MODELS PREDICTING POTENTIAL DEFAULT IN THE CULTURAL SECTOR

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Abstract:
This paper is focused on the possibilities of the default prediction among entrepreneurial entities belonging to cultural branches. Models predicting financial distress are commonly used for branches as manufacturing, construction, eventually services. Therefore their use for cultural entities cannot be suitable and provide reliable answers. Other reason is that cultural entities are too specific, based not only on equity value but also cultural value and using multi-source financing. Traditional mathematical methods used for financial distress prediction cannot be used without further modification for our purposes. Acquired data are available for cultural sector in the Czech Republic and therefore standard analytical approaches can be applied to the cultural sector. Appling standard mathematical methods leads to the modification of commonly used models predicting financial distress. Multiple discriminant analysis and logistic regression are used for authors' model construction. The result is an authors' model which is further evaluated and compared. The model is based on hundreds of observations and therefore the model has a high degree of robustness. It enables that results are statistically significant.

Keywords:
Bankruptcy predictors, cultural entities, financial distress, Czech Republic

JEL classification: G30, Z1

1 Introduction

Prediction of financial distress or potential default is highly interested issue which has been investigated at least for the last sixty years (Altman, 1968 or Beaver, 1966). At the beginning this research topic was connected with the developed market economies and freely tradable businesses. Later the research task has moved to the non-tradable companies and transition economies. The most effort led to economic areas which produced the highest proportion of GDP and therefore the typical investigated areas were and still are manufacturing and construction.

This paper is focused on the sector of cultural industries because it has become a highly monitored and more contributing economic branch in the last several decades. This is true not only for the developed economies but also for transition (nowadays also called posttransition) economies. The Czech Republic is an example of the posttransition economies. Although the work of authors as Florida (2002), Howkins (2001), Hesmondhalght (2007) or summarizing publication by the Czech author Cikánek et al (2009) have many differences, especially there is no consensus which all economic activities can be included in the term cultural industries, the importance of cultural or creative industries for national economies is significant and has been rising for the last decade. This statement can be confirmed by following estimates. According to the European Commission study "the Economy of Culture in Europe" mentioned by Němec (2013) cultural and creative industries created 2.6 percent of GDP in EU-15 in 2003. In the same year that economic branch contributed 2.3 percent to the gross domestic product (GDP) in the Czech Republic. Němec (2013) also provides a comparison for the year 2010. The branch of cultural and creative industries contributed roughly 4.9 percent to the Czech GDP in 2010, based on orientational calculations made on the basis of CZSO data.

The sector of cultural and creative industries has become significant but also it is also affected by internal and external changes in the Czech Republic nowadays. Many entities operating in this sector will have to be transformed in the following years. There are several incentives as the end of transition period of the Czech economy or market exiting of some entrepreneurs due to age, because it is already 25 years after the Velvet Revolution when the command economy has started to be transformed into the free market economy in the Czech Republic. Further information could be found in Čámská and Scholleová (2014). External changes are connected with the recent global economic crisis and new Insolvency Act which became effective in 2008. It has had an impact on the number of insolvency proceedings and it has also changed approaches to model predicting financial distress, detail in Čámská (2015) or Kislingerová and Schönfeld (2014).

The entities operating in the cultural and creative industries are more and more important according to contribution to gross domestic product and employment. They act as business partners, recipients of public grants, subsidies and other types of support or an object of purchase and sale. The aforementioned reasons open a research task if it is possible to predict a default of these entities. The aim of this paper is to construct a model or models predicting possible default which would be applicable by business partners or government authorities. It should help to come into interaction only with entities which are able to survive in the long run period and avoid donating or doing business with entities which will default.

2 Development of cultural and creative industries

Cultural and creative industries have become a highly monitored and more contributing economic branch in the last several decades. It is connected with the deep changes in the society of the most developed countries over the last half-century. Although a sharp rise of demand for entertainment, relaxation and recreation was observable also in 20s and 30s in the 20th century a real growing demand occurred at the beginning of 50s (or after the Second World War) and it lasts essentially to the present. The period of 20s and 30s is typical only for extremely wealthy society classes because lower income classes were able to afford only folk art in the form of cinematography. The 50s of the last century led to the mass character of entertainment, relaxation or recreation because of the deep societal changes which can be simplified into several statement:

- The population has gained an amount of new free time due to a reduction of working hours.
- Employment has increased, especially in the case of women in a significant way. It has had an impact on family incomes because it has created surplus and it has enabled higher living standard.

