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# "SLICE-OF-LIFE" CUSTOMIZATION OF BANKRUPTCY MODELS: BELARUSIAN EXPERIENCE AND FUTURE DEVELOPMENT

**Summary:** After the recent financial crisis commencing in 2007, bankruptcy prediction has become a major concern and, as a result, today we have lots of different approaches to the bankruptcy prediction models but all of them full of limitations. Because of this (and not only) neither the Altman models nor other more recent models (partitioning algorithm, survival analysis, expert systems, neural networks, etc.) are recommended for use with financial companies. In order to overcome these limitations in modern Belarusian practice suffering from a lack of developed bankruptcy theory it is not enough to transfer foreign practice automatically to the reality of its national evolving economic conditions. This study attempts to show how a "Slice-Of-Life" approach, based on national circumstances and priorities, can be used to improve the temporal stability of the accuracy of a financial failure models for Belarusian companies.

**Keywords:** Bankruptcy prediction, customization of bankruptcy models, MDA, logit and probit analysis.

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## 1. Modelling methods

Most of the modern discussion devoted to the problems of bankruptcy prediction are related to modelling techniques, sampling and variable selection, control parameters, model design or validation processes that could affect their reliability.

Modelling techniques, perhaps, are considered the major challenge being discussed today by experts including Belarusian specialists and national legislators. There are four stages in the development of financial distress measures:

- univariate analysis,
- multivariate analysis,
- probit and logit analysis, and
- advanced analytical tools.

Univariate analysis assumes "that a single variable can be used for predictive purposes" [Cook, Nelson 1988]. The univariate model as proposed by William

Beaver provided a "moderate level of predictive accuracy" [Sheppard 1994]. Univariate analysis identified factors related to financial distress; however, it did not provide a measure of the relevant risk [Stickney 1996].

In the next stage of financial distress measurement, multivariate analysis (also known as multiple discriminant analysis or MDA) attempted to "overcome the potentially conflicting indications that may result from using single variables" [Cook, Nelson 1988].

During the 1980s and 1990s, the trend has been to use probit (PR) and logit regression (LR) methods, which require less restrictive assumptions [Stickney 1996]. More recently, probit and logit analysis has been compared to more advanced analytical tools, such as partitioning algorithm, survival analysis, expert systems, neural networks, etc. Research has found that the approaches perform similarly and should be used in combination [Altman, Marco, Varetto 1994].

At the current stage of development in the era of global financial crisis has become vitally important to overcome limited predictive value of bankruptcy prediction models because they rely on time-history market data to predict a market event (default, i.e., the decline in asset values below the value of a firm's liabilities).

Ad interim, business and economic conditions change over short periods of time so the coefficients of any models should also be adjusted. This approach we need to apply to all bankruptcy prediction models. In order to form an accurate model, together with using the probability of bankruptcy is an essential statistic for valuation and other types of financial analysis, one must consider the current macroeconomic conditions, including growth rates, inflation, interest rates, and other macroeconomic information that form real macroeconomic environment.

In such circumstances "Slice-Of-Life" approach to the customization of bankruptcy models should help to overcome some limitations mentioned above. "Slice-Of-Life" approach is a realistic representation of everyday experience in a movie, play, or book advertising-copy technique where a real life problem is presented in a dramatic situation and the item being advertised becomes the solution to the problem. This advertising format is relied upon heavily by detergent manufacturers. Such a definition applies to the description of the usage of mundane realism depicting everyday experiences in art and entertainment. However, we think it also can be used for the customization of bankruptcy models and for Belarusian national bankruptcy prediction models in particular.

## 2. The ratio analysis

At an early stage of bankruptcy theory development financial ratios for bankruptcy prediction were mostly applied by [Ramser, Foster 1931; Fitzpatrick 1932; Winakor, Smith 1935]. Fitzpatrick, for example, used a univariate analysis of 13 ratios to indicate a failure. The Fitzpatrick model did not, however, show a significant relationship with failure. Later on, many studies have evaluated financial ratios as the most effective factors on bankruptcy [Pongsatat, Ramage, Lawrence 2004].

The ratio analysis approach has been defined by the Belarusian bankruptcy legislation as one of the most important ways of assessing the insolvency of national enterprises [Decree No. 1672 of 12 December 2011].

