ARGUMENTA
OECONOMICA
CRACOVIENSIA

No 12 • 2015
ISSN 1642-168X
AOC, 2015; 12: 9–25
DOI: 10.15678/AOC.2015.1202

Barbara Pawełek
Józef Pociecha
Department of Statistics
Cracow University of Economics, Poland

THE USE OF STRUCTURAL EQUATION MODELLING TO SELECT FINANCIAL INDICATORS FOR A BANKRUPTCY--PREDICTION MODEL*

Abstract

The classical tool of bankruptcy prediction is the multivariate discriminant Altman model. The aim of this paper is to present a proposal for the use of structural equation modelling (SEM) to select financial indicators for an Altman-type bankruptcy prediction model. Financial factors, as diagnostic variables in bankruptcy--prediction models, are not in fact directly measurable variables, and they ought to be recognised as latent variables described by various measured financial indicators. So it is possible to use a structural equation modelling (SEM) approach for this purpose. A path diagram in terms of SEM for the Altman model is presented. Based on this diagram, three variants of SEM models for the general Altman model are estimated. The essential problem tackled in this paper is how to appropriately select non-bankrupt firms. Matching pair sample selection methods are applied. The non-bankrupt firms are from the same branch of industry and are similar in size. The major objective of our methodological proposal to use a general SEM model to study corporate bankruptcy is to overcome the difficulties in the modelling of bankruptcy risk through the use of previously-applied methods.

Keywords: corporate bankruptcy prediction, Altman model, structural equation modelling, matching pairs sample selection.

* This work was supported by National Science Centre (NCN), Grant No. N N111 540140.

1. Introduction

Bankruptcy, as a tool for economic purges that eliminates economically ineffective entities and those that cannot operate successfully on the market, is an inherent feature of free market economies. Methods to predict bankruptcy enable company boards to make readjustments to counteract the negative consequences of the scenarios that are foreseen. There are, however, negative social costs, which mainly entail loss of jobs and at least some loss of income on the part of employees at companies that go bankrupt. The company's owners and shareholders also suffer specific losses. What is more, except in cases of intentional corporate failures, bankruptcy implies that management has failed. In the light of all these negative consequences, knowledge of possible threats to a company's survival is highly valued in business (Pociecha & Pawełek 2011).

As the following list makes clear, there are many different roles and viewpoints involved in predicting bankruptcy (Pawełek & Pociecha 2012):

1) company management, in economic decision-making,
2) the bank – in the lending decision process,
3) the auditors – in the process of auditing financial statements,
4) the investor and financial analyst – in the process of making investment decisions on the capital market,
5) government institutions and economic organisations – in assessing the state of the economy.

A statistical model for predicting bankruptcy would seem a useful tool for assessing the likelihood that a company will fail. It usually forms part of the early-warning system for forecasting a company's economic and financial standing. Most bankruptcy-prediction procedures and models can be understood as methods of data classification (Pociecha 2006). Numerous variations on bankruptcy-prediction models have been formulated in the theory and practice of business. A detailed classification is presented by McKee (2000), who defines the following types of procedures and models: one-dimensional ratio models, multi-dimensional discriminant analysis, linear probability models, logit and probit models, classification trees, survival analysis (proportional hazard model), gambling models, expert systems, mathematical programming, neural networks, and rough sets.

Since it is hardly possible to determine the most appropriate models for predicting bankruptcy, a fundamental question should be posed: how reliable is bankruptcy prediction for a specific company? In the statistical sense, the answer to this question is offered by prediction error, which leads to another question: what are the errors committed when predicting corporate failure and what causes them? One error is associated with the value-related character of financial ratios. Of course, national and international accounting standards are available, but the measurement of financial values is still far from being unified. If financial indicators are the synthetic measures that best reflect a company's condition (Wędzki 2009), how does their selection as diagnostic variables in bankruptcy-prediction models influence the accuracy of bankruptcy prediction? We will attempt to answer this question here.

Another possible source of error is the sample-selection method. In the classical approach, population samples are randomised. The populations of companies are not very large, however, so that selection requires independent random samples. This is not how it works in practice, because the populations investigated are not based on random samples but instead on information about insolvent companies filed with court registers over a given period of time. In this way, the analysis covers the entire population rather than just a sample. Based on non-randomised methods, companies that have gone bankrupt are matched with companies that have performed well yet have characteristics that enable them to be compared with their failed counterparts.

Errors in bankruptcy prediction are often caused by cases of so-called strategic bankruptcy. The management boards or owners of thriving companies may deliberately drive their companies into bankruptcy after protecting their assets in tax havens, which is a course of events that bankruptcy-prediction models do not provide for.

