory cycle			x	x		
Z1 debt ratio			x			
Z4 adjusted liabilities/ sales						
Pseudo R-squared	0,786	0,676	0,700	0,720	0,658	0,593
No. of significant variables	2(1)	2(1)	3(3)	2(2)	2(2)	2(2)
Forecast accuracy (%)	97,83	91,30	89,13	91,30	86,96	86,96

Table III. Estimation results for trinomial ordered logit models TLM 95

Ratio \ Model no.	2	4	6	8	9	12
P1 current ratio	x					
P2 quick ratio		x		x		x
P3 cash ratio			x		x	
ROA return on total assets				x		
ROA1 return on total assets		x			x	x
A2 liabilities turnover			x			
Z1 debt ratio				x	x	x
Z4 adjusted liabilities/ sales	x					
Pseudo R-squared	0,258	0,249	0,240	0,222	0,278	0,289
No. of significant variables	2(2)	2(2)	2(1)	2(1)	2(2)	3(2)
No. of signif. limit points	1	2	2	1	1	1
Forecast accuracy (%)	77,46	91,55	91,55	94,37	85,92	91,55

Table IV. Estimation results for trinomial ordered logit models TLM 96

Ratio \ Model no.	1	4	9	12	15	16
P1 current ratio		x				
P2 quick ratio			x			
P3 cash ratio	x			x		
ROA return on total assets			x			
ROA1 return on total assets	x					x
ROE return on equity			x			
R1 gross profit margin						
R2 net profit margin		x		x		
A2 liabilities turnover				x		
A5 inventory cycle					x	x
Z1 debt ratio	x				x	x
Z4 adjusted liabilities/ sales						
Pseudo R-squared	0,464	0,269	0,332	0,261	0,238	0,454
No. of significant variables	3(2)	2(2)	2(2)	3(3)	2(2)	3(2)
No. of signif. limit points	2	1	1	1	2	1
Forecast accuracy (%)	97,18	94,37	77,46	80,29	94,37	97,18