From the economic point of view, one of the problems in the regulation of issues related to bankruptcy is to assess the solvency of the debtor, which is a legal basis for the commencement of bankruptcy proceedings, as well as to determine the ability or inability to restore the solvency of the debtor. Current ratio and (or) working capital ratio are the criteria for the recognition of a company as a solvent at the end of the reporting date.

Accordingly, a company is recognized as insolvent when both current ratio and working capital ratio are below the defined limit at the end of the reporting period.

Insolvency, acquiring sustainable, is a company's insolvency over the four quarters prior to the reporting date. Further, insolvency, having sustained is a company's insolvency over the four quarters prior to the reporting date with the financial liabilities to total assets ratio ($K3$) no more than 0.85 independently of the type of economic activity (Table 1).

Thus, the present Belarusian national methodology of bankruptcy estimation is based on solvency ratio analysis measured by three indicators ($K1$, $K2$ and $K3$), which algorithms are defined by the Regulations No 140/206 of 27 December 2011 approved by the Ministry of Finance of the Republic of Belarus and the Ministry of Economy of the Republic of Belarus [Regulations No 140/206 of 27 December 2011].

**Table 1.** Solvency ratios for the bankruptcy estimation of Belarusian enterprises

| Ratio | Algorithm | Notation | Limit[1] |
|---|---|---|---|
| 1. Current Ratio, CR ($K1$) | $K1 = \frac{KA}{KO}$ | $KA$ – Current Assets (290 BS), $KO$ – Current Liabilities (690 BS) | ≥ 1.0 ÷ 1.7 |
| 2. Working Capital Ratio ($K2$) | $K2 = \frac{CK + DO - DA}{KA}$ | $CK$ – Equity (490 BS), $DO$ – Long Term Liabilities (590 BS), $DA$ – Long Term Assets (row 190 BS) | ≥ 0.05 ÷ 0.3 |
| 3. Financial Liabilities to Total Assets Ratio ($K3$) | $K3 = \frac{KO + DO}{IB}$ | $IB$ – Total of Balance (300 BS) | < 0.85 |

Source: own study on the base of [Regulations No 140/206 of 27 December 2011].

[1] Depending on the type of economic activities.

In conformity with this approach, the National Committee of Statistics and Analysis calculates annual solvency ratios of the Belarusian enterprises based on the official statistical reports (Table 2).

**Table 2.** Annual solvency ratios of the Belarusian enterprises as a percentage at the end of the year (excluding banks, budget and insurance companies, micro-entities and non-affiliated small entities)

| | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *K*1 | 120.7 | 120.6 | 123.0 | 126.4 | 133.1 | 140.7 | 147.6 | 154.3 | 175.7 | 163.6 | 167.2 | 153.4 | 133.3 | 123.9 | 114.2 |
| *K*2 | 9.8 | 6.9 | 5.1 | 4.8 | 9.5 | 13.2 | 12.4 | 12.9 | 13.8 | 2.7 | –2.6 | –6.1 | 25.0 | 19.3 | 12.4 |
| *K*3 | 14.5 | 18.3 | 20.1 | 20.3 | 20.5 | 22.9 | 23.8 | 25.8 | 27.6 | 32.3 | 32.9 | 33.8 | 35.0 | 38.3 | 42.7 |

Source: [http://www.belstat.gov.by/en/ofitsialnaya-statistika/otrasli-statistiki/finansy/annual-data/selected-indicators-of-financial-soundness-and-financial-solvency-of-organizations-of-the-republic-of-belarus/].

In addition, we should add that the same concept for bankruptcy prediction is used in the Russian Federation as we have very close economic relations and the same economic conditions.

**Table 3.** Doing Business 2013–2014 data for Belarus

| Topics | DB 2014 Rank | DB 2013 Rank | Change in Rank |
|---|---|---|---|
| Starting a Business | 15 | 20 | 5 |
| Dealing with Construction Permits | 30 | 37 | 7 |
| Getting Electricity | 168 | 175 | 7 |
| Registering Property | 3 | 3 | No change |
| Getting Credit | 109 | 105 | –4 |
| Protecting Investors | 98 | 95 | –3 |
| Paying Taxes | 133 | 135 | 2 |
| Trading Across Borders | 149 | 150 | 1 |
| Enforcing Contracts | 13 | 13 | No change |
| Resolving Insolvency | 74 | 56 | –18 |

Source: [http://www.doingbusiness.org/reforms/overview/topic/resolving-insolvency#belarus].