Other errors may be caused by the instability of the populations investigated. Those of bankrupt and prospering companies in periods of economic boom are not identical with the same populations at times of economic crisis. Prediction error may therefore occur because the model is based on data from an economic boom, while the prediction itself has been formulated for a company during a recession. This raises the question of whether including business-cycle factors in prediction models raises their predictive capacity (Pawełek & Pociecha 2012).

These considerations lead to the conclusion that bankruptcy prediction should not rely solely on historical financial ratios. Changes in a company's economic environment, including business-cycle factors, have a significant impact on its financial standing and ability to operate as a going concern, which is something bankruptcy-prediction models must be able to cope with if they are to be accurate. The conclusion is that bankruptcy-prediction models should be dynamic rather than, as in the classical approach, static.

Financial factors, as diagnostic variables in a bankruptcy-prediction model, are in fact not directly measurable. Instead, they should be recognised as latent variables, which are described by financial indicators such as liquidity, liability, and profitability. For this purpose, structural equation modelling (SEM) can be used. The aim of this paper is to present a proposal for the use of SEM to select financial indicators for bankruptcy--prediction models. Though there are publications that have investigated similar economic problems with SEM, the authors are not aware of any work in the international literature that directly concerns the problem of bankruptcy prediction using SEM models. An example of a similar approach is provided by Maltritz, Buehn, and Eichler (2012), who used a MIMIC model (Multiple Indicators, Multiple Causes), which is a special kind of SEM group model, to study the determinants of countries' default and sovereign risk. Further examples are provided by Buehn and Eichler (2009), who used SEM modelling to compare the legal and illegal carriage of goods across the US–Mexico border, and Dell'Anno and Schneider (2009), who used SEM models to estimate the size of the shadow economy. Our paper falls within the research strand associated with these authors and publications.

2. A Structural Equation Model for Bankruptcy Prediction

The classical corporate-bankruptcy models assume that variables defined based on economic theory are directly observable. It is assumed that random deviations originate from the erroneous behaviour of entities (companies, industries, countries) or from errors in equations. Therefore, the model's residuals assess that part of the changeability of dependent variables not explained by the linear model of structural equations (Pawełek & Pociecha 2012).

The results of research the authors have conducted as part of their analysis of corporate bankruptcy suggest an alternative approach to the problem of treating measurement errors (errors in variables) as a source of random error (Maddala 2008 pp. 493–521). A discussion of a model that contains errors in variables as an example of a general linear regression model with random explanatory variables appears later on in the paper.

When attempting to identify firms that are likely to collapse, economic categories such as bankruptcy risk, financial standing, profitability, liquidity, reliability, and economic effectiveness can in fact be observed by monitoring financial indicators (financial ratios). Theoretical financial categories are treated as theoretical variables that are not directly observable and referred to as latent variables, theoretical constructs, or latent factors / features. It is assumed that due to the complexity of latent variables and / or measurement errors, observable variables reflect specific latent variables only to a limited extent. In a situation where the variables under consideration are latent, testing a model for observable variables may lead to biased estimations of a model's parameters (γ_{ij}) or of its random component (Konarski 2009, p. 44).

SEM structural modelling facilitates the development and testing of a theoretical model that reflects the postulated structural relations between latent variables. The difference between the classical model and the structural equation model for observable variables is that, instead of the observable variables (Y_j and X_j), structural equations describe latent variables (η_j) and pre-determined variables (ξ_j). Because latent variables are not directly observed, a structural model for them can only be considered as a sub-model of a larger model. A general model must include not only relationships between latent variables, but also relationships between latent relationships and their observable counterparts. A model that combines the observable variables Y_j and X_j with the latent variables η_j and ξ_j is referred to as a measurement sub-model (Konarski 2009, p. 46).

The general SEM model in this paper was used to test the hypothetical relationships between the variables and latent variables of a bankruptcy--prediction model. The use of this model requires the researcher to formulate statements for cause-and-effect relationships between variables. The general SEM model was constructed based on theoretical knowledge and the results of empirical research. Its main objective was to clarify the covariance structure of the observed variables based on a model of an economic process. Verification of alternative theories is accomplished by checking the extent to which the theoretical model is confirmed in the data set. The general SEM model contains two sub-models: a measurement sub-model, which specifies relationships between latent variables and their observable counterparts, and a structural sub-model for latent variables.

The first probabilistic tool for bankruptcy prediction employed multivariate linear discriminant analysis. It was first formulated by Altman (1968) in the form of the Z-score model and it remains the one in most frequent use. Altman chose multiple discriminant analysis as the appropriate statistical technique for assigning an observed object to one of two groups: bankrupt (distressed) companies and non-bankrupt (non-distressed) companies. The Z-score model is a linear discriminant function of measures that are objectively weighted and summed up to arrive at an overall score. This then forms a base for the classification of firms into one of two groups defined *a priori*: distressed companies and non-distressed companies.