- The family budget surplus can be spent on the other services and assets which are dispensable as entertainment, recreation, relaxation and other related activities.
- The demand for entertainment and other related activities is not concentrated only in large cities any more but it covers also regions.
- New branches of entertainment have begun to evolve and even existing branches have strengthened, especially cinematography.

This societal change can be mostly connected with the developed countries but if we consider it deeply it is possible to find comparable characteristics also in the Czech Republic or former Czechoslovakia, in the Central Europe since 50s. The employment of women was high and over time the worked Saturdays were removed as well, so working hours were reduced.

The creative industries of our time are highly innovative and there is a dynamic development connected with available technologies. The evolution of creative and cultural industries has become the area of numerous surveys. We can mention works of Florida (2002), Howkins (2001), Hesmondhalght (2007) or summarizing study by Cikánek et al (2009) in the Czech Republic. These individual authors adopt different approaches which are especially clear in the case of a definition of the creative industries. According to a recommendation of the European Commission the Czech Republic has become used the tri-sectorial table since 2012 (Němec, 2013). The account of culture is divided into three parts following. First the culture sector includes sights, museums, galleries, libraries, scenic arts, visual arts, cultural and artistic education. Secondly the cultural industries consists of film, video games, television, radio, books and printing, music. Thirdly the creative industries contain architecture, design and advertising.

3 Development of the environment

The development of cultural and creative industries was also accompanied by the development of the environment in which entities of these industries operate. In the recent years the most discussions are connected with the global economic crisis which has a serious impact also on the economy of the Czech Republic. The number of insolvency proceedings has risen annually in the Czech Republic since 2008 how it is displayed in Table 1. The development of the economic environment and new Insolvency Act can be detected as reasons of this increase. This changes have started a scientific debate in the field of models predicting financial distress. Klečka and Scholleová (2010) investigated the models' reliability in the case of highly negatively affected Czech glass making industry. Previously created models predicting possible corporate default were labelled as not enough trustworthy. Authors as Hálek (2013) or Karas and Režňáková (2013) came with new approaches. This new as well as previous approaches are exclusively applicable in the industrial branches as manufacturing or constructing. Unfortunately the sector of cultural and creative industries has a lot of differences. Among differences we can name creation of equity value as well as creation of cultural value. There are also influences of economically impalpable terms such as “fashionability”, “artistic value”, “individuality of taste” or “national feelings”. This aspects are from the economic point of view analysed in Kislingerová (2012). Valuation of cultural goods is further solved by Smrčka et al (2014). It also implies that generating profit does not have to be the only aim of the evaluated entity. We can follow with multi-source financing because many entities operating in cultural and creative industries do not cover their costs only by their standard revenues (ticket sales) but also by selling souvenirs and mostly by public subsidies and private donations. Even the ticket sale dos not have to be the main source of revenues. This creates a specific area for approaches predicting corporate default which are described further.

Table 1 – Development of the number of insolvency proposals in the Czech Republic

Year	Insolvency proposals	Bankruptcy	Without recommendation of solution	Reorganization	Discharge of debts
2008	5 236	1 151	2 386	6	1 693
2009	9 396	2 180	3 462	10	3 744
2010	16 101	2 635	3 447	5	10 014
2011	24 466	2 617	3 805	23	18 021
2012	32 656	2 735	4 115	21	25 785
2013	37 613	3 140	4 243	17	30 213
1-2Q 2014	17 820	880	1 500	16	15 424
Total	143 288	15 338	22 958	98	104 894

Source: authors based on statistics of Expert group

4 Methods predicting corporate default

This chapter focuses briefly on methods and approaches of predicting corporate default or financial distress. According to the literature review we will refer works and different approaches. During years several mathematical-statistical methods have been used for creating models predicting possible corporate default. The historical development can be sum up with the most important representatives:

- One-dimensional (univariational) analysis (e.g. Beaver, 1966);
- Multiple discriminant analysis (e.g. Altman, 1968);
- Multiple logistic regression (e.g. Doran, 1989);
- Neuron networks (e.g. Etheridge and Sriram, 1997);
- The method of support vector machines (e.g. Hui and Sun, 2006).