This methodology of bankruptcy estimation is determined by a new Law on Economic Insolvency (Bankruptcy) that was signed by the President of the Republic of Belarus on 13 July 2012 (hereinafter referred to as the Bankruptcy Law 2012) and has been put in force on 25 January 2013.

The Bankruptcy Law 2012, consisting of 20 chapters and 242 articles, accumulates all changes in national bankruptcy (insolvency) legislation of the Republic of Belarus have been made during the past years, corresponds to the current stage of economic development of the Republic of Belarus and takes into consideration the positive practice of its application since 1991, when the base of the modern system of bankruptcy institutions in Belarus was established by acceptance of the Law On Economic Insolvency and Bankruptcy.

In spite of all modern changes in present Belarusian bankruptcy (insolvency) legislation Republic of Belarus has improved its Doing Business 2014 rank and moved to 63$^{rd}$ place from 64$^{th}$ only, out of 189. Table 3 lists the overall "Ease of Doing Business" rank (out of 189 economies) and the rankings by each topic.

As we can see, the Belarusian level of "Resolving Insolvency" topic decreased by 18 positions. At the same time the number of Bankruptcy Cases in Belarusian Commercial Courts during last six years was continually increasing as shown in Table 4.

**Table 4.** Bankruptcy Cases in Belarusian Commercial Courts in 2010–2015

| As of | Supreme Court | Brest region | Vitebsk region | Gomel region | Grodno region | Mogilev region | Minsk region | Minsk city | Total |
|---|---|---|---|---|---|---|---|---|---|
| 01.01.2010 | 10 | 107 | 141 | 184 | 46 | 92 | 149 | 671 | 1 400 |
| 01.01.2011 | 3 | 137 | 121 | 126 | 90 | 103 | 159 | 747 | 1 486 |
| 01.01.2012 | 1 | 124 | 116 | 145 | 124 | 89 | 151 | 767 | 1 517 |
| 01.01.2013 | 1 | 123 | 111 | 146 | 73 | 97 | 179 | 827 | 1 557 |
| 01.01.2014 | 1 | 152 | 128 | 185 | 64 | 124 | 229 | 765 | 1 648 |
| 01.01.2015 | 0 | 162 | 135 | 214 | 102 | 169 | 298 | 956 | 2 036 |

Source: [http://court.by/online-help/bankr_inf/].

Taking into account these issues and other consequences of the imperfections in the Belarusian bankruptcy theory and practice, the need for their future development is becoming clear.

## 3. Statistical methods

Unlike univariate analysis, other types of financial distress measures are based on the usage of bankruptcy prediction models. There are three main types of models used in bankruptcy analysis:

- structural or parametric models,
- non-structural or nonparametric models, and
- semiparametric models.

Structural models, e.g. the discriminant analysis, logit and probit regressions, assume that the relationship between the input and output parameters can be described *a priori*. The main advantage of structural models is that they provide an intuitive picture, as well as an endogenous explanation for bankruptcy. Besides their fixed structure, these models are fully determined by a set of parameters. The solution requires the estimation of these parameters on a training set.

Although structural models provide a very clear interpretation of modelled processes, they have a rigid structure and are not flexible enough to capture information from the data. The non-structural or nonparametric models (e.g., neural networks or genetic algorithms) are more flexible in describing data. They do not impose very strict limitations on the classifier function but usually do not provide a clear interpretation either.

Between the structural and non-structural models lies the class of semiparametric models. These models, like the RiskCalc private company rating model developed by Moody's, are based on an underlying structural model but all or some predictors enter this structural model after a nonparametric transformation.

### 3.1. Discriminant bankruptcy models in Belarusian practice

Although the ratio analysis is simple and fast algorithm for bankruptcy estimation, it has many limitations: multiplicity of sets of ratios, high sensitivity to the quality of the initial data, different methodologies used in the formation of the financial statements indicators (IFRS, GAAP, national methodologies) and different assets' evaluation methods, determine the different values of financial indicators, etc.

Hence, Fisher's MDA method (1936) is still the most common and well-established method. Further, the most influential model remains Altman's 1968 *Z*-score model, the first bankruptcy classification model to apply the MDA technique. Although not as popular as regression analysis, MDA has been utilized in a variety of disciplines since its first application in the 1930s. During those earlier years, the MDA was successfully used mainly in the biological and behavioral sciences.

