HOW TO PREDICT POTENTIAL DEFAULT OF CULTURAL ORGANIZATIONS?

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Abstract

Cultural industries have received increasing academic attention over the past decades. The prediction of default represents a vast area of finance and accounting.Since the companies operating in these industries are considered to be very specific, the performance of classical methods of default prediction is questionable. This paper explores the possibilities of using methods of default prediction in the area of companies operating in cultural branches. On a sample of 3,158 observations of companies operating in the Czech cultural sector, we develop the use of multiple discriminant analysis and logistic regression to predict the financial distress of these companies. The results suggest that these methods can have a high predictive ability, provided the coefficients are accurately estimated.

Keywords: bankruptcy indicators, culture, financial performance, distress

JEL Classification: G30, Z1

1 INTRODUCTION

The sector of cultural industries has in the last three decades become a highly monitored specific economic area. This is connected with numerous facts, one of which is the deep societal changes which have occurred in the most developed countries over the last 50 years. A marked rise of demand for "entertainment" was characteristic even for a part of the 20s and 30s in the 20th century, although during this time this was a demand socially limited to the extremely wealthy and the wealthy echelons of society, whereas the demand among lower income brackets was satisfied with what was essentially folk art in the form of cinematography. A growing demand beginning on the 50s of last century and lasting essentially to the present is, however, characteristic in developed countries in its mass character and insofar as it is highly structured. The entertainment of our time is usually highly innovative, it works with constant emendation of technologies, it is subject to fashions and constant changes, and it has lost the style-creative characteristic for art until the first half of last century. The growing demand has brought about the formation of what is truly an essentially industrial structure in this sector, which has led to the emergence of entirely new branches, such as programming of computer games and applications for mobile devices. If we have mentioned the style-creative role of art lasting until the first half of the 20th century, then our century is characterized by a new style-creativeness, where entertainment and productions of the cultural industry express social life, inter-human relationships and numerous other social facts.

The emergence of an evolution of creative industries has become the subject of numerous surveys, and it would be unsuitable here to treat this problem in a more comprehensive manner – it has been explained many times. In this regard, we can refer especially to the work of Florida (2002), Holden (2004), Hesmondhalght (2007); from the Czech environment might be mentioned comprehensive study of Cikánek et al. (2009). Although the views of individual authors differ in many respects, a core of sorts is always formed by activities which are commercial and at the same time artistic or entertaining.

The significance of creative industries for the economic development of the European Union and specifically also the Czech Republic can be documented by Němec (2013): *"According to our approximate calculations made on the basis of CSO data, cultural and creative industries contributed more broadly to the CR GDP in 2010, almost by 4.9 % (of which cultural industries accounted for 1.9 % and creative industries 3 %)."*

The prediction of financial distress represents a vast area of finance and accounting. However, due to the specifics of cultural companies, the possibilities of using the methods of default prediction, especially in the Czech Republic, remain relatively undiscovered. Although there exist some models adapted to the Czech environment (such as the Altman's Z-score), their predictive ability for the companies operating in cultural industries is questionable and needs to be tested.

The goal of this paper is to analyze the possibilities of using methods of default prediction in the area of companies operating in cultural branches and to develop a set of coefficients which allow a sufficient predictive ability of such methods. We will present the use of multiple discriminant analysis and logistic regression to predict the financial distress of these companies and test their predictive ability.

2 SAMPLE ANALYSIS

We will focus more comprehensively on the methodology of predicting financial distress, and then on a definition of the data sets and finally on the analysis itself and the results thereof.

2.1 Methods Predicting Financial Distress

Numerous statistical methods are used for the prediction of financial distress. The following can be mentioned:

- 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);
- Models that take into account the evolution of firm's financial health over time, such as terminal failure processes (Du Jardin, 2015).

For specific sectors, other methods can be applied, such as the general equilibrium analysis to predict bank and their clients' default (see e.g. Machek et al., 2014). Most often, the methods are based on the values of financial ratios.While it is known that accounting information is not always reliable (see e.g. Tyll and Pohl, 2015), it is perhaps the most practical source of information that the users of bankruptcy prediction models can quickly obtain.