The initial sample was composed of 66 firms with 33 firms in each of the two groups. After the initial groups had been defined and the firms had been selected, balance sheet and income statement data were collected. Next, a list of potentially helpful variables (financial ratios) was compiled for evaluation. These were then assigned to five standard ratio categories: liquidity, profitability, leverage, solvency and activity, which were chosen based on their prevalence and on their potential relevance to the study.

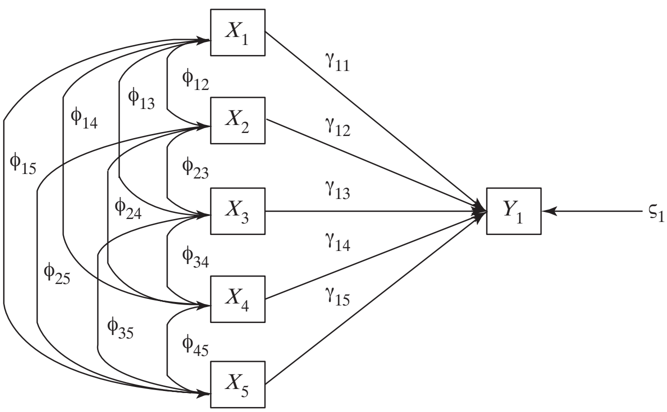
The final linear discriminant function (Altman's model) is as follows:

$$Y_1 = 0.012\,X_1 + 0.014\,X_2 + 0.033\,X_3 + 0.006\,X_4 + 0.999\,X_5,$$

where:

Y_1 – Overall Index (Altman's Z-score),
X_1 – Working Capital / Total Assets,
X_2 – Retained Earnings / Total Assets,
X_3 – EBIT / Total Assets,
X_4 – Market Value of Equity / Book Value of Total Debt,
X_5 – Sales / Total Assets.

Let us now present Altman's model in terms of SEM graphically (Fig. 1):

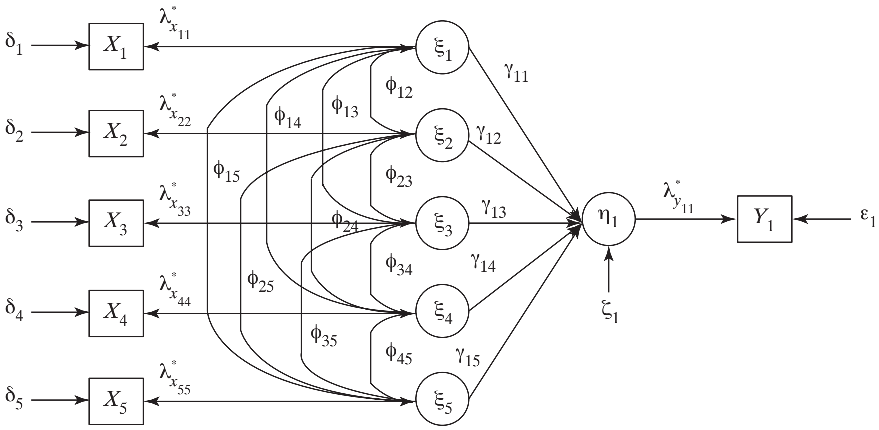


γ_{1j} – parameters of the model, ϕ_{ij} – covariates among variables X_i and X_j ($i, j = 1, \ldots 5$), ζ_1 – random error of Y_1.

Fig. 1. Path Diagram of Altman Model (without Errors of Measurements)

Source: prepared by the authors.

If we assume that Altman's model reflects the real dependencies among the latent variables η_1 and ξ_j ($j = 1, \ldots, 5$) represented by Y_1 (Altman's Z-score) and the observed financial indicators X_j ($j = 1, \ldots, 5$), we can construct a general SEM model that takes errors of measurement into account. Fig. 2 shows a path diagram of such a model.



δ_j – measurement error of financial indicator X_j, ξ_j – latent variable, η_1 – latent variable representing a firm's financial standing, λ^* – loading factors, ε_1 – measurement error of Y_1.

Fig. 2. Path Diagram of Altman Model (with Errors of Measurements)

Source: prepared by the authors.

The model presented in Fig. 2 cannot be identified: we have 21 different elements in the covariance matrix and an estimation of 28 parameters is needed. The idea of SEM modelling is to test various hypothetical relationships between observable and latent variables based on the general scheme set out in Fig. 2. To apply the model the researcher must formulate assumptions about the cause-and-effect relationships between variables, which are then verified by checking the extent to which the model is confirmed by the set of data (Pawełek & Pociecha 2012). The paper now considers an empirical method of constructing an SEM model based on Altman's scheme in the context of research into corporate bankruptcy risk at Polish manufacturing companies in 2007–09.