Prior to the development of quantitative measures of company performance and implementation of MDA, agencies were established to supply a qualitative type of information assessing the credit-worthiness of particular merchants. For instance, the forerunner of the well-known Dun & Bradstreet, Inc. (NYSE: DNB) traces its history back to 1841, with the formation of The Mercantile Agency in New York City by Lewis Tappan, later called R.G. Dun & Company. The company was formed to create a network of correspondents who would provide reliable, objective credit information. Nowadays the company maintains information on more than 220 million companies worldwide and has been listed on the Fortune 500.

One of the first classic works in the area of ratio analysis and bankruptcy classification was performed by William Beaver. Beaver found that a number of indicators could discriminate between matched samples of failed and non-failed companies for as long as five years prior to the failure. William Beaver's work, published in 1966 and 1968 (cited after [Altman 2000, p. 3]), was the first to apply a statistical method, *t*-tests to predict bankruptcy for a pair-matched sample of firms. Beaver applied this method to evaluate the importance of each of several accounting ratios based on univariate analysis, using each accounting ratio one at a time.

Altman was the first to employ the MDA, which assumed that, for two populations, the independent variables are distributed with each group according to a multivariate normal distribution with different means but equal dispersion matrices. In his model, the two groups were bankrupt and non-bankrupt companies, and the independent variables were five common financial ratios that could be obtained by publicly available financial statements. The MDA obtains a linear combination of the independent variables that maximizes the variance between the populations relative to within group variance.

Altman initially selected twenty two financial ratios on the basis of their popularity in academic literature and their potential relevancy to the bankruptcy prediction. After evaluating the discriminant powers of the variables in an iterative process, he selected the best five variables [Altman 2000, p. 9]:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5,$$

where: $X_1$ – working capital/total assets,
$X_2$ – retained earnings/total assets,
$X_3$ – earnings before interest and taxes/total assets,
$X_4$ – market value of equity/book value of total liabilities,
$X_5$ – sales/total assets.

After establishing the optimal $Z$-score cut-off for bankrupt and non-bankrupt companies, any company can be classified with fairly high accuracy by zones of discrimination:

$Z > 2.99$ – “safe” zones,

$1.81 < Z < 2.99$ –“grey” zones,

$Z < 1.81$ – “distress” zones.

Later on the $Z$-score model was adopted for private firms’ application (not publicly traded entities) [Altman 2000, p. 24], and, at last, the $Z$-score model was adapted for non-manufacturers [Altman 2000, p. 26].

Nowadays, the second generation of $Z$-score model, created by Altman, Haldeman and Narayanan in 1977, was constructed. The new model called ZETA is the 7-variable model.

In our national Belarusian practice we also have an example of MDA models. One of these models is Savitskaya’s model that was estimated using an initial sample composed of 200 Belarusian enterprises. These enterprises were all agricultural enterprises from the period between 1995 and 1998 [Savitskaya 2006]:

$$Z = 0.111X_1 + 13.239X_2 +1.676X_3 + 0.515X_4 + 3.8X_5,$$

where: $X_1$ – working capital/current assets,
$X_2$ – working capital/noncurrent assets,

$X_3$ – sales/average current assets,
$X_4$ – earnings before interest and taxes/average current assets,
$X_5$ – equity/total assets.

The above mentioned model was not adopted officially or used practically. Even for the purposes of the failure prediction of the national agricultural enterprises there were no reasons to implement it: most of them are potential bankrupts because of low efficiency of agricultural production in Belarus. So, it is interested mostly from the theoretical point of view.

### 3.2. Bankruptcy models based on logistic and probit regression analysis

A survey of the literature shows that the majority of international failure prediction studies employ the MDA, which has many disadvantages. For instance, a sample should consist of multivariate normal distributed observations with equal variance-covariance matrices, whereas the variables typically used in bankruptcy studies are not normally distributed [Eisenbeis 1977; McLeay 1986]. Secondly, the samples of failing and non-failing companies are assumed to be drawn at random from their respective populations. However, the matched pairs' technique violates this assumption. For example, matching on the basis of company size leads to too many small companies in the non-bankrupt sample, as small companies are more likely to go bankrupt than large companies. Similarly, matching on the basis of industry will lead to too many companies from recession-hit industries in the non-bankrupt sample. In addition to these two assumptions, most MDA studies have used a linear classification rule, which is only optimal if the restriction of equal group covariance matrices is satisfied. Yet, the evidence indicates that this restriction does not usually hold in bankruptcy studies [Lennox 1999].