Multiple discriminant analysis (MDA) is a statistical method which is used in economics not only in the theory of investment but also for the assessment of banking house client credibility, especially in the area of predicting financial distress. It began to be used especially after the publication of Altman's paper (1968). MDA is a statistical technique used for classifying a certain object into previously given classes in dependence to the values of several factors. The first step is the formation of so-called training aggregates, i.e. observation aggregates where the class to which they belong is known. The formation of a decisive rule, which enables univocal classification of objects into one of the classes, occurs. In the case of a linear discriminant function, the decisive rule has the shape of a linear combination of several signs. The output of linear MDA, therefore, is an aggregate of discriminant coefficients, including a linear member. The discriminant function (the decisive rule, also the

Z-score) has the following shape in the case of the n-sign (in this article Z_k will continue to denote the discriminant function for businesses in the culture sector in the Czech Republic):

$$Z_k = a_0 + a_1 x_1 + a_2 x_2 + \ldots + a_n x_n \tag{1}$$

where a_i is the discriminant coefficient, x_i is the value of the sign and n denotes the number of signs.

Multiple logistic regression is another statistical classification method which enables the prediction of category variables on the basis of independent variable values. Probability-describing outputs are modelled with the aid of logistic functions. The output of logistic regression is the probability that the given object belongs to a different class, i.e. the logarithm of proportion of probability that the given object belongs to a certain class, and the probability that it belongs to another referential class. Expressed formally,

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

where L_k will continue to signify the score for businesses in the culture sector in the Czech Republic, $p$denotes the probability that the objects fall into a certain class, a_i denotes the regression coefficient, $x_i$is the value of the sign and $n$denotes the number of signs. The regression coefficients thus reflect the effect of independent variables on the relative probability that the object falls into a certain class as against the referential class.

The advantage of the above-mentioned approaches is their simplicity and fast and practical applicability for the classification of objects into classes. A clear disadvantages that it is an approximation of reality which is almost always burdened by a certain error and should therefore not be utilized mechanically, but rather in the context of deeper analysis (Neumaierová and Neumaier, 2014).

In this regard, it should also be mentioned that subjects from the culture sector are usually considered highly specific for various reasons. Firstly, their financing usually does not fulfill standard concepts insofar as multi-source financing occurs in numerous areas. Therefore, turnovers for sold products and services (turnovers from ticket sales in the given case) are only one of the incomes, often by no means the main one. This aspect can often transpire to be problematic in the case of application of methods to the “culture” sector, for placing it into a context for deeper analysis appears to be almost impossible here. In the following passages we will show that input data are necessary for the implementation of analytical methods, whilst we will see that none of these data touch the specific problems of the branches which, for the purpose of simplification, we have defined as “multi-source” financing, with the awareness that the real range of particularity is substantially larger and is connected with both economically impalpable terms such as “fashionability”, “artistic value”, “individuality of taste” or “national feeling”. From the economic perspective this aspect is analysed by Kislingerová (2012).

On the other hand, these terms may necessarily play a significant role in the case of “creative” industries, but not in relation to past data. The preceding data are always given as firm and will withstand essentially standard economic research. An important moment, however, is the ability of the prediction and whether the models would – at least theoretically – fail in a larger degree than usual, which should be given by uncertainty in the issue of incomes dependent to non-economic decision-making processes. What is at issue is that incomes dependent on political or other decisions should in essence be of higher risk as regards prediction of acquisition or non-acquisition thereof than funds from ticket sales or collected in another economically definable manner. As we will demonstrate later on specific results, it seems that these funds are with high probability at least as predictable as standard incomes.

2.2 Specifying the Dataset

Data from the Bisnodecompany, or more precisely the MagnusWeb interface working over the Albertina database, were used. On the basis of available data, companies with at least five employees and doing business in the CZ-NACE 90 were selected. In general, creative, artistic and entertainment activities, especially the scenic arts, supportive activity for the scenic arts, artistic creation and operation of culture facilities belong here.

The acquired sample of companies has been cleared of unusable observations (incorrectly reported data, such as zero or nonsensically high indicator values), by which the number of observations was reduced to a total of 3,158 cases. This sample was divided into two classes – “safe” and “distress”. The “distress” class included observations among which events of the “bankruptcy”, “inability to repay”, “forfeiture recorded” and “negative equity” types were recorded. The remaining companies were classified as “safe”. A training aggregate for MDA and logistic regression was gained from this sample.

The condition of five employees ensures that an adequately representative number of companies will be contained in the sample; at the same time, individual activities with a dominance of artistic creation among which the concept of default caused by entrepreneurial activity can be conceived only with difficulty have been eliminated. The acquired number of subjects is marked, among others, clearly due to the fact that trading companies in this sector emerge once only as production grounds for specific performances or a smaller number of performances; in the event of failure, they depart from the economic environment fairly rapidly; contrariwise, in the event of success they continue for a longer period.