3. The Selection of Financial Indicators for an Altman-type SEM Model

This study is based on a data set drawn from manufacturing companies in Poland. The data for 2007 came from the Law Gazette of the Polish Government (*Monitor Polski B*), and from the EMIS database. Thirty financial indicators useful in bankruptcy prediction were examined

(Pawełek, Pociecha & Sagan 2013): liquidity ratios (4 variables), liability ratios (10 variables), profitability ratios (7 variables), productivity ratios (9 variables), and a zero-one variable that equals 1 if a company went bankrupt in 2009 and 0 in other cases.

This allowed us to distil by calculation four of the five financial indicators (X_1, X_2, X_3, X_5) in Altman's original model. Because of the different accounting systems used in Poland and the United States, we were unable to find data for Altman's X_4, which is Market Value of Equity / Book Value of Total Debt. Instead, we decided to substitute Shareholders' Equity / Liabilities for X_4, which is economically similar to Altman's original X_4.

The empirical data set for 2009 contained 59 bankrupt firms (B). There then arose the problem of how to select non-bankrupt firms (NB) to achieve a balanced sample of 59 bankrupt firms in 2009 and 59 non-bankrupt firms for the same time period.

Matched pairs sample-selection methods were applied. A firm in good financial condition (non-bankrupt) from the same sector and of a similar size was selected as a counterpart for each bankrupt firm. The quantity of total assets was chosen as a measure of the firm's size. The pairing criterion variable (C) was defined as: C = log (Total Assets). This criterion variable seemed appropriate for matched pairs because its distribution in the populations of bankrupt and non-bankrupt firms was very similar. The distribution parameters of variable C are presented in Table 1.

Table 1. Distribution of the Variable C = log (Total Assets) in Groups of Bankrupt and Non-bankrupt Firms

Group	Mean	St. Dev.	Skewness	Kurtosis	Minimum	Maximum
B	4.455	0.503	0.784	0.571	3.560	5.811
NB	4.518	0.444	0.459	–0.255	3.620	5.630

Source: authors' own calculations.

A graphical comparison of the distribution parameters of variable C is presented in Fig. 3.

The empirical distributions of the matching criterion variable (C) are presented in the form of histograms in Fig. 4.

In Altman's original model, the Z-score variable was a continuous one, but it was interpreted by him in fact as a categorical variable. He found the following cut-off points for variable Z:

1.81 or less – high chance of bankruptcy (zone I – no errors in bankruptcy classification),

2.67 or above – low chance of bankruptcy (zone II – no errors in non-bankruptcy classification),

1.81 $Z < 2.67$ – area of uncertainty (grey area).

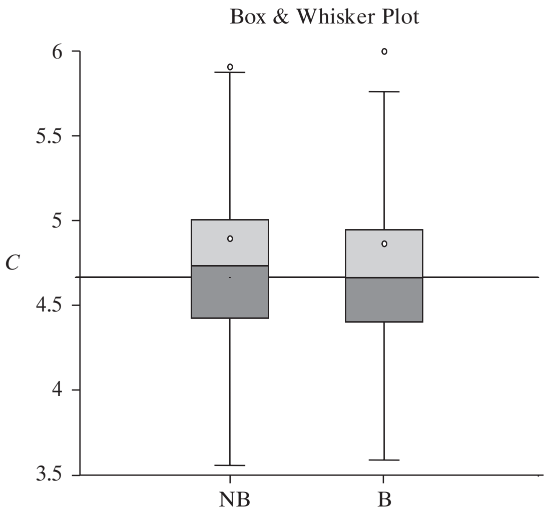


Fig. 3. Comparison of Size Measure (Variable C) Parameters in Bankrupt and Non-bankrupt Groups of Firms

Source: authors' own calculations.

We introduced the following six categories of bankruptcy risk (financial standing):

1 = *VS_B* – very strong risk of bankruptcy,
2 = *S_B* – strong risk of bankruptcy,
3 = *SL_B* – medium risk of bankruptcy,
4 = *LS_B* – moderate risk of bankruptcy,
5 = *L_B* – low risk of bankruptcy,
6 = *VL_B* – very low risk of bankruptcy.

Similarly, we categorised variables X_1–X_5 according to their quartile values. We introduced the following cut-off points as levels of bankruptcy risk: *Q1*(*B*), *Q2*(*B*), *Me*{*Q2*(*B*), *Q2*(*NB*)}, *Q2*(*NB*), *Q3*(*NB*). Finally, we obtained the categorical variables *N1–N5* instead of X_1–X_5.