For the above reasons, the popularity of the MDA method declined considerably after the 1980s. At the same time, new methods have emerged based on the logit and probit methods, which partially help to avoid using the above premises.

The logistic regression (or logit regression) analysis was put forth in the 1940s as an alternative to Fisher's classification method, linear discriminant analysis. Initially it was used extensively in numerous disciplines, including the medical and social science fields. Unlike the MDA, the logistic regression does not assume multivariate normality and provides several statistics that indicate the significance of each variable. It also handles relatively smaller sample sizes better than the discriminant analysis.

The logistic regression is often used in conjunction with or instead of the discriminant analysis to relax the conditions for optimality that the latter method imposes on the data. This is particularly the case when variables used to design models, such as financial ratios, exhibit characteristics that depart significantly from these conditions.

As with a discriminant function, an observation will be classified in one of two groups depending on its score.

Ohlson was the first to question the MDA model, particularly regarding the restrictive statistical requirements imposed by the model. To overcome the limitations, in 1980 Ohlson employed the logistic regression to predict a company’s failure. He used the logit model and US companies to develop an estimate of the probability of a failure for each company. He argued that this method overcomes some of the downsides of the MDA, which requires the assumption of a normal distribution of predictors and suffers from the arbitrary nature of identifying non-failed “matching” companies [Wang, Campbell 2010].

Ohlson selected nine independent variables that he thought should be helpful in predicting bankruptcy, but provided no theoretical justification for the selection. Ohlson then selected industrial companies traded in 1970–1976 on the US stock exchange for at least three years. He ended up with 105 failed companies and 2058 non-failed companies. Three models were estimated: the first to predict a failure within one year, the second to predict a failure within two years and the third to predict a failure in one or two years. He then used a logistic function to predict the probability of a failure for the companies using each model [Wikil Kwak, Xiaoyan Cheng, Jinlan Ni 2012]:

$$Z = -1.32 - 0.407X_1 - 6.03X_2 - 1.43X_3 - 0.0757X_4 - 2.37X_5 - 1.83X_6 - 0.285X_7 - 1.72X_8 - 0.521X_9,$$

where: $X_1$ – log (total assets/GNP price level index),
$X_2$ – total liabilities/total assets,
$X_3$ – working capital/total assets,
$X_4$ – total current liabilities/total current assets,
$X_5$ – one if total liabilities exceeds total assets, zero otherwise,
$X_6$ – net income/total assets,
$X_7$ – funds from operations/total liabilities,
$X_8$ – one if net income was negative for the last two years, zero otherwise,
$X_9$ – (net income – lag (net income))/|net income| + |lag (net income)|.

In the Belarusian national practice, we also have an example of the creation of logit regression model. The latest bankruptcy model by Savitskaya is a logit regression model, which was tested on data of 2,160 Belarusian agricultural enterprises of 2003 [Savitskaya 2007, p. 658, 659]:

$$Z = 1 - 0.98X_1 - 1.8X_2 - 1.836X_3 - 0.28X_4,$$

where: $X_1$ – working capital/current assets,
$X_2$ – working capital/average current assets,
$X_3$ – equity/total assets,
$X_4$ – equity/average current assets.

Interpretation of the model: $Z \leq 0$ – stable financial situation; $Z \geq 1$ – unstable financial situation, the probability of bankruptcy is high.

Values between 0 and 1 show the level or degree of financial stability.

Another commonly used approach is the probit analysis which is very similar to the logistic regression. The main difference between them is that the probit function assumes a cumulative standard normal distribution, whereas the logistic function assumes a binomial distribution. Both methods employ the maximum likelihood estimation and should produce very similar results, especially with large sample sizes.

As such, the probit analysis is a type of the regression used to analyze binomial response variables. The idea of the probit analysis was originally published in Science by Chester Ittner Bliss in 1934 [Bliss 1934, p. 38, 39]. In 1947, a professor of statistics at the University of Edinburgh by the name of David Finney took Bliss' idea and wrote a book called *Probit Analysis* [Finney 1947]. Today, the probit analysis is still the preferred statistical method in understanding dose-response relationships.

There is no example of probit models developed in our Belarusian practice.

### 3.3. An extension of the bankruptcy models

All above mentioned statistical methods have high accuracy of prediction and could easily interpret the results of the analysis. The MDA, LR and PR parametric models used in bankruptcy analysis are widely discussed among specialists. Countless academic investigations are devoted to applications, comparisons or reevaluations of the above mentioned models. Table 5 presents the main financial failure models, the generalization of which ability was studied in the financial literature. It also shows the correct classification rates of sound and failed companies that are achieved with each model, including the sample size used to test model accuracy, companies' sectors of operations, and the period of time during which data were collected.