2.3 Employed Methodology

MATLAB (Statistics Toolbox) software was used for classification – specifically, the following functions:

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

The results were subsequently verified on other companies circulating in the culture sector, and comparison with other bankruptcy models – Taffler’s model (Taffler and Tisshaw, 1977) and Altman’s model (the modified version for 2000)– was also undertaken; verification of ability to predict default over a longer period – which we consider to be an especially interesting attempt towards a logical conclusion as regards higher riskiness of multi-source financing (under the assumption that one or more financial sources are dependent on political decisions connected with handling public funds or on the decisions of sponsors) – was also undertaken. In contrast to classical models, the so-called “grey zone” was not defined, for its univocal delimitation is impossible with respect to the available data, and a warning signal, i.e. classification into the grey zone area, can be provided by a Z_k or L_k value approaching zero. This applies especially in the context of the time development of these indicators. From the nature of the classes, moreover, the requirements for classification into the “safe” class are relatively strict: Negative equity is sufficient for classification of a company as “distress”.

The fact of negative equity is among the numerous specifics of subjects in the culture sector. This of course does not concern all entrepreneurial activities. However, in the NACE-CZ 90 category, the appearance of negative equity will, with a high degree of probability, be relatively common. Especially among productions, there are no grounds to expect other real assets besides gathered know-how. In this regard, it represents rather a potential than a real knowledge or capability advantage on the market. Moreover, it is not the property of a trading company or other subject – producer which is at issue, but ability and potential gained on a contractual basis in the form of providing services or performances by the carriers of this know-how. As we can see, the position of the producer is very weak and vulnerable in this sense, and investors are no doubt aware of this. If the main asset of a production is the right for temporary utilization of abilities on the basis of contractually bound creative and other workers – carriers of know-how required for creating a cultural good, we must then consider this entire sector as extremely risky from an investor's perspective.

But let us return to the basic assumption that, even given maximally "creative" accounting, it is not possible in the case of a production – unless a strong investor injects capital into the business – to achieve a state of affairs where the trading company (producer) would not be in a state of over-indebtedness, i.e. that its liabilities would not exceed its assets. As we have argued above – in the bounds of our assumption, this is given to a significant extent by the logic of doing business in this sector as such. From the perspective of insolvency law, this is one of the few situations where the expression of Section 3 para. 3 of Insolvency Act is justified – where over-indebtedness is indeed defined as a situation in which the sum of the debtor's liabilities exceeds the value of its property, although when fixing the value of its property, account is taken of further administration thereof, possibly of the further operation of its business if it can reasonably be assumed, whilst bearing in mind all circumstances, that the debtor will be able to continue in the administration of property or in the operation of the business. In recent times, several analyses have been undertaken of situations resulting in insolvency proceedings, from which it stems that this expression is misused more often than it is used (Smrčka et al., 2013; Schönfeld et al., 2014). This is to say that entrepreneurial subjects which fulfill the condition of over-indebtedness as one of the forms of debtor bankruptcy have a tendency not to make their bankruptcy public and utilize the largest possible timeframe either for attempts to rescue the company by means of high-risk trades, or contrariwise for excision of property from the creditors' reaches. Both of these approaches have the same result for the creditor – minimization of the recoverability of their receivables.

This all means that over-indebtedness can be a fairly standard state of affairs in numerous companies or any other organizational structure used as a legal form of activity in the area of the creative industries, culture or artistic creation. Despite this, we will retain as valid the rule that negative equity is a reason to classify a subject into the "distress" group.

For classification, the same signs which appear inAltman's bankruptcy model (seeAltman, 1968 and Altman, 2000) were used,

- x_1 = net working capital / assets
- x_2 = retained earnings / assets
- x_3 = EBIT / assets
- x_4 = total equity / total liabilities
- x_5 = sales / assets

Sign x_1 expresses the hypothesis that companies with a deteriorating financial situation will have rather a negative liquidity expressed with the aid of net working capital. Sign x_2 reflects the stability of the company, for it contains retained earnings from previous years. Sign x_3 is the level of a company's asset viability when abstracting from tax influences and capital structures. Sign x_4 expresses the extent to which the company's assets can lose their value before the company's liabilities exceed the value of its assets and the company becomes unable to repay. Sign x_5 is the classic asset turnover and thus measures the efficiency of the company's asset usage.