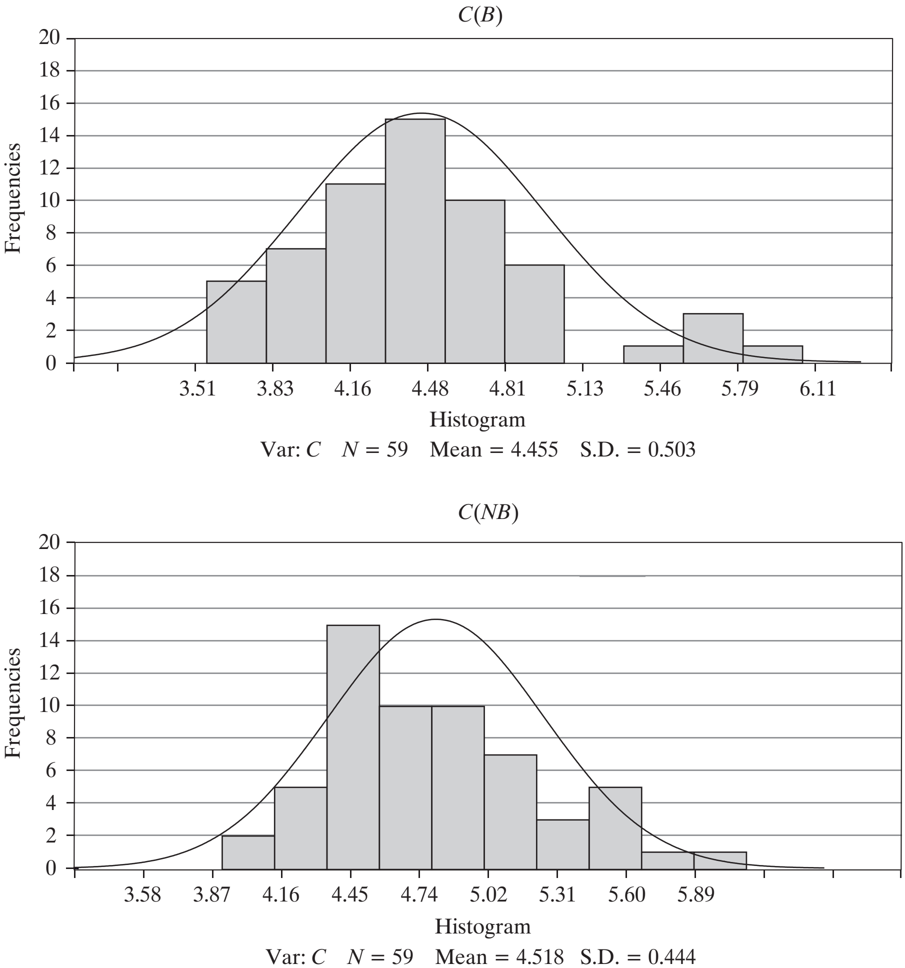


Fig. 4. Empirical Distributions of Matching Criterion Variable *C* in Groups of Bankrupt and Non-bankrupt Firms

Source: authors' own calculations.

We then used the homogeneity test of the hypothesis that the marginal distributions of two categorical variables with the same number of categories (6) are the same. The results are presented in Table 2.

In interpreting the results presented in Table 2 we can say that in the group of bankrupt firms (B) the marginal distribution pairs of categorical variables were usually different – except for pairs *N1–N4* and *N2–N3*, where the marginal distributions were not significantly different. A different situation prevailed in the group of non-bankrupt firms. Here, the pairs of categorical variables investigated either had similar marginal distributions or, due to the absence of some of the categories regarded as categorical variables, no homogeneity test could be performed to find them.

Table 2. Results of the Homogeneity Test for the Marginal Distributions of Pairs Categorical Variables

Group	Variable vs. Variable	Chi-Square	D.F.	*P*-value
B	*N1* vs. *N2*	12.933	5	0.024
	N1 vs. *N3*	13.786	5	0.017
	N1 vs. *N4*	3.117	5	0.682
	N1 vs. *N5*	10.302	5	0.067
	N2 vs. *N3*	8.289	5	0.141
	N2 vs. *N4*	16.122	5	0.007
	N2 vs. *N5*	21.978	5	0.001
	N3 vs. *N4*	22.565	5	0.000
	N3 vs. *N5*	35.427	5	0.000
	N4 vs. *N5*	19.873	5	0.001
NB	*N1* vs. *N2*	1.745	5	0.883
	N1 vs. *N3*	3.289	5	0.656
	N1 vs. *N4*	5.705	5	0.336
	N1 vs. *N5*	No	5	No
	N2 vs. *N3*	7.163	5	0.209
	N2 vs. *N4*	10.935	5	0.053
	N2 vs. *N5*	No	5	No
	N3 vs. *N4*	8.088	5	0.151
	N3 vs. *N5*	No	5	No
	N4 vs. *N5*	No	5	No

No – homogeneity test cannot be performed.