**Table 5.** Examples of the main parametric models used in bankruptcy analysis

| Models | Model accuracy (%) | | | Sample size, units | | Methods/factors | Sectors | Period |
|---|---|---|---|---|---|---|---|---|
| | healthy | failed | total | healthy | failed | | | |
| Altman, 1968 | 97.0 | 93.9 | 95.5 | 33 | 33 | MDA/5 | Manufact. | 1946–<br>–1965 |
| Deakin, 1977 | 98.0 | 89.0 | 94.4 | 86 | 57 | MDA/14 | Various | 1964–<br>–1971 |
| Ohlson, 1980 | Not mentioned | Not mentioned | 96.1 | 2,058 | 105 | LR/9 | Industry | 1970–<br>–1976 |
| Altman&Lavallee, 1981 | 81.5 | 85.2 | 83.3 | 27 | 27 | MDA/5 | Various | 1970–<br>–1979 |
| Taffler, 1983 | 95.7 | 100.0 | 97.8 | 46 | 46 | MDA/4 | Manufact. | 1969–<br>–1976 |
| Zmijewski, 1984 | 99.5 | 62.5 | 97.7 | 800 | 41 | PR/6 | Industry | 1972–<br>–1978 |
| Platt et al., 1994 | 95.5 | 94.3 | 95.2 | 89 | 35 | LR/6 | Gas&oil | 1982–<br>–1988 |

Source: own study on the base of [Bellovary, Giacomino, Akers 2007].

Statistical models for corporate default prediction are of practical importance but all of them have certain limitations:

- the forecast accuracy depends on the selection of the most descriptive variables – financial ratios, and
- the reduction of statistical reliability prediction for distant future.

Therefore, there are other complex techniques for bankruptcy prediction based on non-parametric algorithms. Among other statistical methods applied to bankruptcy analysis are the gambler's ruin model [Wilcox 1971], option pricing theory [Black, Scholes 1973; Merton 1973], recursive partitioning [Frydman, Altman, Kao 1985], neural networks [Tam and Kiang 1992] and rough sets [Dimitras et al. 1999], to name a few. Mostly, the creation and development of these models was possible due to modern electronic technologies that have facilitated the use of Big Data and mathematical algorithms to predict future financial problems. In 1956, engineer Bill Fair and mathematician Earl Isaac found FICO (NYSE: FICO) on the principle that data, used intelligently, can improve business decisions. Nowadays FICO is a leading analytics software company, helping businesses in more than 80 countries make better decisions that drive higher levels of growth, profitability and customer satisfaction [FICO 2014].

In recent years, the area of research has shifted towards non-structural and semi-parametric models since they are more flexible and better suited for practical purposes than purely structural ones. For example, corporate bond ratings published regularly by rating agencies such as Moody's (NYSE: MCO) or Standard & Poor's (NYSE: S&P) strictly correspond to company default probabilities estimated to a great extent statistically. Moody's RiskCalc model is basically a probit regression estimation of the cumulative default probability over a number of years using a linear combination of non-parametrically transformed predictors [Falkenstein 2000].

## 4. Samples and methods

In this section we present the methodological concept for bankruptcy prediction in accordance with "Slice-Of-Life" customization approach and taking into account the different characteristics and specificities of local legislation. We consider this concept, based on national circumstances and specifics, can be used to improve the temporal stability of the accuracy of a financial failure models for Belarusian companies.

### 4.1. Data collection

We consider that it is necessary to choose companies required by law to file their annual reports and select companies in the same activity and of the same size to control for size and sector effects. We need to select income statement and balance sheet data, which have been the main sources of information for failure models since

[Altman 1968]. This set of data is used to calculate ratios, and these ratios should be subsequently used to design models.

As for Belarus, this type of information is collected by The National Statistical Committee of the Republic of Belarus. Unfortunately, we do not have another source of information about national companies as in France, where the database "Diane" provides financial data on more than one million French firms, or in Pakistan – databases of Karachi Stock Exchange (KSE) and Securities and Exchange Commission of Pakistan (SECP).

The peculiarity of The National Statistical Committee of the Republic of Belarus database consists in the fact that there are no indications if a company has been declared bankrupt. So, we need to select bankrupts from bankrupt's database of The Belarusian Supreme Court.