The further emphasis is put especially on techniques which are user friendly and therefore users without high mathematical-statistical education are able to use them without errors. A clear disadvantage of all approaches is that they will be always only an approximation of reality (even in the case of learning neural networks). The consequence is that a certain amount of errors occurs always and users have to take it into account. First the users should know all models' limitation (Čámská, 2014) otherwise it does not have sense to use them. Secondly they should not used models automatically but as a part of deeper analysis (Neumaierová and Neumaier, 2014).

5 Methodology

This paper uses methods which enables fast classification of business entities in the defined categories. These methods for are multiple discriminant analysis (MDA) and logistic regression and they will be used for authors' model construction. Both methods are statistical and they are used for the assessment of credibility or prediction of default by banks, other institutions and by academic staff. Multiple discriminant analysis has been used for default prediction since 1968 when Edward Altman introduced his most cited paper in the area of corporate default predictions. The beginning of multiple discriminant analysis are connected with Fisher (1936). Multiple discriminant analysis is a technique which helps to classify certain objects (in our case business entities) into several groups (in the case of financial distress typically safe zone, grey zone and unhealthy/bankrupt zone). First we collect observations into groups according to the classification which means that it has to be known into which group each observation belongs. Secondly we formulate a decisive rule based on quantified characteristics of observations. This rule enables to classify the observations into defined groups. The decisive rule can have a shape of a linear as well as polynomial combination of several characteristics. According to Agarwal and Taffler (2007) there is no evidence that nonlinear combinations provide better results and therefore this paper uses the discriminant function in a linear shape how it is displayed by the equation 1.

$$Z_k = a_0 + a_1 x_1 + a_2 x_2 + \cdots + a_n x_n \qquad (1)$$

Z_k is the discriminant function (also called Z-score), a_i is a value of the discriminant coefficient, x_i is a value of quantified characteristic of the concrete observation and n displays the number of used characteristics. The used characteristics are in our case values of financial ratios derived from accounting statements. The characteristics which appear in Altman model are used also in this paper. According to Altman (1968) and Altman (2000) these characteristics are five financial ratios and namely:

- X_1 = net working capital (current assets – short term liabilities)/total assets,
- X_2 = retained earnings/total assets,
- X_3 = EBIT/total assets,
- X_4 = equity/total liabilities,
- X_5 = sales/total assets.

Multiple logistic regression is another statistical tool which can be used for the creation of model predicting corporate default. The dependent variable is a probability if an evaluated entity belongs to a different class (in our case safe or distress). Independent variables are entity's characteristics (in our case financial ratios). The logistic regression can be expressed as the logarithm of proportion of probabilities. The nominator contains the probability that the evaluated entity belongs to a certain class and the denominator contains the probability that the evaluated entity belongs to another class. It can be written as the equation 2.

$$L_k = \ln\left(\frac{p}{1-p}\right) = a_0 + a_1 x_1 + a_2 x_2 + \cdots + a_n x_n \qquad (2)$$

L_k signifies the score for the evaluated entity, p means the probability that the entity is classified as a certain class and a_i is a value of the discriminant coefficient, x_i is a value of quantified characteristic of the concrete observation and n displays the number of used characteristics.

6 Models' construction

The following chapter is focused on the construction of models based on multiple discriminant analysis and logistic regression for the sector of creative industries in the Czech Republic. First it is necessary to obtain data. We will specify the data source and requirements which these data have to fulfil. Second step is data clearing and dividing them into referential classes (safe and distress). It is followed by a selection of a training aggregate. Final step is a model creation. The high quality researches should not finish by this point but they should validate created models and compared them with already existing approaches. As examples of existing approaches Altman model (the modified version for 2000 in Altman, 2012) and Taffler model (Taffler and Tisshaw, 1977) have been chosen.