Source: authors' own calculations.

Polychoric correlation coefficients for ordinal variables were calculated to check the results of the homogeneity test. A polychoric correlation matrix for the sets of bankrupt and non-bankrupt firms is presented in Table 3.

The results presented in Table 3 confirmed the homogeneity testing, i.e. that the marginal distributions of pairs of categorical variables with the same number of categories were the same. We can see that a stronger correlation in the group of bankrupt firms was found only between *N1–N4* (polychoric correlation coefficient 0.693) and between *N2–N3* (polychoric correlation coefficient 0.744). A different picture emerged of the non-bankrupt population. Here, except for those between *N1–N4* (0.665) and *N2–N3* (0.894), most of the polychoric correlation coefficients were low, which was a similar situation to that of the bankrupt firms. The difference was that in this case the homogeneity test did not prove that there was a significant difference between the ordinal variables considered.

Table 3. Polychoric Correlation Coefficients for Ordinal Variables

Group	Correlation Matrix					
B		*N1*	*N2*	*N3*	*N4*	*N5*
	N1	1.000				
	N2	0.470	1.000			
	N3	0.229	0.744	1.000		
	N4	0.693	0.230	–0.007	1.000	
	N5	0.076	0.231	0.213	0.025	1.000
NB		*N1*	*N2*	*N3*	*N4*	*N5*
	N1	1.000				
	N2	0.201	1.000			
	N3	0.118	0.894	1.000		
	N4	0.665	0.294	0.326	1.000	
	N5	–0.040	0.070	0.100	–0.208	1.000

Source: authors' own calculations.

The work done at the next stage involved estimating SEM models for the data set of Polish manufacturing companies described above. We have seen the general scheme (path diagram) of the Altman model in Fig. 2. The task now was to test possible links between the observed and latent variables in relation to the general model. Three variants of estimated SEM models for the general Altman model (Fig. 2) are presented in Fig. 5–7.

When we compare Fig. 2 with Fig. 5 we can see estimates of δ_j variance $j = 1, \ldots, 5$ – measurement errors of financial indicators in the form of the categorical variables *N1–N5*; λ^* – loading factors for the latent variables *Eta_1* and *Eta_2*; γ_1 and γ_2 – parameters of the model; *Ksi_1* – latent variable (financial standing) and *Y* – overall index as a tool for classifying the bankrupt and non-bankrupt firms. We also attempted to interpret the latent variables *Eta_1* and *Eta_2*. *Eta_1* was influenced by *N1* (the level of liquidity) and *N4* (the level of liability). Finally, it was possible to interpret *Eta_1* as a latent variable representing the level of solvency. *Eta_2* was influenced by *N2* and *N3* (categories of profitability) and by *N5* (economic effectiveness). Taken together, *Eta_1* and *Eta_2* could be understood as a latent variable representing the economic quality of a firm's operation. The model presented in Fig. 5 is a simple SEM version of Altman's classical model. The symbols γ_1 and γ_2 (–) are correct (higher level of *Eta_1* and *Eta_2* – lower risk of bankruptcy).

The goodness of fit statistics for the first variant of the proposed SEM model are set out in Table 4.

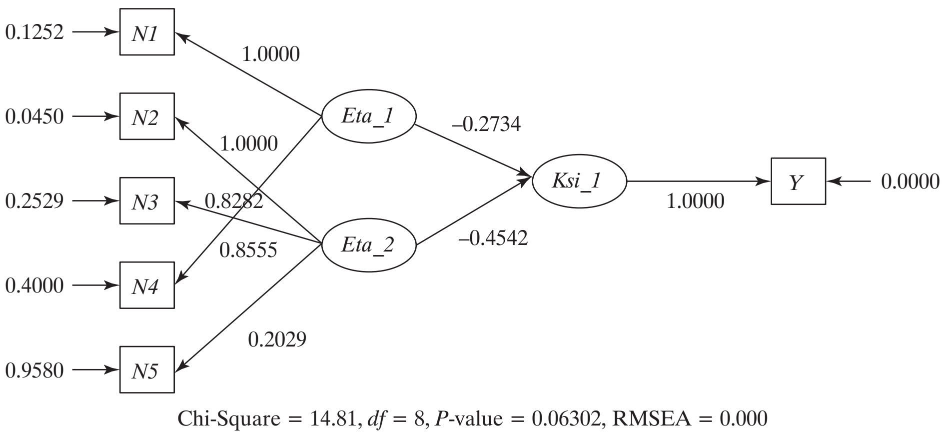


Fig. 5. General SEM Bankruptcy-prediction Model – Variant I

Source: authors' own calculations.