### 4.2. Covered periods

We should take into consideration that the most forecasting models rely on the assumption that the relationship between the dependent variable (i.e. failure probability) and all independent variables is stable over time [Zavgren 1983]. Yet, there is evidence that this stability is highly questionable [Charitou, Neophytou, Charalambous 2004] and that the true forecasts of a model may be unreliable if this assumption is incorrect [Mensah 1984]. Indeed, all models are sensitive to some parameters that describe macro-economic environments, and any change may influence their accuracy [Mensah 1984; Platt, Platt, Pedersen 1994]. In practice, then, models need to be re-estimated frequently to counterbalance the effects of such phenomena [Grice, Ingram 2001].

In their attempts to overcome or reduce model instability, some authors have suggested taking macro-economic factors responsible for this phenomenon into account [Mensah 1984; Platt, Platt, Pedersen 1994; Grice, Dugan 2003; Pompe, Bilderbeek 2005]. Mensah [1984], for example, developed four models using samples from the 1972–1973, 1974–1975, 1976–1977, and 1978–1980 periods, each period representing a different economic environment. He found that the accuracy and structure of the models changed over the four time periods. Given Mensah's findings that models can change in such short subsequent time periods as two years, we would expect dramatic differences from Altman's model which was derived from a sample that included companies from up to 50 years ago.

They also showed that by using some economic indicators (growth rate, interest rate, inflation rate, oil prices, etc.) to weight traditional explanatory variables, it became possible to stabilize results. However, this solution is applicable only *a posteriori* when one knows what the nature of the macro-economic changes was and how to mitigate their effects. *A priori*, no one knows what should be done. Other authors demonstrated that one could take advantage of sampling variations caused by changes in the economic environment and that one might improve model accuracy in the short term by using measures representing variation of ratios over time (standard deviation, coefficient of variation). However, the stability of model accuracy in the long term was not studied by Dambolena and Khoury [1980] and Betts and Belhoul [1987].

To collect data from different economic periods, changes in the national economic situation should be analysed in order to define recessionary and downturn periods. The changes in both gross domestic product (GDP) and numbers of business failure during recessionary and downturn periods should clearly illustrate how downturns were preceded and followed by periods of growth, some more pronounced than others.

There is a sense to choose three periods; hence three sets of models would be designed. The first calculates with data collected from $t - 1$ period and will be tested with data from $t_0$ and $t_1$ (estimation and test over a period of growth). The second set calculates with data collected from $t_1$, and will be tested with data from $t_2$ and $t_3$ (estimation over a period of growth, and test over a period of downturn). Finally, the third set designs using data collected from $t_3$, then will be tested with data from $t_4$ and $t_5$ (estimation over a period of downturn and test over a period of growth).

We need to analyse model performance using data collected over a downturn period, either for estimation and test purposes. This would have required the downturn period to last at least three years: one year to collect data for estimation tasks, and the following two years to collect data for prediction tasks.

### 4.3. Sample selection

Another major concern is the time period from which to select the companies for the estimation sample. As shown by a number of specialists, Altman's 1968 model, which was based on a broad selection of companies over a 20-year period (Table 5), does not retain its effectiveness over time and across different industries. Altman himself admitted that "a 20-years period is not the best choice since average ratios do shift over time. Ideally, we would prefer to examine a list of ratios in time period in order to make predictions about other firms in the following period (t+1). Unfortunately, it was not possible to do this because of data limitations" [Altman 2000, p. 7].

In addition, the MDA, LR and PR models are traditionally mono-period models relying on a snapshot of a company's financial profile taken at a particular point in time.

As business and economic conditions change over short periods of time, so the coefficients of any models should also be adjusted. We need to apply this approach to all bankruptcy prediction models. In order to form an accurate model, together with using of probability of bankruptcy is an essential statistic for valuation and other types of financial analysis, one must consider the current macroeconomic conditions, including growth rates, inflation, interest rates, and other macroeconomic information that forms real macroeconomic environment.

Moreover, the estimation sample should include companies from the same industry and comparable macroeconomic environments resembling the current environment. Such "Slice-Of-Life" customization should be implemented into each bankruptcy model because any change in environmental conditions may greatly reduce a model's accuracy. It has been demonstrated that variations in economic cycles (alternating periods of economic growth and downturn or recession) and, to a lesser extent, changes that companies may face in terms of interest rates, credit policy, tax rates, competitive structures, technological cycles and institutional environment, have an influence on financial ratio distributions and on the boundary between failed and non-failed companies. This influence may result in models having poor prediction reliability. Of course, other parameters may play a role, especially when models are used with data that are outside their scope of validity [Du Jardin, Severin 2012].