We can find even here several problematic moments or parameters which we should perhaps relativize whilst taking into account the particularity of the branch. For instance, "retained earnings from previous years" is a concept in numerous legal forms utilized in this area of the problem, for the entire system of multi-source financing is in essence usually fixed so that no undivided profit arises, and if so, it should be conserved in the form of marginal reserves.It applies that injections from public funds secure the remainder of financing for estimated incomes from turnovers and from sponsoring or supplementary entrepreneurship, as the case may be. Under the concept of "remainder", it is most certainly impossible to expect that some or other "surplus", i.e. profit, is to be generated.

Despite this, we have decided also in this case to retain all parameters in the original form insofar as prior to proceeding to the expression of an adjusted bankruptcy model, it is necessary first to test its standard form. Moreover, as we will speedily show, a significant moment of each model is the expression of decisive rules.

2.4 Multiple Discriminant Analysis

The decisive rule can be expressed with the aid of acquired coefficients. The resulting classifying functions have the following forms, and the resulting Z-score can be expressed with the aid of the following function:

$$Z_k = 0.142 + 1.615x_1 + 1.03x_2 + 0.437x_3 + +0.001x_4 + 0.013x_5 \tag{3}$$

If the value of the function is higher than 0, the business is classified into the "safe" category. Otherwise, it is possible to classify it into the "distress" category. We can define the above-mentioned "grey zone" as an area of results approaching zero insofar as the more the result approaches zero, the more problematic the subject.

2.5 Logistic Regression

The regression function for the natural logarithm of the proportion of probability can be expressed with the aid of the following function:

$$L_k = -0.32 + 2.905x_1 + 2.083x_2 - 0.839x_3 + +0.277x_4 + 0.624x_5 \tag{4}$$

The statistical significance of the estimated coefficients is described in the following table. It is clear that the estimate is relatively precise; only the coefficient at sign x_3 is statistically insignificant.

Tab. 1 – The Statistical Significance of Model Coefficients (Logistic Regression). Source: our analysis

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

Note: *** - p< 0.001, ** - p< 0.05, * - p< 0.1

It can be deduced from the relation (2) that the probability that the object falls into the "distress" class is given by the relation

$$p_{distress} = \frac{1}{1+e^{L_k}} \tag{5}$$

This relation, however, does not have to be utilized in practical applications, for a negativeL_k value signifies that the given probability is higher than 50 %, which suffices for classification into the "distress" category. If the L_k value is positive, the object can be classified as "safe".

The following tests were conducted to test the reliability and prediction ability of the models. First, the discriminant ability of the given five signs for business conditions in the culture sector (or more precisely, CZ-NACE 90, i.e. a specific sample of businesses in the culture sector) was tested in the form of a bi-selective pair t-test for a mean value.

2.6 Discriminant Ability of the Signs

The discriminant ability of individual signs has to be verified in order to verify the reliability of the model. To verify that the averages of values of individual vary for the "safe" and "distress" classes, a bi-selective pair t-test on a mean value was used on a sample of 321 randomly selected companies in both classes. The results are shown in table 2. The differences in the mean values of all the signs are statistically significant, which is suggested by the highly marked differences in the averages of individual signs in the "safe" and "distress" categories. Financially healthy companies demonstrate higher values in these signs than firms threatened by bankruptcy.

Tab. 2 – Mean Values of the Signs and the Significance Test. Source: our analysis

Sign	Meanvalue „safe“	Meanvalue „distress“	T-statistic
x_1	0.27	-0.08	8.59*
x_2	0.03	-0.66	7.14*
x_3	0.02	-0.31	9.55*
x_4	5.89	0.50	4.18*
x_5	1.08	0.79	4.68*

Note: * Statistically significant ($p < 0.001$ on the level $\alpha = 0.05$).

3 PREDICTIVE ABILITY OF THE MODELS

The predictive ability of the models was tested for one up to four accounting periods (tables 3 and 4). It is clear that the predictive ability drops in time, yet it nevertheless remains relatively high even four years prior to recording a negative event. From the perspective of longer-term prediction ability, multiple discriminant analysis demonstrates a slightly higher success rate in a series of 1-3 %; it is identical in the case of four years until bankruptcy.