Table 4. Goodness of Fit Statistics: General SEM Model – Variant I

Measure	Value
Degrees of Freedom	8
Weighted Least Squares Chi-Square	14.8064 ($P = 0.0630$)
Root Mean Square Error of Approximation (RMSEA)	< 0.05
Goodness of Fit Index (GFI)	0.9955
Adjusted Goodness of Fit Index (AGFI)	0.9881

Source: authors' own calculations.

The first variant of the SEM model presented above does not take into account possible covariates between the latent variables *Eta_1* and

Eta_2. Variant II (Fig. 6) presents the estimated covariates between these variables.

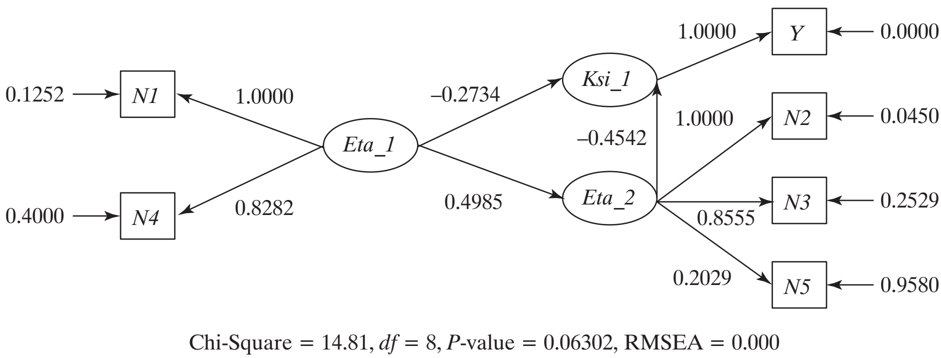


Fig. 6. SEM Bankruptcy-prediction Model – Variant II

Source: authors' own calculations.

As in variant I, the latent variable of solvency, *Eta_1*, depends on *N1* (liquidity level) and *N4* (liability level) and influences the economic quality of a firm along with *Eta_2*. Through the latter, it then influences *Ksi_1* (financial standing) as a latent variable. A possible reverse situation is presented in Fig. 7.

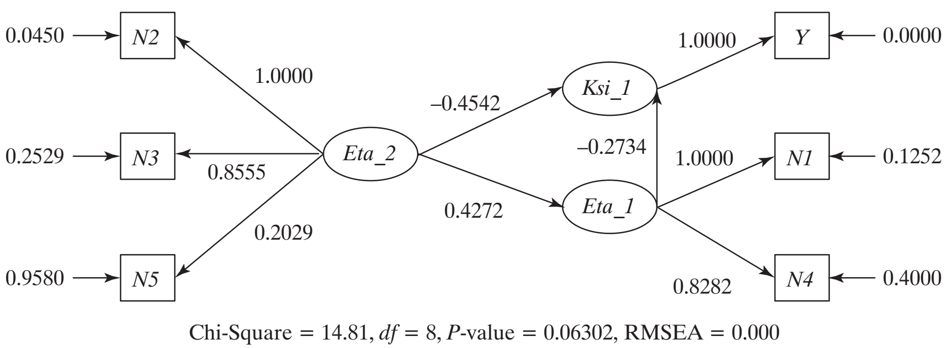


Fig. 7. SEM Bankruptcy-prediction Model – Variant III

Source: authors' own calculations.

In this variant, the economic quality of a firm, *Eta_2*, which is described by *N2* and *N3* (categories of profitability) and *N5* (economic effectiveness), influences the latent variable of solvency, *Eta_1*, and, through *Eta_1*, influences *Ksi_1* (financial standing) as a latent variable. Correct signs of the estimated structural parameters were observed in both situations (Fig. 6 and 7). That the study did not address the question of which SEM version of the Altman model fits economic reality best, but instead contented itself with showing the theoretical links among its latent constructs was one possible shortcoming. Another, but one that will require a separate study to redeem it, involves back-testing the SEM approach to determine whether it is a superior method. This can be achieved through the application of logistic regression and multivariate discriminant analysis to categorical versions of financial ratios in the form of observed explanatory variables.

In concluding this section it should be noted that the SEM models presented above were estimated using the weighted LSM method based on an asymptotical covariance matrix and a polychoric correlation matrix. The calculations were performed with the aid of LISREL 9.1.

4. Conclusions

The major objective of our methodological proposal to use a general SEM model to study corporate bankruptcy is to overcome the difficulties in the modelling of bankruptcy risk through the use of previously-applied methods. The theoretical and empirical investigations presented in the paper have demonstrated SEM modelling as a promising tool for the fruitful study of bankruptcy prediction. The research examined the use of SEM methodology in the selection of financial indicators for bankruptcy-prediction models as a subsidiary aim.