So, according to the seven periods ($t_{-1} \div t_5$) seven samples should be examined. Balance sheets and income statements should be selected from seven consecutive years and firms be chosen at random from among bankrupt and non-bankrupt in the database.

### 4.4. Variable selection

Choosing a subset of variables from an initial set is essential to the prudence of a model, but also essential for its accuracy and generalization ability. This task is difficult because the evaluation criterion used to select variables is often non--monotone: only an exhaustive search of all possible combinations will lead to the best subsets.

But the resulting combinatorial explosion often makes these searches impossible. It is for that reason that most methods rely on heuristic procedures that carry out a limited search in the space of all combinations. These procedures are made up of three basic elements: a search method that explores a subspace of all possible combinations and generates a set of candidate solutions; an evaluation criterion to evaluate the subset under examination and select the best ones; a stopping criterion to decide when to stop the search method.

### 4.5. Modelling methods

As has been pointed out above, traditional methods such as MDA, LR and PR are mono-period models which rely on a snapshot of a company's financial profile taken at a particular point in time. So, models rely on data that measure changes to a firm's financial health over a number of consecutive years should be also used.

## 5. Conclusions

Meanwhile, the situation in bankruptcy analysis has changed dramatically. Larger data sets with the median number of failing companies exceeding 1000 have become available. 20 years ago the median was around 40 companies and statistically significant inferences could not often be reached. The spread of computer technologies and advances in statistical learning techniques have allowed the identification of more complex data structures. Basic methods are no longer adequate for analyzing expanded data sets. A demand for advanced methods of controlling and measuring default risks has rapidly increased, in anticipation of the New Basel Capital Accord adoption.

In such conditions, we consider that:

1. It is impractical and unrealistic to attempt to create an absolutely stable bankruptcy model by including more and more macro-economic factors into the bankruptcy model.

2. It is necessary to create an automatic “mechanism” making “Slice-Of-Life” customization for any bankruptcy model. Maybe, it would make sense to incorporate such an algorithm of customization into the national bankruptcy (insolvency) legislation. This should provide the directions for the national ranking growth of Resolving Insolvency methodology of Doing Business report of the World Bank and the International Monetary Fund [World Bank Group].

3. Such “Slice-Of-Life” customization should include not only new set of bankruptcy models’ parameters but also certain new economic indicators taking into consideration economic environment and recessionary and downturn periods.

4. Except for issues encountered when deciding how to form the prediction model, the ideal process would include a large sample size of both bankrupt and non-bankrupt companies chosen randomly from the overall population of companies.

5. The ratio of bankrupt to non-bankrupt companies in the sample should reflect the ratio observed in the overall population. This would eliminate errors resulting from the prior probabilities adjustment we employed for functions.

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## PODEJŚCIE „SLICE-OF-LIFE" DO DOSTOSOWANIA MODELI UPADŁOŚCIOWYCH NA BIAŁORUSI

**Streszczenie:** Po ostatnim kryzysie finansowym rozpoczętym w 2007 r. przewidywanie bankructwa stało się poważnym problemem i, w rezultacie, dziś mamy wiele różnych podejść do modeli przewidywania upadłości, ale wszystkie z nich pełne ograniczeń. W związku z tym (i nie tylko), ani model Altmana, ani nowsze modele (algorytm podziału, analiza przeżycia, systemy eksperckie, sieci neuronowe itd.) nie są zalecane do użytku w firmach sektora finansowego. W celu przezwyciężenia tych ograniczeń w nowoczesnej praktyce białoruskiej cierpiącej z powodu braku rozwiniętej teorii upadłości nie wystarczy przenieść praktykę zagraniczną automatycznie do rzeczywistości ewoluujących warunków gospodarczych Bałorusi. Autor próbuje pokazać, jak podejście „Slice-Of-Life", oparte na warunkach i priorytetach krajowych, może być wykorzystane do poprawy stabilności czasowej dokładności modeli niewydolności finansowej dla białoruskich przedsiębiorstw.

**Słowa kluczowe:** przewidywanie upadłości, dostosowanie modeli upadłościowych, MDA, analiza logitowa i probitowa.