7 Dataset

Data are obtained from the MagnusWeb interface which is working over the corporate database Albertina and owned by the Bisnode company. The aim is to create model for entities working in the cultural and creative industries and therefore business entities working in this branch have to be obtained. According to the classification of economic activities CZ-NACE the group CZ-NACE 90 is selected because it fulfils paper's conditions. This group contains entities focusing on creative, artistic and entertainment activities. Micro companies are too much dependent on the owner and his/her creativity and therefore the condition that the entity has to have more than five employees. It means that micro companies are omitted. It has consequences that individual artistic activities (coded as CZ-NACE 90.03) are excluded. It consists of activities as painting, graphic art, writing, independent journalism etc. Our sample at the end contains following subparts of CZ-NACE 90:

- 90.01 production of live theatre performances, concerts, operas, dance and other stage performances,
- 90.02 supportive activities for the scenic arts with the production of activities contained in 90.01,
- 90.04 the operation of concert halls, theatres or other spaces for the performance of artists.

8 Sample preparation

The obtained sample from the MagnusWeb interface has to be prepared for the further analysis. First step is clearing. Unusable observations are omitted. It means that observations which have incorrectly reported data, data reported equal to zero or observations whose values of selected indicators are significant outliers. At the end the number of observations in the sample is equal to 3 158 cases. The cases have to be divided into referential groups – safe and distress. The distress groups contains observations with events as bankruptcy, inability to repay, forfeiture recorded and negative value of equity. The remaining cases are classified as safe.

The negative value of equity is a questionable condition. From the perspective of insolvency law there can be two conditions which start an insolvency proposal. These conditions are inability to repay and over-indebtedness. Over-indebtedness means that the sum of all the debtor's liabilities exceeds the value of its property and as well as the debtor is not able to continue in the administration of property or in the operation of business. Several analysis have shown that the condition of over-indebtedness is often more misused than it is used (Kotoučová, 2010 or Smrčka, Arltová and Schönfeld, 2013 or Schönfeld, Smrčka and Kislingerová, 2014). It means that business entities which fulfil the condition of over-indebtedness do not make their bankruptcy publicly known. They lengthen the timeframe because of high-risk trade operations which should rescue the company or of excision of assets from the creditors' reaches. The consequences are that the recoverability rate of receivables is minimized. Some entities with the negative value of equity are able to continue in the administration and operations but due to the legal insolvency rule and mentioned researches the negative value of equity is mostly connected with high risk of default.

9 Results

Results are two models predicting financial distress operating in the sector of cultural and creative industries. First model is based on the multiple discriminant analysis and the second on the logistic regression. Both models were obtained with the MATLAB (Statistic Toolbox) Software, concretely following function:

- discriminant functions for multiple discriminant analysis,
- the mrnfit function for logistic regression.

10 Multiple discriminant analysis

Z_k, the discriminant function (also called Z-score), which is generally introduced by the equation 1, is specified for our data sample. We obtained the decisive rule with the acquired coefficients. The result is expressed by the equation 3.

$$Z_k = 0.142 + 1.615x_1 + 1.032x_2 + 0.437x_3 + 0.001x_4 + 0.013x_5 \quad (3)$$

X_1, …, X_5 are values of financial ratios which were already specified. The function Z_k has a constant (0.142) and it implies that the cut off point between safe and distress zone has to be equal to zero. If the value of Z_k is higher than 0 the business entity is classified as safe, if the value is lower than 0 than the business entity is classified as distress and the probability of bankruptcy is high. Grey zone is not defined in our model which is strictly polarised.

Logistic regression

L_k, the logistic regression function, which is generally introduced by the equation 2, is specified for our data sample by the equation 4.

$$L_k = -0.32 + 2.905x_1 + 2.083x_2 - 0.839x_3 + 0.277x_4 + 0.624x_5 \qquad (4)$$

From the equation 2 it can be derived that the probability of distress can be expressed as the function 5 shows.

$$p_{distress} = \frac{1}{1+e^{L_k}} \qquad (5)$$

If the L_k has a negative value than the probability of distress is higher than 50% and that evaluated business entity is classified in the distress zone. If the L_k has a positive value than the probability of distress is lower than 50% and that evaluated business entity is classified in the safe zone.