Although Altman (1968) suggests not using discriminant analysis for more than a two-year historical period, it is clear that the predictive ability does not fall in a dramatic way in this case of prediction ability. It is evident that the values of all five signs drop with an approaching bankruptcy. The real predictive ability of classic bankruptcy models is also telling for a similar period (Machek, 2014). On the other hand, it is adequate in practical applications of a 1-2 year period for timely detection of a signal of negative development of a company's financial situation.

Tab. 4 – Predictive ability of the Model (Multiple Discriminant Analysis). Source: our analysis

Number of years until bankruptcy	Number of observations	Number of correct detections		Number of bad 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

Tab. 5 – Predictive ability of the Model (Logistic Regression). Source: our analysis

Number of years until bankruptcy	Number of observations	Number of correct detections		Number of bad 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

4 DISCUSSION

Multiple discriminant analysis and multiple logistic regression are, in the case of subjects defined as NACE-CZ 90, capable of longer-term prediction of financial distress. The high ability of models to predict financial distress in the sector of subjects operating in the culture sector (CZ-NACE 90 in the given connection) is therefore surprising and it will be apposite to attempt an interpretation of this state of affairs.

A highly probable explanation appears to be the assumption that the influence of multi-source financing and the approaching uncertainty of future incomes connected therewith are lower than we expected at the beginning of the work. One can arrive at this from two related, albeit not identical reasons. The first is the possibility that, of the surveyed subjects, only a minority suffer real dependence to financing from public funds, so the influence of this phenomenon is not large. Although we do not have the possibility to present more detailed statistical data, we consider this to be probable to a relatively small degree. With respect to the CZ-NACE 90 characteristic, we are convinced that the dependence to public budgets must necessarily be marked especially in groups 90.01 and 90.04.

The second possible reason is the variant that financing from public funds – although based on potentially uncertain decision-making of a political type, i.e. an economically irrational method – is adequately reliable and predictable in time as one of the incomes.

The decision as to which of these theses is more correct and corresponds more to the situation is not possible without a series of detailed case studies and especially without the possibility to survey thoroughly the influence and development of individual income layers of subjects accepted into to the surveyed aggregate. As was stated above, we consider the second possibility more probable, i.e. that the irrationality of political decision-making in the public funds sector aimed at culture is constant and in principle predictable thanks to this. A certain role can then be played also by the “enforceability” of support from public funds, when the pertinent subjects react adversely to attempts to change the system and adjustment of subsidy flows, likewise to potential changes in the mechanisms of the division thereof, which then leads to more frequent retention of the status quo than to advancement of changes.

Another possible explanation seems to be the circumstance that support from public budgets is in many cases placed in a truly predictable manner, at least within a certain time horizon – this concerns the places and bodies of the state administration or self-government which proceed along the path of apportionment of long-term grants (three or five-year), which clearly increases the financial stability of the environment as a whole. In other cases, culture facilities are connected directly to the municipal budget, and its fulfillment is decided upon to some degree in advance, which enables adjustment also of activity and costs. Of course, this then means that such facilities are able to reduce or strengthen their activity in dependence to the degree of certainty the pertinent budget provides to them. Then, however, financial distress could occur only through criminal or extremely irresponsible conduct on the parts of the managers of the production or culture facility.

5 CONCLUSION

While companies operating in the cultural sector are very specific and deserve academic attention, the past literature has been particularly silent on the possibilities of default prediction for these companies. In this article, we presented the use of multiple discriminant analysis and multiple logistic regression to predict financial distress and tested their predictive ability. We suggest that when the coefficients of the models are accurately specified and adapted to a particular environment, their predictive ability can be considered high, even in long term.

Several managerial implications arise from the study. Since the application in practice of these models is quick and straightforward (the financial ratios can be obtained directly from the financial statement of a particular firm and the relationships are linear), the models can be used by professionals to predict a potential financial distress of a company, and to take timely measures to avoid it.

The study also has some limitations. In contrast to classical models of bankruptcy prediction, the so-called “grey zone” was not defined. However, a decreasing value of zero of the models’ function, or a value approaching zero, can be and seen as a warning signal.

There are multiple challenges for the future research. First, the predictive ability on an international level should be analyzed as well. While there are undeniable differences of companies operating in Czech cultural industries from other companies, it would be interesting to observe if the same differences exist in other countries, and if the bankruptcy prediction methods (in particular, the multiple discriminant analysis and multiple logistic regression) perform well enough. Second, the cultural industry as defined by this study is relatively broad and it does certainly not capture the great variability in cultural company forms. The development of a model which takes into account such variability would be interesting and could represent one of the directions of the future research.

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