The proposal presented here stems from the usefulness of structural equation modelling for the statistical testing of hypothetical relationships between observable financial indicators and latent economic variables. As such, it deserves to be in frequent and regular use as a statistical tool for financial analysis.

Bibliography

Altman, E. I. (1968) "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy". *The Journal of Finance* Vol. XXIII(4): 589–609, http://dx.doi.org/10.2307/2978933.

Buehn, A. and Eichler, S. (2009) "Smuggling Illegal versus Legal Goods across the US-Mexico Border: A Structural Equations Model Approach". *Southern Economic Journal* 76: 328–50, http://dx.doi.org/10.4284/sej.2009.76.2.328.

Dell'Anno, R. and Schneider, F. (2009) "A Complex Approach to Estimate Shadow Economy: The Structural Equation Modelling" in M. Faggini and T. Lux (eds) *Coping with the Complexity of Economics*. Milan: Springer.

Konarski, R. (2009) *Modele równań strukturalnych* [Structural equation models]. Warsaw: PWN.

Maddala, G. S. (2008) *Ekonometria* [Econometrics]. Warsaw: PWN.

Maltritz, D., Buehn, A. and Eichler, S. (2012) "Modelling Country Default Risk as a Latent Variable: A Multiple Indicators Multiple Causes Approach". *Applied Economics* 44: 4679–88, http://dx.doi.org/10.1080/00036846.2010.528369.

McKee, T. E. (2000) "Developing a Bankruptcy Prediction Model via Rough Sets Theory". *International Journal of Intelligent Systems in Accounting, Finance and Management* 9, http://dx.doi.org/10.1002/1099-1174(200009)9:3<159::aid-isaf184>3.3.co;2-3.

Pawełek, B. and Pociecha, J. (2012) "General SEM Model in Researching Corporate Bankruptcy and Business Cycles" in J. Pociecha and R. Decker (eds) *Data Analysis Methods and Its Applications*". Warsaw: C.H. Beck.

Pawełek, B., Pociecha, J. and Sagan, A. (2013) "Latent Transitions with Mixture Rasch Model of Bankruptcy Risk in the Classification of Polish Firms" in *Programme and Book of Abstracts*. Proceedings of the Conference of the International Federation of Classification Societies (IFCS), Tilburg, the Netherlands, 14–17 July.

Pociecha, J. (2006) "Dyskryminacyjne metody klasyfikacji danych w prognozowaniu bankructwa firmy" [Discriminant data classification methods in estimating bankruptcy risk] in *Taksonomia 13, Klasyfikacja i analiza danych – teoria i zastosowania* [Taxonomy 13. Data classification and analysis – theory and applications]. Academic Papers of the Wrocław University of Economics No. 1126.

Pociecha, J. and Pawełek, B. (2011) "Bankruptcy Prediction and Business Cycles" in *Contemporary Problems of Transformation Processes in Central and East European Countries*. Lviv: Lviv Academy of Commerce.

Wędzki, D. (2009) *Analiza wskaźnikowa sprawozdania finansowego* [Ratio analysis of financial statements]. Volume 2. Second edition. Kraków: Oficyna Wolters Kluwer Business.

Abstract

Zastosowanie metody modelowania równań strukturalnych do wyboru wskaźników finansowych w modelu predykcji bankructwa

Klasycznym narzędziem prognozowania bankructwa jest model Altmana w postaci wielowymiarowej funkcji dyskryminacyjnej. Celem pracy jest przedstawienie propozycji wykorzystania modeli równań strukturalnych (SEM) do wyboru wskaźników finansowych predykcji bankructwa w modelu typu Altmana. Czynniki finansowe, jako zmienne diagnostyczne w modelach prognozowania bankructwa, nie są zmiennymi bezpośrednio i jednoznacznie mierzalnymi, mogą więc być traktowane jako zmienne ukryte, opisywane przez różnie definiowane wskaźniki finansowe. Możliwe jest zatem wykorzystanie metodologii SEM. W pracy przedstawiono wykres ścieżkowy, w kategoriach SEM, dla modelu Altmana. Wychodząc od tego diagramu, zaproponowano trzy warianty

SEM dla uogólnionego modelu Altmana, estymując ich parametry. Głównym problemem rozważanym w pracy jest właściwy wybór firm niebankrutów do próby bankrutów. Zastosowano tutaj metodę parowania, wybierając firmy z tej samej branży i podobnej wielkości. Przedstawiona propozycja wykorzystania modeli równań strukturalnych do badania bankructwa firm pozwala przezwyciężyć trudności modelowania ryzyka bankructwa, jakie pojawiają się przy stosowaniu dotychczasowych metod.

Słowa kluczowe: prognozowanie bankructwa firm, model Altmana, modele równań strukturalnych, metoda parowania.