The following table 2 describes the statistical significance of the estimated values of coefficients. P value is lower than 0.001 for all coefficients except X_3. It means that only the characteristic displayed by X_3 is statistically insignificant. X_3 represents traditional return ratio. Profitability is partly in contrast with the aim of entities belonging to cultural and creative industries as it is already discussed above. We have expected problematic moments of some parameters because of the branch specificity. Many entities do not create profit or other types of surplus as their main aim. It continues also in the value of retained earnings which display cumulative profits from previous years. Multi-source financing (in numerous legal forms) causes that no undivided profit arises because any surplus have to be conserved in the form of marginal reserve funds.

Table 2 – The statistical significance of model coefficients

Coefficient	P-value	Standard Error
–0.32*	0.0838	0.189
2.905***	8.348e-11	0.447
2.083***	3.414e-11	0.314
-0.839	0,110	0.525
0.277***	1.285e-06	0.057
0.624***	2.619e-05	0.148

Source: own authors' analysis

11 Prediction ability of models

The prediction ability of models has to be also verified. Firstly we will use data in-sample and we will verify our created models based on the multiple discriminant analysis and logistic regression. The prediction ability is verified in the different time events. In the case of bankruptcy or distress the time events are calculated as years before bankruptcy. In the case of the classification in the safe zone the time event is connected with the year of evaluation. Table 3 displays results for model's accuracy based on the multiple discriminant analysis. Table 4 displays results for model's accuracy based on the logistic regression. The prediction ability achieves almost 80% 1-2 years before bankruptcy/evaluation in the case of safe entities. The overall results are comparable for the model based on the multiple discriminant analysis and the logistic regression. There are not significant differences which is caused by the same used characteristics of the entities and by testing using data in-sample. Although there are recommendations that models predicting financial distress based on the discriminant analysis break some model's assumptions and for the purpose of predicting corporate distress models based on the logistic regression are more robust (detail in Čámská, 2015).

Unfortunately the number of observations significantly decreases during years. This is caused by low discipline to publish accounting statements and by short history of many business entities. The business entities have to publish regularly/annually their financial statements according to the law but many researches confirm that over 70% of companies do not publish their financial statements on time or at all (e.g. CRIF – Czech Credit Bureau, a. s., 2013). There are also significant differences among industries. The second reason is a short history which can be explained following. The business entities in the evaluated sector emerge only as production grounds for specific performances. If these performances are not successful the business entities exit the economic environment rapidly.

Table 3 – Prediction Ability of the Model Based on the Multiple Discriminant Analysis

Number of years before bankruptcy/evaluation	Number of observations	Number of correct detections		Number of incorrect detections	
		Number	%	Number	%
1	354	277	78.25	77	21.75
2	306	232	75.82	74	24.18
3	232	155	66.81	77	33.19
4	149	90	60.40	59	39.60

Source: own authors' analysis

Table 4 – Prediction ability of the model based on the logistic regression

Number of years before bankruptcy/evaluation	Number of observations	Number of correct detections		Number of incorrect detections	
		Number	%	Number	%
1	354	275	77.68	79	22.32
2	306	219	71.56	87	28.44
3	232	149	64.22	83	35.78
4	149	90	60.40	59	39.60

Source: own authors' analysis

12 Models' comparison

This chapter we will continue with larger data sample which contains all 3 158 cases. This will be supplemented also by models' comparison. Our results will be compared with the results of original Altman model and Taffler model which are the already existing well known models predicting financial distress.

The comparison is based on working with terms as Type I Error and Type II Error. Type I Error is when business entities classified as distress are detected by the model as safe. It is a huge mistake which can have a serious impact on the business because related business entities come into interaction with an ailing business unit without knowledge about it. Type II Error is not so serious in our case because the safe business entity is classified as distress. It can lead to loosing business opportunities because of risk avoiding when the other businesses do not come into interaction with this incorrectly classified entity.

Results of models' comparison are include in table 5. The number of incorrect classifications in the case of distress entities is comparable in the case of our models constructed with multiple discriminant analysis and logistic regression as well as of Altman model. The value of Type I Error is 14.55% in the case of multiple discriminant analysis, 13.61% in the case of logistic regression and 18.30% in the case of Altman model. Altman model shows slightly weaker results. It has lower prediction ability. Taffler model has terrible poor results because half of observations are classified incorrectly. It means that the model is not able to classify correctly 50% of distress companies. It is not a case of the sector of culture and creative industries itself but it is common for the model, proved by Machek (2014). The value of Type II Error is higher than the value of Type I Error for all models except Taffler model. It means that models predicting financial distress have difficulties to classify safe business entities correctly. It is probably connected with cultural specifications that many of these companies do not create the profit as the main aim. Many indicators/characteristics used in the models are based on the current or long term profit. In the case of logistic regression the value of Type II Error does not exceed 20% and in the case of multiple discriminant analysis 22%. The models with high prediction ability are generally connected with the statement that the value of errors cannot exceed 20-25%. Take in mind that models predicting financial distress are only the simplification of reality and they do not work as a natural law.
Results in table 5 prove that models constructed by this research have higher precision than models used for the comparison. This is caused by adaptation of models to conditions, firstly of the Czech environment and secondly of the particularity of the culture sector.

Table 5 – Prediction Ability (Models' Comparison)

	Correct classifications		**Incorrect classifications**	
	Number	**%**	**Number**	**%**
Multiple discriminant analysis				
Type I error	182	85.45	31	14.55
Type II error	2,303	78.20	642	21.79
Logistic regression				
Type I error	184	86.38	29	13.61
Type II error	2,390	81.15	555	18.85
Altman model				
Type I error	174	81.70	39	18.30
Type II error	1,955	66.38	990	33.61
Taffler model				
Type I error	106	49.77	107	50.23
Type II error	2,171	73.72	774	26.28

Source: own authors' analysis

13 Discussion

Our research showed that it is possible to use multiple discriminant analysis and multiple logistic regression for prediction of future possible corporate default in the specific industry branch which was presented as the sector of cultural and creative industries. At the end business entities belonging to CZ-NACE 90 were used. We had doubts and we did not expect that our constructed models will have high prediction ability. It was caused by the influence of multi-source financing and uncertainty of future incomes. The first explanation can be discovered as characteristics of surveyed business entities. It is possible that only minority of companies really depends on the financing or donating from public or private sources. If it is true then the influence of multi-source financing and uncertainty of future incomes is not so significant in our sample. Unfortunately we cannot have the possibility to presented statistical data more detail because this piece of information is not available. According to the division of CZ-NACE introduced above we believe that the dependence on public budgets have to be connected especially with groups 90.01 and 90.04. The second explanation arises from the stability of public support. In a certain time horizon there are long-term grants from public sources which enables the stability. Secondly in some cases the cultural entities are directly connected with municipal budgets and therefore imbalances of cash flows are reduced.

Model valuating financial situation of entities belonging to specific sector as cultural and creative industries have been constructed by authors. The model was also tested using not only data in-sample but also data out-sample. Results were compared with explanatory power of original Altman Z-Score formula and Taffler model. Obtained results show that new created model provides better inputs for a decision making process than previously created models which do not respect any specifics of that particular branch. There are not significant differences between construction approaches – multiple discriminant analysis and logistic regression which should be prefer because of its robustness.

14 Conclusion

Our research proved that it is possible to predict financial distress in the specific sector as cultural and creative industries. Models constructed by our research team are not difficult for further usage. Firstly their use does not need high statistical knowledge. Secondly they are based only on financial characteristics which are available in financial statements which should be regularly published. These financial measures are traditionally used because they represent parts of Altman Z-Score formula. Because of simplicity of constructed model it may find an application by related business entities, donators and providers of public support, subsidies and cultural grants. Financial distress could occur as a consequence of criminal or extremely irresponsible management because this research did not prove that instability of multi-source financing would be the most often reason.

There are many challenges for the further research. Models predicting financial distress can be modified due to specifics of culture entities. Financial measures represented in Altman Z-Score have a good explanatory power for profit organizations from manufacturing and construction industry but they do not respect any specifics of cultural and creative industries. It is possible to reduce the weight of profit in the models. The data sample should be broaden because not all entities belonging to cultural and creative industries are contained by CZ-NACE 90. The last step is international comparison. It would show if there are differences among companies operating in the Czech Republic and other countries. It would prove if the bankruptcy prediction methods have enough prediction ability for their users. These methods cannot provide unreliable results because it would influence the decision making process in incorrect way and lead to serious negative consequences.

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